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Air-Fuel Boiler Consumption Analysis Based On Artificial Neural Networks

(Tobruk Distillation Plant as case study)

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***Abstract*— a boiler is the main component. The distillation plant in Tobruk employs a water tube boiler to generate 90 t/h with 30 bar. The fundamental function in boiler production is air/fuel ratio consumption, which has a significant impact on boiler production and boiler age. Deviations in airflow (AF) consumption, fuel flow (FF) consumption, and rising flue gas temperatures (FGT) will lead to tubes bending and boiler explosion; therefore, forecasting air and fuel consumption will assist the air fuel ratio controller to reduce operation casts and save the boiler. Two objectives of this study have been achieved, the first is to find out the relationship's curves consumption for air, fuel and flue gas temperature and consumption deviation using curve fitting equations. The second part is to develop a flue gas temperature (FGT) prediction by using an Artificial Neural Network (ANN). Six years of boiler data have been collected, eliminated, and classified. The curve-fitting tool and ANN are applied to figure out the air and fuel consumption. Equations for three cases are extracted from curves. ANN is built with validation of 0.9999, and the test value is 0.9998.**

Keywords—Airflow, Fuel flow, Flue gas temperature, ANN, Curve fitting, Boiler

I. INTRODUCTION

Water tube boilers are commonly utilized in industrial establishments. It is utilized in steam power plants, desalination plants, and refineries, among other things. Heavy oil is used in boilers because it is less expensive than other types. The optimization of fuel in the boiler is significant for environmental protection and energy consumption [1]. Optimization of the composition of the fuel mixture amongst the three gas types (coke, natural, and blast) is offered for use as a workspace in power plant dispatching services [2]. The Emission NOx model of a coal-fired boiler with a Different Evaluation (DE) optimized Least Square Support Vector Machine (LSSVM) is presented, and the model shows promising results in NOx emission prediction [3]. Predicting model of the boiler drum has been built to predict the drum level and feed architecture is used for the static model and ANN for the dynamic model [4]. Deep Neural Network (DNN) is applied to predict the boiler's SO_2 for a better understanding of SO_2 distribution. DNN gave the best prediction and more accuracy than the other methods. The error is reduced from 36.66% to 76.38%. [5]. Comparing between tools, an accurate online support vector regression (AOSVR) and SVR and ANN for the Nitrogen Oxide emission model. NOx can be estimated by the model and meet the demand as well. the results illustrate the model can predict and learn under varying conditions [6]. The combustion of a 600 MW coal-fired boiler is monitored and optimized using LabVIEW. Open Platform Communication (OPC) and Artificial Neural Networks (ANN) are used to visualize and predict boiler parameters. The results demonstrate that the fly ash and nitrogen oxide (NOx) content were reduced by 20% and 23%, respectively, and that the boiler efficiency was enhanced [7]. Boiler efficiency has been improved, and the air/fuel has been premixed by adding the air/fuel preheater to the boiler. ASPEN HYSYS has been applied and the results were boiler efficiency increased by 4% and fuel demand is decreased to 4.92% [8].

In this paper, real data from the water tube boiler is used. it over six years. It is extracted from daily sheets and then collected, processed, and classified. Air and fuel consumption and flue gas temperature are analysed and applied to intelligent techniques. The objectives of this paper are to determine air and fuel consumption deviations and to predict air and fuel consumption. The curve-fitting tool is used to determine the deviation of air and fuel consumption, and the artificial neural network (ANN) is used to build an air and fuel, predictive model. This paper is organized into several sections. The first is an introduction, and the second section is a problem statement and description to describe the problem. Theoretical ANN the application with Curve fitting and ANN are illustrated in sections three, four, and five. Section six is the results and discussion then the conclusion.

II. Problem Statement and Descriptions

Tobruk's desalination plant produces 4000 m3/day, it has three water tube boilers. The boilers run on crude oil. When crude oil is burned, it produces gases and ashes (fly ash and bottom ash), and that ash makes coating layers on the tubes' surfaces in the boiler. The heat transfer is reduced because of the coating layers, therefore decreasing the boiler's efficiency and making the boiler unable to reach the desired load. This issue raises the air and fuel demand, which messes up all boiler parameters, especially the flue gas temperature. That problem occurred during the course of six years of operation. The issue can be stated as NOx emissions and boiler efficiency reduction, which are represented by rising flue gas temperatures and crude oil fuel demand. A boiler has three inputs: Air Flow (AF), Fuel Flow (FF), and Feed Water (FW), and two outputs: Steam Flow (SF) and Flue Gas Temperature (FGT). During the six years of operation, the boiler parameters AF, FF, FW, SF, and FGT have been increased; table 1 shows the varying range of boiler input and output parameters. The increased amount of air and fuel causes overheating on the boiler's tubes, resulting in tube bending or explosions. Finding out the excess amount of air and fuel might help to manage the air-fuel ratio.

TABLE 1. VARYING RANGE OF BOILER PARAMETERS

Boiler Parameters	Min. quantities	Max. quantities
AF	63899 t/h	68180
FF	5452 t/h	5815 t/h
FW	96 t/h	99 t/h
SF	95 t/h	100 t/h
FT	158 C^o	200 C^o

The real-time boiler data is organized and classified into three categories. The first category represents when the boiler was brand new, the second category represents when the boiler parameters have a little deviation, and the third category represents when the boiler parameters have more deviation. The objective of this study is to how to manage that deviation using artificial intelligent techniques.

III. ANN METHODS

Intelligent analysis and prediction are important techniques for scientific research. ANN, Fuzzy Logic (FL), and Fuzzy Neural Networks (FNN) can be considered famous intelligent techniques and applications for researchers. An Artificial Neuron is essentially a technological approach to biological neurons. It has a mathematical approach with numerous inputs and just one output. ANN is made up of many simple processes that are linked together [9]. The back-propagation (BP) network of ANN is commonly used for research. Figure 1 illustrates the feedforward network, which consists of a hidden layer, an input layer, and an output layer. Fig. 1 illustrates the FNN structure [10].

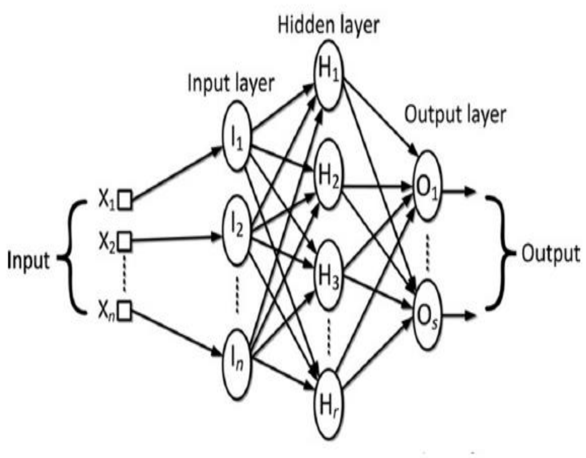

Fig. 1. Simple FNN structure [10].

ANN has several transfer functions that can be used. The sigmoid function is commonly used, and it has. Other functions in MATLAB, the tansig and logsig functions are available, they can be used according to the system [11].

IV. FUEL AIR CONSUMPTION DEVIATION

six years of real data covering about 600 days of boiler operation have been collected. The maintenance days, trip days, unstable operation days have been eliminated. Table 2 shows the air and fuel consumption in the Tobruk desalination plant. The data is classified into three categories: the designed parameters category, or case 0 which represents the first two years of operation; this category is considered as brand new boiler operation; case 1, which represents the four years of operation; and case 2 which represents the six years of operation. The data is classified based on the increasing of the flue gas temperature, which has range from 159 C^o to 200 C^o over six years of operation. This temperature is a function of air and fuel consumption. The average of the parameters has been taken in this study. The curve-fitting application in MATLAB is applied to extract the suitable relationship between air, fuel and flue gas temperature. Table 2 and 3 illustrates the processed data, that deviations in air and fuel consumption lead to deviations in flue gas temperature and boiler production. The difference between case 0 and other cases is defined as a deviation from standard boiler consumption parameters.

TABLE 2. SHOWS CASE 0 AND CASE 1

Case 0			Case 1		
FF Kg/h	AF m^3/h	FGT C^o	FF Kg/h	AF m^3/h	FGT C^o
5469	64098	*159*	5534	64940	*170*
5472	64135	*160*	5576	64960	*171*
5475	64176	*161*	5588	64980	*172*
5483	64200	*162*	5597	64999	*178*
5496	64396	*163*	5597	65277	*179*
5500	64675	*164*	5613	65537	*180*
5519	64782	*165*	5633	65677	*181*
5525	64799	*168*	5646	65709	*182*
5530	64840	*169*	5651	65854	*183*
			5667	65883	*184*
			5685	65890	*185*
			5697	65855	*186*
			5705	65875	*187*
			5723	65895	*188*
			5742	66112	*189*
			5756	66146	*190*

TABLE 3 SHOWS CASE 0 AND CASE 2

Case 0			Case 2		
FF Kg/h	AF m^3/h	FGT C^o	FF Kg/h	AF m^3/h	FGT C^o
5469	64098	*159*	5763	66235	*191*
5472	64135	*160*	5777	66288	*192*
5475	64176	*161*	5782	66475	*193*
5483	64200	*162*	5795	66501	*194*
5496	64396	*163*	5810	66579	*195*
5500	64675	*164*	5815	66776	*196*
5519	64782	*165*	5823	66919	*197*
5525	64799	*168*	5837	67236	*198*
5530	64840	*169*	5841	67463	*199*
			5852	67897	*200*

According to the extracted data, the deviations in air and fuel consumption can be seen in table 2 and 3, it is clear that the boiler began with fuel at 5469 kg/h, air at 64098 m3/h, and 159 c^o, after six years, the air/fuel flow increased gradually up to 5852 kg/h, 67897 m3/h, and 200 c^o. The curves in Fig. 2 and 3 (case 0 and case 2) illustrate the relationship between air and fuel consumption over six years, and the curves in Fig. 4 and 5 show the relationship between flow gas temperature and fuel flow over six years. The slopes of the curves illustrate the gradual increase in FF, AF, and FGT.

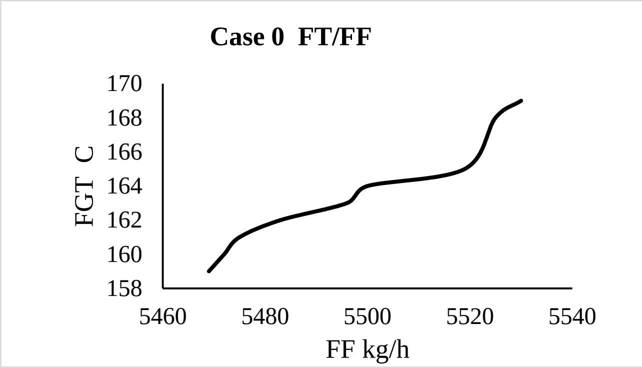

Fig. 2. Relationship between AF and FF case 1

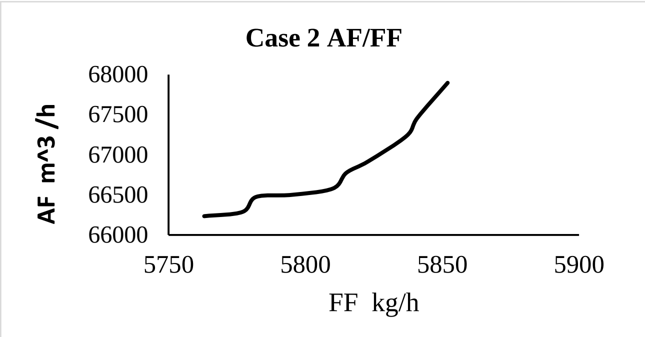

Fig. 3. Relationship between AF and FF case 2

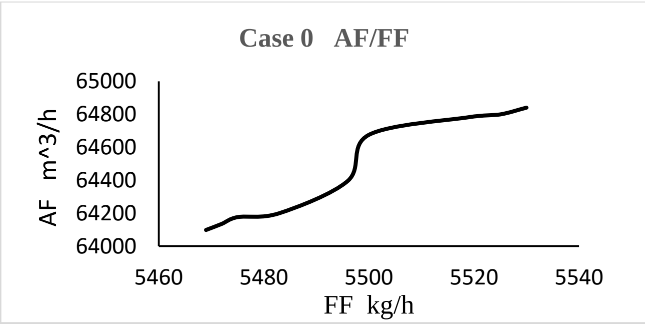

Fig. 4. Relationship between FT and FF case 1

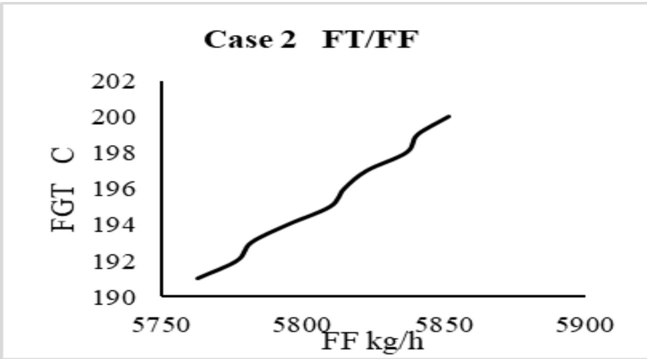

Fig. 5. Relationship between FT and FF case 2

The curve fitting tool generates three equations based on the boiler data. Based on the curves which are most of them quit linear so the equations (1), (2), and (3) might be represents the real data, where y (0) represents case 0, y (1) represents case 1, and y (2) represents case 2.

$$y(0) = 167.7 + 27x(1) - 21x(2) - 14.5x(1)^2 + 19x(1)x(2) - 8.55x(2)^2 - 57.3x(1)^3 + 75.3x(1)^2x(2) - 20.8x(1)x(2)^2 \quad (1)$$

$$y(1) = 183 - 4.3x(1) + 7x(2) + 1.8\,x(2)^2 - 2.1x(1)x(2) + 5.1x(1)^3 - 3x(1)^2\,x(2) \quad (2)$$

$$y(2) = 196 + 4x(1) + 0.37x(2) + 2.3x(1)^2 - 3.26x(1)x(2) + 0.543x(1)^3 - 1.5x(1)^2x(2) \quad (3)$$

Where y (0), y (1), and y (2) represent the flow gas temperature for case (0), case (1), and case (2) respectively. *x* (1) represents the air flow and *x* (2) represents fuel flow. These equations can be used for predicting the flow gas temperature, air flow, and fuel flow.

The air and fuel deviation of the boiler have big impacts on the FGT. they can be seen in Tables 4 and 5. The fuel flow deviations are between 0 to 42 kg/h and from 0 to 278 m^3/h. that deviations have accord for 24 months. The averages of case 0 for fuel, air, and flue gas temperatures are taken as references for other cases; the averages are 5496 kg/h, 64455 m^3/h, and 164 c^o. based on case 0 are reference values, therefore the difference values between the cases 1 and 2 and the reference values are calculated to obtain the deviations for all cases. Fig. 6–9 illustrate the slope deviations for cases 1 and 2 based on case 0, which show a gradual increase in fuel and air quantities over six years of boiler operation and consequently an increase in flue gas temperature as well. it is clear the fuel deviations go linear for case 1 and case 2. Table 6 illustrates the excess quantities of air and fuel per month. These quantities are calculated based on the standard reading in case 0.

TABLE 4. DEVIATIONS OF CASE 1

Average of Case 0			**Deviations of Case 1**		
FF Kg/h	AF m^3/h	FGT C^o	FF Kg/h	AF m^3/h	FGT C^o
5496	64455	164	38	485	6
			80	505	7
			92	525	8
			101	544	14
			101	822	15
			117	1082	16
			137	1222	17
			150	1254	18
			155	1399	19
			171	1428	20
			189	1435	21
			201	1400	22
			209	1420	23
			227	1440	24
			246	1657	25
			260	1691	26

TABLE 5. DEVIATIONS OF CASE 2

Average of Case 0			**Deviations Case 2**		
FF Kg/h	AF m^3/h	FGT C^o	FF Kg/h	AF m^3/h	FGT C^o
5496	64455	164	267	1780	27
			281	1833	28
			286	2020	29
			299	2046	30
			314	2124	31
			319	2321	32
			327	2464	33
			341	2781	34
			345	3008	35
			356	3442	36

TABLE 6. AIR-FUEL EXCESS CONSUMPTION VALUES

Increasing quantity Case 1			**Increasing quantity Case 2**		
FF Kg/h	AF m^3/h	Time/ Month	FF Kg/h	AF m^3/h	Time/ Month
42	20	3	14	53	4.8
12	20	4.5	5	187	7.2
9	19	6	13	26	9.6
0	278	7.5	15	78	12
16	260	9	5	197	14.4
20	140	10.5	8	143	16.8
13	32	12	14	317	19.2
5	145	13.5	4	227	21.6
16	29	15	11	434	24
18	7	16.5			
12	0	18			
8	20	19.5			
18	20	21			
19	217	22.5			
14	34	24			

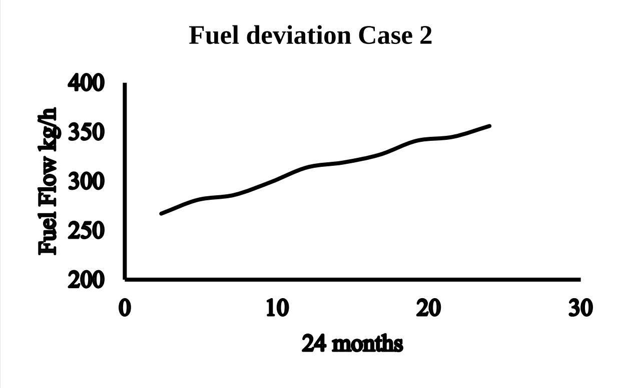

Fig. 6 Fuel flow deviations curve case 1

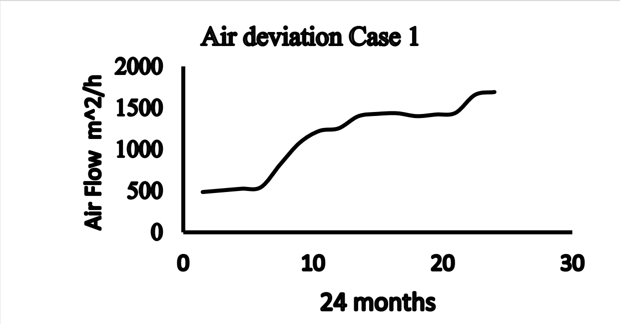

Fig. 7.AF Deviation curve case 1

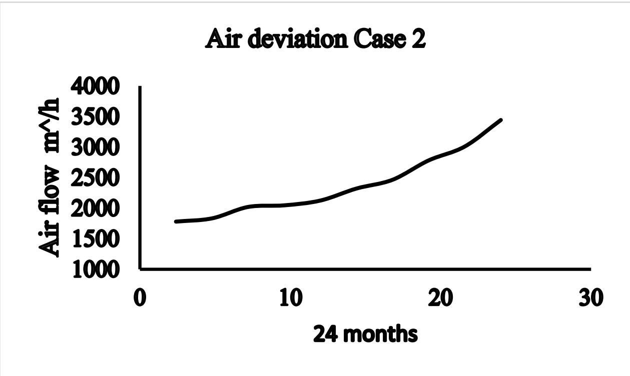

Fig. 8 fuel flow deviation curve case 2

V. Air-Fuel Prediction model

One of the intelligent prediction techniques is an ANN tool. The ANN is applied to real boiler data. In Table 4, the data is organized from lowest to highest values and then divided into two parts, inputs with the target part and sample part. Fig. 10 illustrates the network structure that is used in this paper. The inputs to the ANN are airflow and fuel flow, and the output is flue gas temperature. As Kwon pointed out, rising flue gas temperatures indicate increased air and fuel consumption; thus, the AF and FF were used as inputs and the FT as output. Fig. 11 shows the results of network training. The training shows a validation of 0.9999 and a testing result of 0.9998.

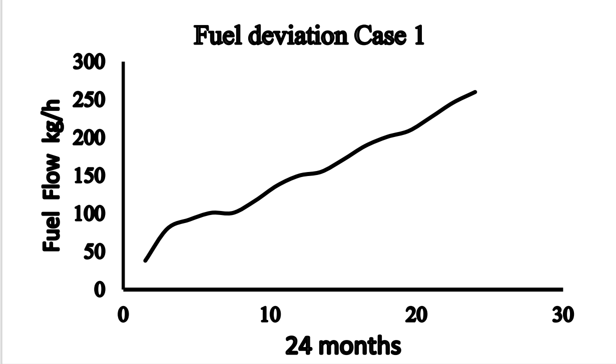

Fig. 9 Air flow deviation curve case 2

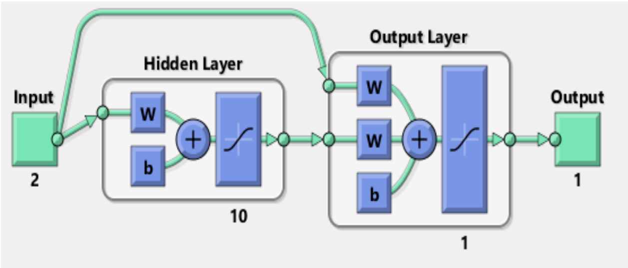

Fig. 10. The network structure of Air-Fuel

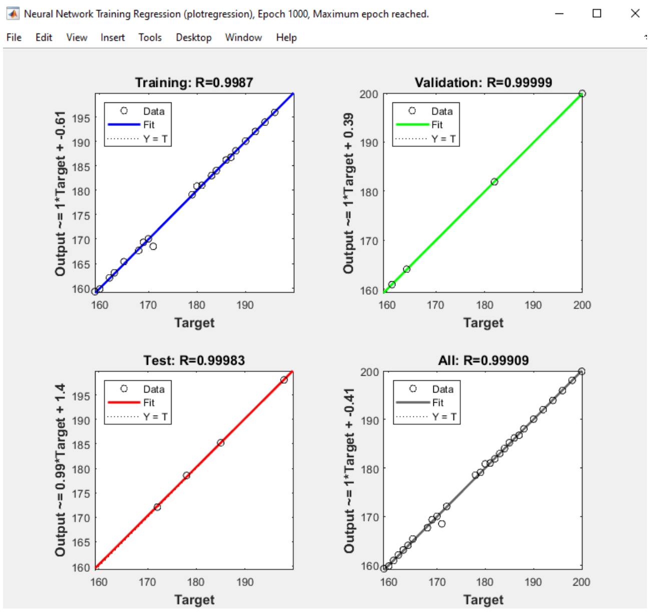

Fig. 11. Training, validation, and testing

VI. Results and Discussion

Two tools have been applied to the boiler data for air/fuel prediction: the curve-fitting tool and the ANN technique. Curve fitting was used twice: once to extract the equivalent equations of air and fuel consumption based on cases 0, 1, and 2, and again to extract the equivalent equations of air and fuel consumption deviations based on the differences between case 0 and the other cases. An ANN tool has been applied to build the prediction model.

Equations (1), (2), and (3) depict the increase in air flow and fuel flow over the six-year period. In Figures 4 and 5, there are strong relationships between gas flow temperature and fuel flow; the relationship appears to be linear, so it could be used to predict air and fuel consumption. In the comparison between cases 0 and 2 in AF and FF, the curve in figure 3 shows consuming small quantities of air with big quantities of fuel, and the temperature is increased linearly in figure 5.

Figures 6–9 show the deviation or increase in air and fuel consumption during the past six years. Figures 6 and 8 show the fuel increase in cases 1 and 2, and the slops have different values: slop 1 in case 1 starts from 50 kg/h to 260 kg/h, and slop 2 in case 2 starts from 281 kg/h to 356 kg/h, with the note that slop 2 is closer to the horizontal line. The fuel deviations are quite linear, but the air deviation is concave. By using the curve fitting tool for cases 1 and 2 to obtain the deviation equations based on AF and FF, equations 4 and 5 represent the relationships between AF and FF for cases 1 and 2, respectively.

$$f(T_{case1}) = 12.97 + 0.7AF + 6.2FF - 1.54AF^2 + 1.41AF.FF \quad (4)$$

$$f(T_{case2}) = 14.2 + 4.4AF + 3.3FF - 0.2AF^2 - 0.96AF.FF \quad (5)$$

ANN is applied to obtain the predicted FGT, which is an indicator of air and fuel consumption. Figures 11 and 12 illustrate the results of the airflow, fuel flow, and flue gas temperature. The validation of the system is 0.9999. Figure 12 illustrates the air/fuel consumption error and air/fuel sample. These are indicators that the ANN system is working properly.

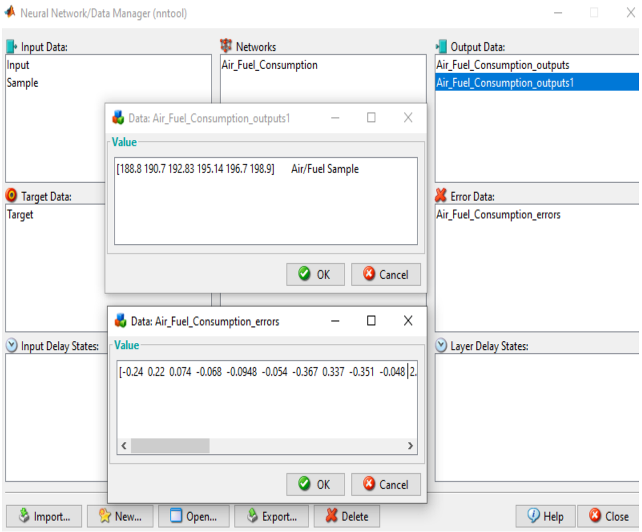

Fig. 12. Air/fuel consumption errors and sample ANN results

VII. CONCLUSION

An analysis and prediction model using the curve-fitting tool and ANN is presented; both methods are used to figure out air and fuel consumption. The deviation consumption equations (4) and (5) are extracted from curves; they can be used for predicting AF, FF, or FGT. On the other hand, an ANN model has been presented to predict FGT based on AF and FF. An accurate estimate of air and fuel consumption can be predicted by FGT because the ANN was built with an accurate validation of 0.9999 and a test of 0.9998 with very small errors. The equations and ANN model are suitable for water tube boiler calculations and predicting boiler parameters. Further work, such as boiler operation costs, can be calculated based on airflow and fuel flow.

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