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NEURAL NETWORK BASED MODEL OF AN INDUSTRIAL OIL-FIRED BOILER SYSTEM

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ABSTRACT
In this study, an oil-fired boiler system is modeled as a multivariable plant with two inputs (feed water rate and oil-fired flow rate) and two outputs (steam temperature and pressure). The plant parameters are modeled using artificial neural network, based on experimental data collected directly from the physical plant. A two-layer feed-forward neural network with Hyperbolic tangent sigmoid transfer function (Tansigmoid) and linear output neurons (Purelin) are used at the hidden and output layer respectively to fit the neural network model. The neural network model is then trained off-line with Levenberg-Marquardt Back Propagation Algorithm (trainlm). The neural network model when subjected to test, using the validation input data; shows that the simulated model outputs for both temperature and pressure agree closely with the actual plant outputs, with regression value of 0.97. Furthermore, Proportional Integral Derivative (PID) Controller is used to control the neural network model. Simulation studies results indicate the effectiveness of the developed technique.

Keywords: *Boiler Modeling, Neural Network Model, Regression, Mean Square Error, PID controller.*

1. INTRODUCTION
Neural networks have been applied successfully in the modeling and control of dynamic systems. The universal approximation capabilities of the multilayer perceptron make it a popular choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers [1, 2, 3]. The feed-forward Neural Network is another paradigm that is very common, with only a unidirectional (i.e. from left to right) signal flow. It is composed of hierarchy of processing units, organized in a series of two or more mutually exclusive sets of layers (no feedback within layers or to layers preceding that under consideration) [4, 5, 6]. The feed forward Neural Networks are organized in layers: Input Layer, Hidden Layer and Output Layer [7, 8, 9, 10] as shown in Figure 1.

The inter connection within the network are such that every neuron in each layer is connected to every neuron in the adjacent layers. Each node in a layer receives its input from the output of the previous layer nodes or from the network input. The connections between nodes are associated by scalar connection (synaptic) weights (w) that are iteratively adjusted during the training processes. An additional node with a constant output (usually 1) is often added to the input and hidden layers. This additional node is called the Bias Node [7, 8, 11].

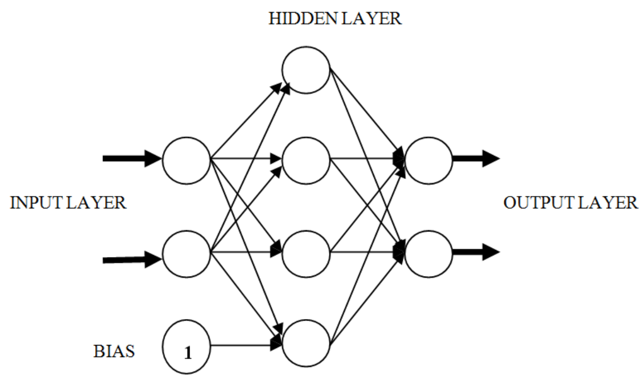

Figure 1. Simple feed forward neural network with three layers.

An interesting and important feature of a Neural Network trained using back-propagation is that no knowledge of the process it is being trained to emulate is required [11, 12]. Also, they learn from experience rather than programming. Provided that adequate input/output data is available, a Neural Network may

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be used to model the dynamics of an unknown plant. There is no constraint as to whether the plant is linear or nonlinear, provided that the training data covers the whole envelope of plant operation [11, 13]. Artificial Neural networks (ANN) have been trained to perform complex functions in various fields, including pattern recognition, identification, traffic prediction, classification, speech, vision, and control systems [3,14,15]. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings [11, 16, 17].

Investigation of the dynamics of power plant boiler requires detailed models with representation of plant components [18, 19, 20]. Large-scale models are generally based on first-principle equations (i.e. mass, momentum and energy balances), with phenomenological correlations (e.g. heat transfer correlations), and may be considered as knowledge models [21, 22]. However, to justify the basic structure of oil-fired boilers control systems, a different kind of model may be very helpful where only first-cut dynamics is captured in order to reveal the essential input-output interactions [23]. Such models may be called interpretation or identification models. Successful identification of nonlinear plant models is more problematic since, in addition to stimulating the dynamics, the plant must now be exercised across the operating range over which modeling is needed. One strategy which gave acceptable results in earlier work is to step the control inputs to drive the plant through its range of operating points while superimposing pseudo random binary signals at the same time [23]. This operation is difficult to effect while the boiler is in operation. On the other hand, to handle such a complex system with several inputs and outputs is complicated [24]. Therefore, the input and output data collected from the physical boiler plant will be used for system modeling. The aim of this study is to develop an ANN-based model of an Industrial Oil Fired Boiler System as a multivariable plant with two inputs (feed water rate and oil-fired flow rate) and two outputs (steam temperature and pressure). The accuracy of the model is verified by comparing the measured and simulated model outputs for temperature and pressure. A Proportional Integral Derivative Controller is then developed for the neural network model, which is then used to carry out simulation studies of the model on closed-loop to verify effectiveness of the controller on the model. Finally, the performance of the neural network model is compared with that of an ARX model obtained in [25] to verify any marginal improvement gained.

2. BOILER SYSTEM MODEL

Figure 2 shows the main components of a boiler system, which can be modeled as a strongly coupled multivariable system [26]. This makes it very interesting from a control engineering perspective.

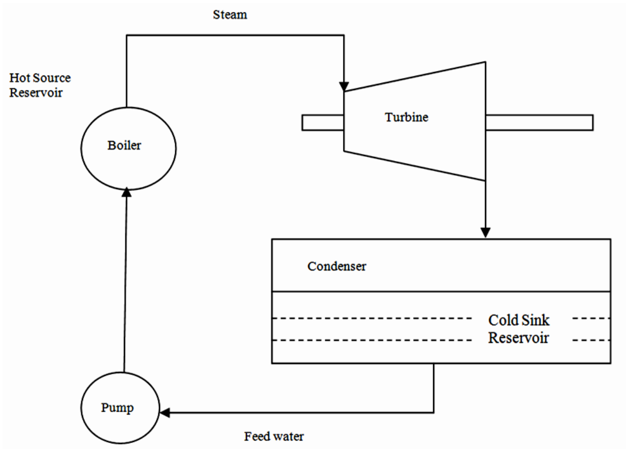

Figure 2. Components of a steam boiler plant

In a thermal power plant a heat source, usually fueled by coal, oil, or gas is used within a boiler to convert water to high-pressure steam. The steam expands and turns the blades of a turbine, which turns the armature of a generator, producing electric power. A condenser converts any remaining steam to water, and a pump returns the water to the boiler [19, 27].

2.1. Data collection and pre-processing

The raw data is collected directly from a physical boiler plant at Savannah Sugar Company Limited Numan in North-Eastern Nigeria. During production with the boiler in operation, a set of data, which a sample is given appendix A, is collected. A sampling period of 30 seconds is selected as a good compromise between the need of a low sampling rate according to the control design and the desire of the boiler engineers to have new control actions computed sufficiently rapidly after important perturbations. The input-output data for model construction and validation is collected during different days. Therefore, the involved input sequence is detected by production constraints. The data is taken from where inputs suffered significant variations. However, it is checked a posteriori that the considered sequence is persistently excited.

The input raw data is converted to equivalent input flow rate data as follows: The raw data are taken using pressure and temperature gauges, but these quantities are controlled by flow control valves hence the need to convert the input variables into flow rates. The control valve characteristics are related to the pressure by [28, 29]:

$$P = 20\times10^{3} Q_i^{\;2} \tag{1}$$

Where P, is pressure of the fluid, Q_i is the flow rate of the fluid.
From equation (1), the flow rate is obtained as:

$$Q_i = \sqrt{\frac{P}{20\times10^{3}}} \tag{2}$$

2.2 Assumptions of the boiler model

A two-layer feed-forward neural network with Matlab sigmoid transfer function is employed in the hidden neurons and Purelin function is used in the linear output neurons. These can fit multi-dimensional mapping problem arbitrarily well, given consistent data and enough neurons in its hidden layers [30, 31]. The Levenberg-Marquardt Back propagation is used as training algorithm.

2.2. Model choice

A simple two-layer feed-forward neural network with sigmoid hidden neurons and linear output neurons have universal approximation capabilities given consistent data and enough neurons in its hidden layer [3, 30, 31]. This makes it very attractive for nonlinear modeling.

3. BOILER SYSTEM CONTROL

The oil-fired boiler system (OFBS) is a very complex for which adequate model and well organized control functions may result in real benefit both in terms of efficiency and plant availability [18, 26, 33, 34]. Hence, sophisticated distributed control systems (DCS) have been applied to OFBS, incorporating traditional proportional integral derivative (PID) controllers, model-based feed forward compensators, parameter scheduling, Boolean functions and so on [20, 24, 34, 35]. The search for the optimum operating conditions of a boiler plant and a way to control them is not an easy task, because a steam boiler is a very complex system in which all the variables are interrelated [24, 26, 36].

3.1. Design of PID controller

A PID controller is a simple three-term controller. The transfer function of the most basic form of PID controller is used [37].

Figure 3 shows the schematic diagram of the PID controlled boiler plant. PID controllers 1 and 2 are used to control the feed water rate and oil feed rate respectively. The plant block shown, is the neural network model of the actual boiler plant. The scope block is a display unit that displays the plant outputs.

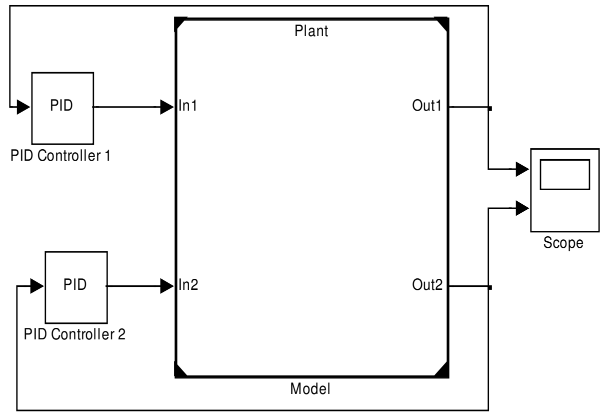

Figure 3. Schematic diagram of the PID controlled boiler plant

4. TEST RESULTS

Figure 4 show the plot of feed water rate in meter cube per seconds against time in seconds. The plot is generated from the collected data from the plant while in operation. A sample of the data is given in appendix A

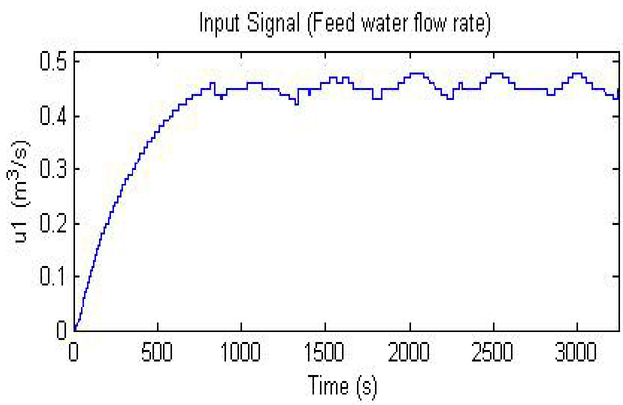

Figure 4. Feed water flow rate $u1$

Figure 5 show the plot of steam temperature in Degree Celsius against time in seconds. The data for this plot is generated from the collected data.
Figure 6 show the plot of oil feed rate in meter cube per seconds against time in seconds. The plot is generated from the collected data.

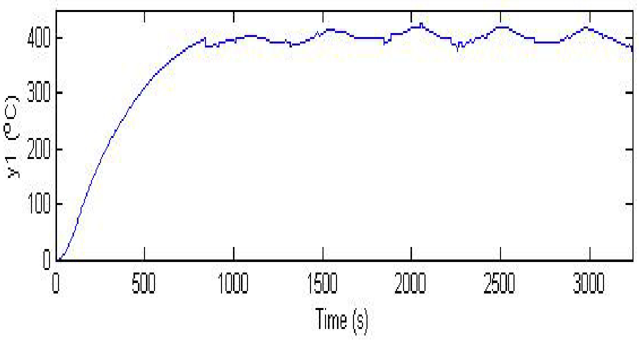

Figure 5. Steam temperature $y1$

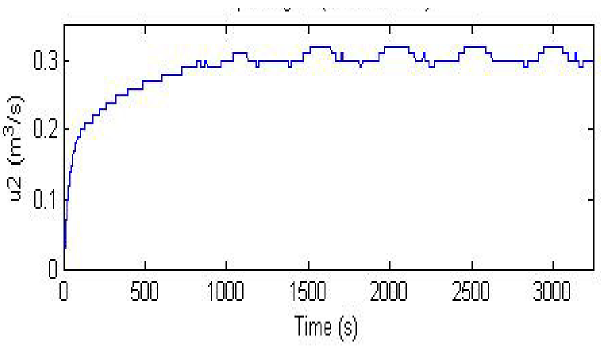

Figure 6. Oil feed rate $u2$

Figure 7 show the plot of steam pressure in Kilo-Pascal against time in seconds, using the collected data.

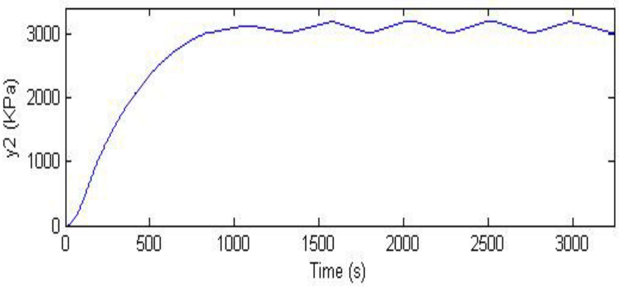

Figure 7. Steam pressure $y2$

The data of Figure 4 through Figure 7 are used to create the neural model, train it and also for validation.

4.1. Model structure

A feedforward neural network with a single hidden layer is employed. Hyperbolic tangent sigmoid transfer function (Tansigmoid) and linear output neurons (Purelin) function are used at the hidden and output layer respectively. Twenty (20) neurons are used at the hidden layer. The choice of the number of network inputs and the number of nodes in the hidden layer is informed by experience gained on linear modeling of the boiler plant [25]. In general, these dimensions are chosen by trial-and-error, a process greatly assisted by the availability of the powerful Levenberg-Marquardt training algorithm (trainlm).

Tansigmoid, Purelin and trainlm are functions in the Neural Network toolbox® of MATLAB®.

Figure 8 show the architecture of the two-layer feed-forward network that is used for the neural network modeling of the boiler plant.

4.1.1. Model training

Samples are divided into three:

Training Set (*60%*): These are presented to the network during training, and the network is adjusted according to its error.

Validation Set (*20%*): These are used to measure network generalization, and to halt training when generalization stops improving.

Test Set (*20%*): These have no effect on training and so provide an independent measure of network performance during and after training.

The partition ($60\%, 20\%, 20\%$ for training/ test/ validation) is such that the training, test and validation sets have even distributions of output values.

The network is trained offline using Levenberg-Marquardt Back propagation Algorithm (trainlm) [17, 30, 32].

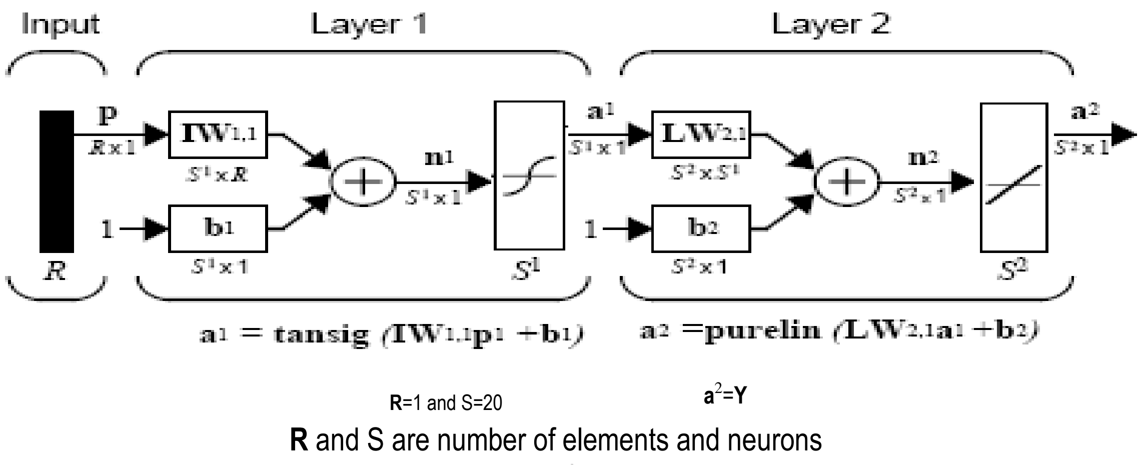

Figure 8. Architecture of the two-layer feed-forward network

4.2. Model result analysis

The key indicators of a good model are regression value R, mean square error MSE and Performance value [5, 30]. One of the sign of a good model is that the training set performance and that of the test set are fairly similar.

Figure 9 shows the plot of MSE against the number of Epoch. From the figure, it can be seen that the training and test sets have similar performance with performance value of 34.2802 at 30 epochs (iterations). It is always possible to get good performance on a training set, but another important thing is to have the model perform well on new data, especially the validation data. Regression R values measure the correlation between outputs and targets. An R value of one (1) means a close relationship and zero (0) a random relationship. Mean Squared Error MSE is the average squared difference between outputs and targets. Lower value of MSE is better and zero means no error [24].

Figure 10 show the regression plot for the boiler model which is the plot of simulated model output against actual boiler plant output (target). As shown in figure 10, the value of $R > 0.9$ and $MSE < 40$ indicate that the model obtained is acceptable.

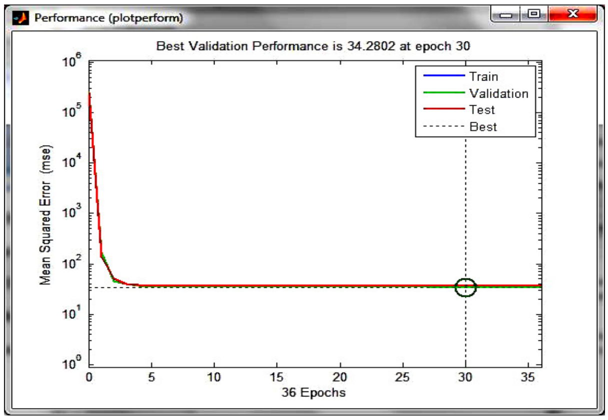

Figure 9. Performance plot

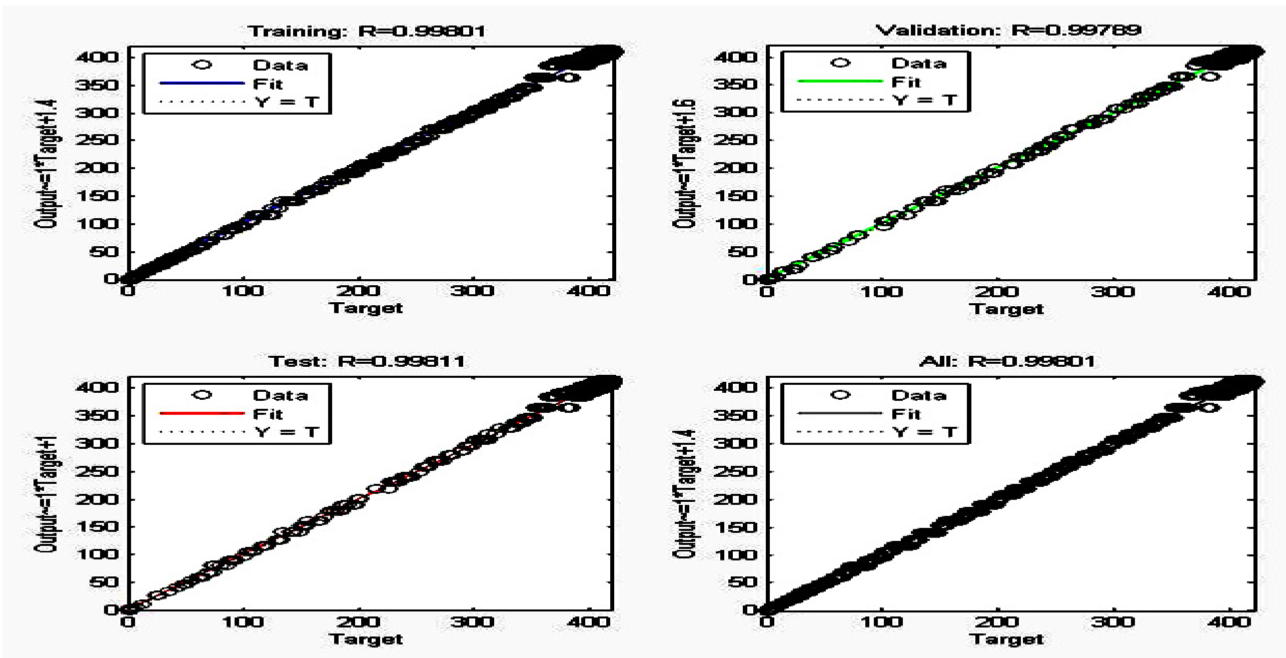

Figure 10. Regression plot

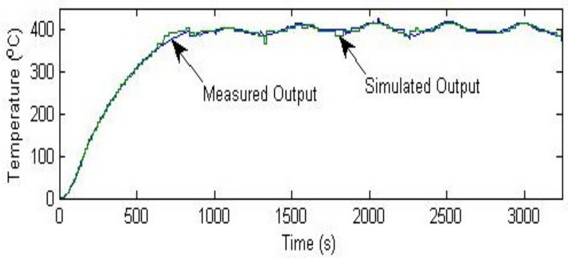

Figure 11. Measured and simulated model output temperatures

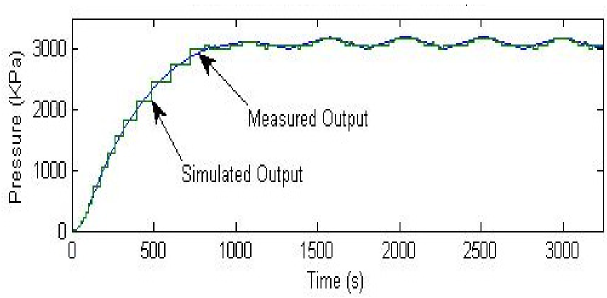

Figure 12. Measured and simulated model output pressures

4.3. PID Controller Simulation Results and Discussions

A simulation study is carried out to determine the degree of improvement that could be gained in Savannah Sugar Company Numan's boiler plant by the application of PID control.

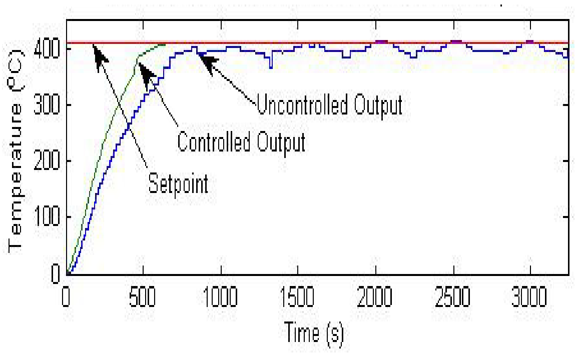

Figure 13. PID controlled temperature output of boiler plant (NN Model)

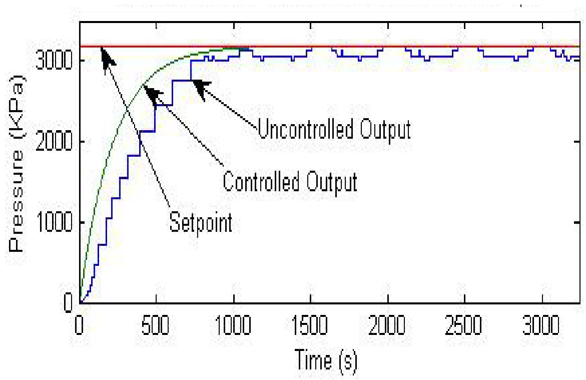

Figure 14. PID controlled pressure output of boiler plant (NN Model)

Figure 13 and Figure 14 show the tracking response for the steam temperature and pressure using PID controller with the Neural Network model. It is observed that the temperature and pressure track the set point steadily and the rise time for the output pressure of the Neural Network model is relatively shorter compared to that of ARX model shown in Figure 18.

The PID controller is tuned using Ziegler-Nichols tuning method [37 – 39, 42].

4.4. ARX Model Structure

An ARX model structure (Autoregressive Moving Average together with Recursive Least Square) has been chosen and the parameters are estimated using MATLAB® Identification Toolbox as detailed in [25].

4.5. Simulation

In this study, it is observed that using solely the data set that capture only first-cut dynamics (first-cut data set) of the boiler-plant for system modeling [14], the identified ARX model performed well on open-loop and closed-loop as shown in Figure 15 through Figure 18. On the other hand, the neural network trained with the first-cut data set didn't perform well on either open-loop or closed-loop as shown in Figure 19 and Figure 20. On open-loop, the neural network is unable to model the boiler plant start-up dynamics as can be seen in Figure 19. While on closed-loop, no rise time is observed as the controller tracked the set-point at zero seconds as seen in Figure 20.

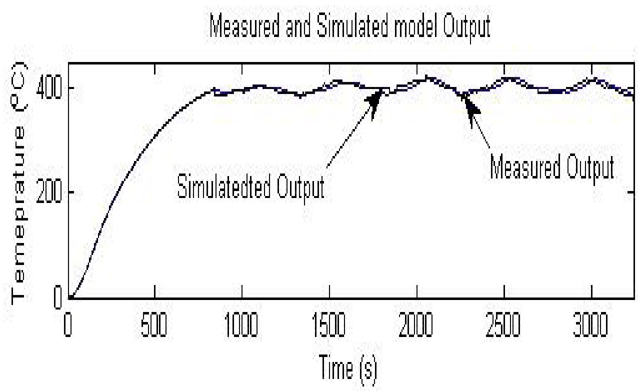

Figure 15. Measured and simulated model output temperature

Table 1. PID controller parameters

PID Tuning Parameters	ARX Model		Neural Network Model	
	Temperature	Pressure	Temperature	Pressure
K_P	350	1390	170	1200
K_I	220	1230	160	1000
K_D	10	5	10	10
Output Limit Upper	0.475	0.31	430	3250
Output Limit Lower	0	0	410	3155
Output Initial Value	0.1	0.1	430	3250

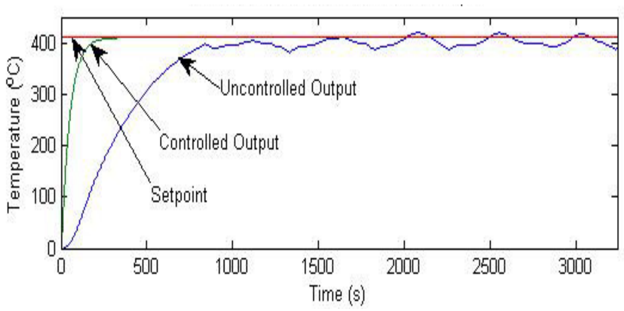

Figure 16. PID controlled temperature output of boiler plant (ARX model)

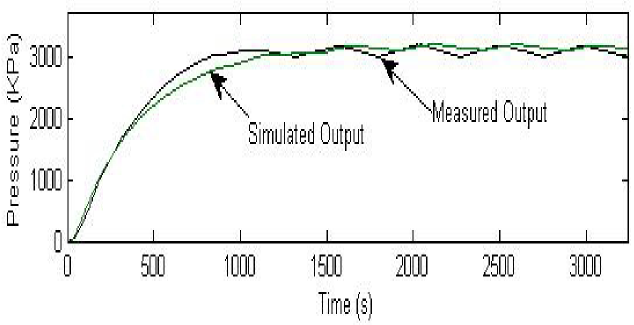

Figure 17. Measured and simulated model output pressure

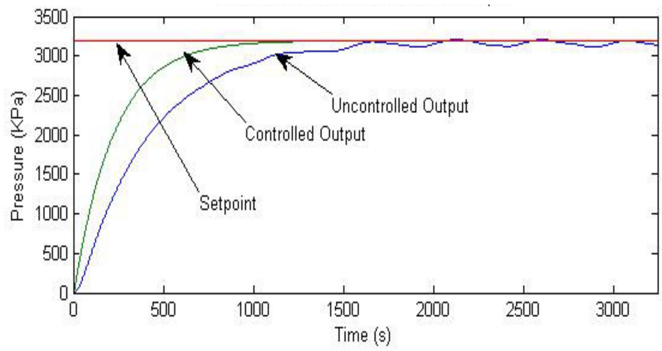

Figure 18. PID controlled pressure output of boiler plant (ARX model)

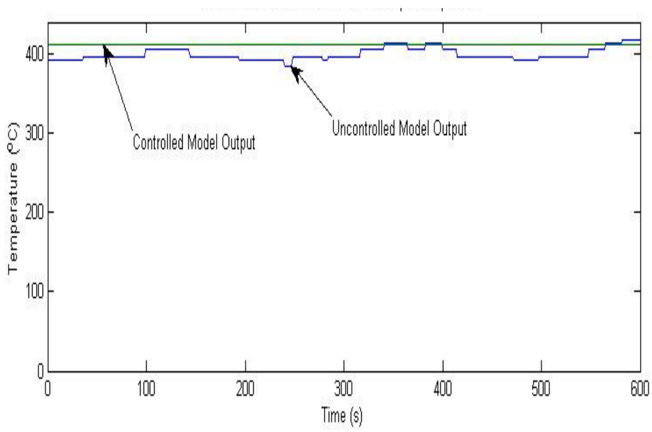

Figure 19. PID controlled temperature output of boiler plant (NN Model)

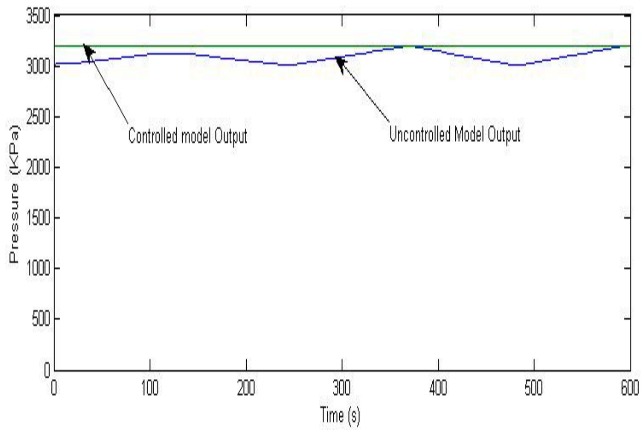

Figure 20. PID controlled pressure output of boiler plant (NN Model)

On inspection, it is evident that the neural network perceives the first-cut data set to be bias or incomplete, not covering the start-up dynamics of the boiler plant. Hence, the use of neural network model trained with first-cut data set is limited to boiler-plant output prediction (i.e. Step Ahead Prediction SAP) when the boiler is already in operation [18]. However, when the data set is extended to include the start-up dynamics (start-up data set) of the boiler plant, the trained neural network is able to model the boiler plant start-up characteristics and also predict the boiler plant output SAP as shown in Figure 11 through Figure 14.

5. CONCLUSION

This study is concerned with the application of feedforward neural network to offline modeling and PID control of a simulation model of a 3.2MW, oil-fired, drum-type boiler-turbogenerator unit at Savannah Sugar Company Numan in North-Eastern Nigeria. The aim is to demonstrate the potential advantages of these relatively new techniques for nonlinear modeling of boiler plant compared with conventional linear ARX approaches, while highlighting some of the limitations and areas of potential difficulty for practical application.

As expected the simulated ARX model output temperature and pressure show good prediction behavior as shown in Figure 15 and Figure 17. This is expected because the plant is modeled around its operating point [23, 40, 41, 43]. Hence only marginal improvement is observed in the neural network model shown in Figure 11 and Figure 12. But on application of PID controller, marked improvements are observed in terms of rapidity, tracking error, stability and smoothness of control signals as shown in Figure13 and Figure 14. The proposed neural network structure is very simple and easy to implement.

6. ACKNOWLEDGEMENT

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APPENDIX: SAMPLED INPUT/OUTPUT (EXPERIMENTAL DATA)

S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)
1	0	0	0	0	1081	0.46	0.31	404	3120	2161	0.45	0.3	401	3105
2	0	0	0	0	1082	0.46	0.31	404	3120	2162	0.45	0.3	401	3100
3	0	0.01	0	0	1083	0.46	0.31	403	3115	2163	0.45	0.3	400	3100
4	0	0.01	0	0	1084	0.46	0.31	403	3115	2164	0.45	0.3	400	3100
5	0	0.01	0	0	1085	0.46	0.31	404	3120	2165	0.45	0.3	400	3100
6	0	0.02	0	0	1086	0.46	0.31	404	3120	2166	0.45	0.3	400	3100
7	0	0.02	0	0	1087	0.46	0.31	404	3120	2167	0.45	0.3	400	3100
8	0	0.03	0	0	1088	0.46	0.31	404	3120	2168	0.45	0.3	400	3100
9	0	0.03	0	0	1089	0.46	0.31	404	3120	2169	0.45	0.3	399	3100
10	0	0.04	0	0	1090	0.46	0.31	404	3120	2170	0.45	0.3	399	3095
11	0	0.05	0	0	1091	0.46	0.31	404	3120	2171	0.45	0.3	399	3095
12	0	0.05	0	0	1092	0.46	0.31	404	3120	2172	0.45	0.3	399	3095
13	0	0.05	0	0	1093	0.46	0.31	404	3120	2173	0.45	0.3	399	3095
14	0	0.06	0	0	1094	0.46	0.31	404	3120	2174	0.45	0.3	399	3095
15	0	0.06	0	0	1095	0.46	0.31	404	3120	2175	0.45	0.3	398	3095
16	0.01	0.07	0	0	1096	0.46	0.31	404	3120	2176	0.45	0.3	398	3090
17	0.01	0.07	0	0	1097	0.46	0.31	404	3120	2177	0.45	0.3	400	3090
18	0.01	0.07	0	1	1098	0.46	0.31	404	3120	2178	0.45	0.3	400	3090

S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)
19	0.01	0.08	0	2	1099	0.46	0.31	404	3120	2179	0.45	0.3	400	3090
20	0.01	0.08	1	4	1100	0.46	0.31	404	3120	2180	0.45	0.3	400	3090
21	0.01	0.09	1	5	1101	0.46	0.31	404	3120	2181	0.45	0.3	400	3090
22	0.01	0.09	1	7	1102	0.46	0.31	404	3120	2182	0.45	0.3	400	3085
23	0.01	0.09	1	8	1103	0.46	0.31	404	3120	2183	0.45	0.3	400	3085
24	0.01	0.1	1	9	1104	0.46	0.31	404	3120	2184	0.45	0.3	400	3085
25	0.01	0.1	1	11	1105	0.46	0.31	404	3120	2185	0.44	0.3	400	3085
26	0.01	0.1	2	12	1106	0.46	0.31	404	3120	2186	0.44	0.3	400	3080
27	0.02	0.1	2	13	1107	0.46	0.31	404	3120	2187	0.44	0.3	400	3080
28	0.02	0.1	2	14	1108	0.46	0.31	404	3120	2188	0.44	0.3	400	3080
29	0.02	0.11	2	17	1109	0.46	0.31	404	3120	2189	0.44	0.3	400	3080
30	0.02	0.11	3	19	1110	0.46	0.31	404	3120	2190	0.44	0.3	400	3080
31	0.02	0.11	3	22	1111	0.46	0.31	404	3120	2191	0.44	0.3	400	3080
32	0.02	0.11	3	24	1112	0.46	0.31	404	3120	2192	0.44	0.3	400	3075
33	0.02	0.12	4	27	1113	0.46	0.31	404	3120	2193	0.44	0.3	400	3075
34	0.02	0.12	4	29	1114	0.46	0.31	404	3120	2194	0.44	0.3	400	3075
35	0.02	0.12	4	31	1115	0.46	0.31	403	3115	2195	0.44	0.3	400	3075
36	0.02	0.12	4	34	1116	0.46	0.31	403	3115	2196	0.44	0.3	400	3075
37	0.03	0.13	5	36	1117	0.46	0.31	403	3115	2197	0.44	0.3	400	3075
38	0.03	0.13	5	38	1118	0.46	0.31	403	3115	2198	0.44	0.3	400	3070
39	0.03	0.13	5	41	1119	0.46	0.31	402	3110	2199	0.44	0.31	400	3070
40	0.03	0.13	6	45	1120	0.46	0.31	402	3110	2200	0.44	0.31	400	3070
41	0.03	0.14	6	48	1121	0.46	0.31	402	3110	2201	0.44	0.31	400	3070
1042	0.46	0.31	400	3110	2122	0.46	0.31	410	3140	3202	0.44	0.3	386	3033
1043	0.46	0.31	400	3110	2123	0.46	0.31	410	3140	3203	0.44	0.3	386	3033
1044	0.46	0.31	400	3110	2124	0.46	0.31	410	3135	3204	0.44	0.3	386	3030
1045	0.46	0.31	400	3110	2125	0.46	0.31	410	3135	3205	0.44	0.3	386	3030
1046	0.46	0.31	400	3110	2126	0.46	0.31	410	3135	3206	0.44	0.3	386	3030
1047	0.46	0.31	400	3115	2127	0.46	0.31	407	3135	3207	0.43	0.3	385	3030
1048	0.46	0.31	400	3115	2128	0.46	0.31	407	3135	3208	0.43	0.3	385	3028
1049	0.46	0.31	400	3115	2129	0.46	0.31	406	3135	3209	0.43	0.3	385	3028
1050	0.46	0.31	400	3115	2130	0.46	0.31	406	3130	3210	0.43	0.3	385	3025
1051	0.46	0.31	400	3115	2131	0.46	0.31	406	3130	3211	0.43	0.3	385	3025
1052	0.46	0.31	400	3115	2132	0.46	0.31	406	3130	3212	0.43	0.3	385	3025
1053	0.46	0.31	400	3115	2133	0.46	0.31	406	3130	3213	0.43	0.3	384	3025
1054	0.46	0.31	400	3115	2134	0.46	0.31	406	3130	3214	0.43	0.3	384	3022
1055	0.46	0.31	400	3115	2135	0.46	0.31	405	3130	3215	0.43	0.3	384	3022
1056	0.46	0.31	400	3115	2136	0.46	0.31	405	3125	3216	0.43	0.3	384	3020
1057	0.46	0.31	400	3115	2137	0.46	0.31	405	3125	3217	0.43	0.3	384	3020
1058	0.46	0.31	400	3115	2138	0.46	0.31	405	3125	3218	0.43	0.3	384	3020
1059	0.46	0.31	400	3115	2139	0.46	0.31	405	3125	3219	0.43	0.3	384	3020
1060	0.46	0.31	400	3115	2140	0.46	0.31	405	3125	3220	0.43	0.3	384	3022
1061	0.46	0.31	400	3115	2141	0.46	0.31	404	3125	3221	0.43	0.3	385	3022
1062	0.46	0.31	400	3115	2142	0.46	0.31	404	3120	3222	0.43	0.3	385	3027
1063	0.46	0.31	400	3115	2143	0.46	0.31	404	3120	3223	0.43	0.3	385	3027
1064	0.46	0.31	400	3115	2144	0.46	0.31	404	3120	3224	0.43	0.3	385	3026
1065	0.46	0.31	403	3115	2145	0.46	0.31	404	3120	3225	0.43	0.3	386	3026
1066	0.46	0.31	403	3115	2146	0.46	0.31	404	3120	3226	0.43	0.3	386	3029
1067	0.46	0.31	403	3115	2147	0.46	0.31	403	3120	3227	0.43	0.3	386	3029
1068	0.46	0.31	403	3115	2148	0.46	0.31	403	3115	3228	0.43	0.3	386	3032
1069	0.46	0.31	403	3115	2149	0.45	0.3	403	3115	3229	0.43	0.3	385	3032
1070	0.46	0.31	403	3115	2150	0.45	0.3	403	3115	3230	0.43	0.3	385	3026
1071	0.46	0.31	403	3115	2151	0.45	0.3	403	3115	3231	0.43	0.3	385	3026

S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)	S/N	FW (m^3/s)	OF (m^3/s)	TEP (^oC)	PRE (KPa)
1072	0.46	0.31	403	3115	2152	0.45	0.3	403	3115	3232	0.43	0.3	385	3025
1073	0.46	0.31	403	3115	2153	0.45	0.3	402	3115	3233	0.45	0.3	383	3025
1074	0.46	0.31	403	3115	2154	0.45	0.3	402	3110	3234	0.45	0.3	383	3018
1075	0.46	0.31	403	3115	2155	0.45	0.3	402	3110	3235	0.45	0.3	375	3018
1076	0.46	0.31	403	3115	2156	0.45	0.3	402	3110	3236	0.45	0.3	375	3017
1077	0.46	0.31	403	3120	2157	0.45	0.3	401	3110	3237	0.45	0.3	375	3017
1078	0.46	0.31	403	3120	2158	0.45	0.3	401	3110	3238	0.45	0.3	375	3017
1079	0.46	0.31	403	3120	2159	0.45	0.3	401	3110	3239	0.45	0.3	375	3017
1080	0.46	0.31	403	3120	2160	0.45	0.3	401	3105	3240	0.45	0.3	375	3017

FW—Feed Water, OF—Oil Feed, TEP—Temperature, PRE—Pressure