Neural Network Approach for Predicting Drum Pressure and Level in Coal-fired Subcritical Power Plant

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Abstract

There is increasing need for tighter controls of coal-fired plants due to more stringent regulations and addition of more renewable sources in the electricity grid. Achieving this will require better process knowledge which can be facilitated through the use of plant models. Drum-boilers, a key component of coal-fired subcritical power plants, have complicated characteristics and require highly complex routines for the dynamic characteristics to be accurately modelled. Development of such routines is laborious and due to computational requirements they are often unfit for control purposes. On the other hand, simpler lumped and semi empirical models may not represent the process well. As a result, data-driven approach based on neural networks is chosen in this study. Models derived with this approach incorporate all the complex underlying physics and performs very well so long as it is used within the range of conditions on which it was developed. The model can be used for studying plant dynamics and design of controllers. Dynamic model of the drum-boiler was developed in this study using NARX neural networks. The model predictions showed good agreement with actual outputs of the drum-boiler (drum pressure and water level).

Keywords: NARX Neural Networks, subcritical coal-fired power plant, drum-boiler, gPROMS modelling and simulation

Introduction

1.1 Background

Drum-boiler (Fig.1) is a critical component of thermal power plants such as coal-fired subcritical power plants and many industrial processes. In the power industry in many countries, it has become needful for thermal power plants to be more tightly controlled to follow changes in electricity demand. This is due to more stiff regulations and addition of renewable energy systems into the electricity grid. Achieving this will require better process knowledge and more robust control systems. This can be facilitated through modelling and simulation. This approach is preferred to the option of experimenting with the actual plants for safety and economic reasons.

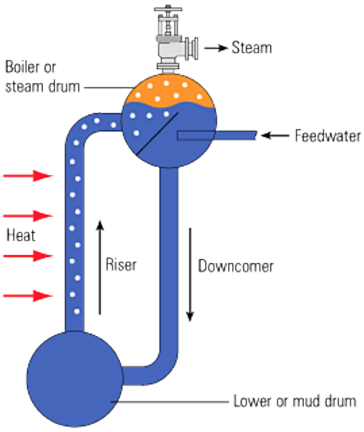

Figure 1 Drum-boiler*

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1.2 Motivation

Drum-boilers in coal-fired subcritical power plants have complicated geometry with complex phase equilibrium and steam bubbles distributed below water level in the drum. Ideally, adequate representation of the dynamic nature of such system will involve laborious and computationally-intensive distributed parameter modelling. Models of such complexity are unfit for control purposes. Simpler lumped and semi-empirical models have been shown to considerably capture the complex dynamics of drum-boilers [1-4]. However, for control purposes these non-linear models still have to be reduced in model order and then linearized [5]. The performance of linear models usually deteriorates away from operating point and as a result the model cannot be trusted if big changes in operating conditions are expected.

For an already existing plant where operating data can easily be obtained, it is considered that a data-driven approach commonly referred to as system identification is more convenient. Data-driven models incorporates all the complex underlying physics and performs very well so long as it is used within the range of conditions on which it was developed. More importantly, the approach avoids exact determination of model parameters which often vary unpredictably. The methodology is already widely in use: conventional system identification is commonly used for controller design in the industry [6] and commercially available ESMER multiphase flow meter is based on advanced system identification technique (neural networks) [7].

Neural network models have been found to be less difficult to develop compared to models based on conventional system identification. This is because more careful and rigorous design of the test experiment for data acquisition is required in conventional system identification. Also, in some cases, neural network models have shown better prediction accuracy compared to models based on conventional system identification [8]. Neural network-based models are adaptive and have rapid response with good accuracy if developed properly and can be used for real-time simulation among others [9].

1.3 Aims and Novelty

The aim of the study is to model subcritical boiler drum level and pressure dynamics using NARX (Nonlinear AutoRegressive with eXogenous inputs) neural networks. Neural networks have been used for predicting boiler performance in the past. Yusoff [10] used neural network for emission monitoring from biomass-fired boilers. Romeo and Gareta [11] and Teruel *et al.* [12] used neural networks for predicting fouling and slagging in boiler furnace. Li and Fang [13] identified superheater model of an ultra-supercritical boiler using neural networks, and Rusinowski and Stanek [14] used neural network to develop correlations for predicting flue gas temperature. Whole boiler/thermal power plant models built with neural networks have also been reported [8-9,15-19].

Most of the studies so far on application of neural networks in boiler modelling either as stand-alone or as a component of a thermal power plant are based on feedforward neural networks. In contrast, NARX neural network (recurrent neural networks) is used in this study. Recurrent neural networks such as NARX neural network have been shown to outperform feedforward neural networks in predicting time-series data [20] and thus are more suitable for dynamic modelling [21].

NARX neural networks have been used for dynamic modelling reactor-exchangers [22], crude preheater [23], hydraulic suspension dampers [24], unsteady separation control [25], gas turbines [26-27], magnetic levitation [28] among others. There is yet to be a case of data-driven drum-boiler models based on NARX neural networks to the best of our knowledge.

2. Neural Networks

Neural Network (NN) is a computational paradigm inspired from the structure of biological neural networks and their way of encoding and solving problems. They are able to identify underlying highly complex relationships based on input-output data only.

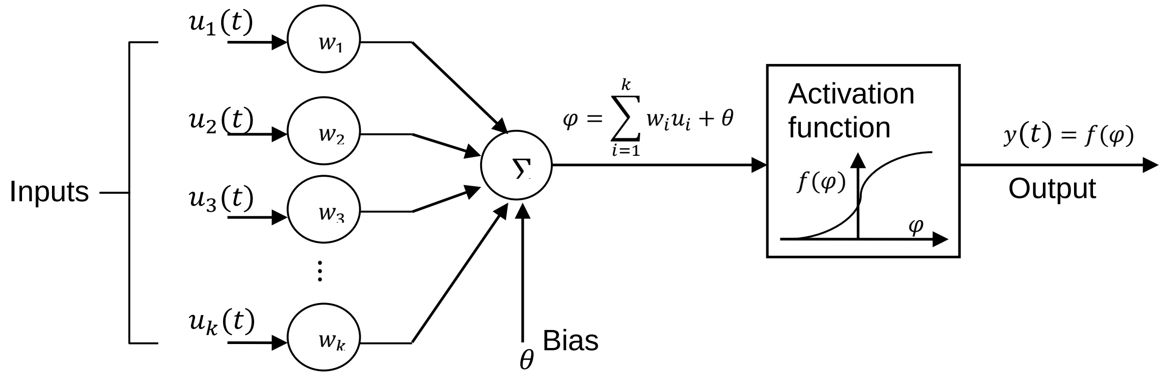

Figure 2 Nonlinear model of neurone with sigmoid activation function [29]

NN comprises of interconnections of the basic building blocks called neurones (Fig.2) organised in layers: the input, hidden and output layers. The inputs to a neurone, ($u_1(t)$,$u_2(t)$, $u_3(t)$ … $u_k(t)$), are either the network inputs or outputs of neurones in the previous layer and an externally applied bias (θ). The bias can either increase or lower the sum of the inputs (φ) depending on its value. Also, the input channels are associated with synaptic weights (w_1, w_2, w_3 … w_k) which can have both positive (excitatory) and negative (inhibitory) values. The bias and weights are both adjustable parameters and development (training) of NN is about determining optimal values for the parameters for specific cases. The activation (or transfer) function is typically sigmoid function in the hidden layer and either linear or sigmoid functions in the output layer. More details on NN can be found in Haykin [29] among several other books.

Depending on signal flow configuration, NN can be classified into feedforward and recurrent NN. In feedforward NN, the outputs are calculated directly from the inputs through feedforward connections [21]. Feedforward NN is mostly static networks. Recurrent NN on the other hand are dynamic and have at least one feedback loop. The network outputs are therefore not the result of the external inputs only.

NARX NN belongs to the recurrent NN class. They have a feedback connection enclosing several layers of the network (Fig. 3). The architecture includes tapped delay lines (TDL) which plays the role of holding past values of the input. This feature makes them more suitable for multi-step-ahead predictions (time-series prediction) than feedforward networks [21]. It is therefore more appropriate to use them for dynamic modelling. The inputs are normally a sequence of input vectors that occur in a certain time order.

A NARX model is generally defined by the equation:

$$y(t) = f\left(y(t-1), y(t-2), \dots, y\left(t-n_y\right), u(t-1), u(t-2), \dots, u(t-n_u)\right) \qquad (1)$$

In the equation, $y(t)$ is the current value of predicted output signal expressed as a function of the previous values of the output signal $\left(y(t-1), y(t-2), \dots, y\left(t-n_y\right)\right)$ and previous values of an independent (exogenous) input signal $\left(u(t-1), u(t-2), \dots, u(t-n_u)\right)$. The terms n_y and n_u are respectively the orders of the output and exogenous input respectively. The previous values are recorded using TDL and the nonlinear polynomial function (f) approximated using a feedforward NN. Consequently, typical architecture for a first order NARX NN (where n_y and n_u in Eq. 1 are both equal to 1) has the form shown in Fig.3.

3. Data Collection

Collection of data is a crucial step in model development using neural networks. Bear in mind that it is not possible to incorporate a priori knowledge into an NN model, the model is only as good as the data [21]. Also, NN model do not have the ability to extrapolate accurately beyond the range of the data used in their development, they only generalize well within the data range. As a result, the data must sufficiently cover the input conditions that the NN model is intended to be used.

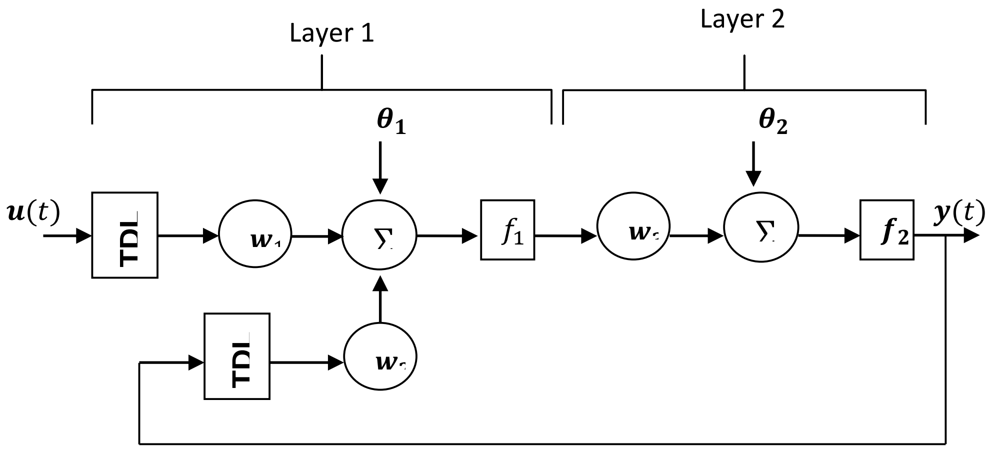

Figure 3 Typical NARX neural network architecture [21]

In this study, the data is obtained from simulations of a detailed first principle model of the drum-boiler model same as Åström and Bell [3]. The first principle model is based on a 160 MWe P16-G16 power plant at Öresundsverket in Malmö, Sweden. Complete details of this model can be obtained from Åström and Bell [3]. It is shown in Åström and Bell [3] that the model captures the drum-boiler dynamics accurately through validations with plant data at medium and high loads respectively. In this study, the first principle model was executed using gPROMS ModelBuilder®. Thermodynamic properties of water/steam were obtained using IAPWS-95 formulation in Aspen Properties via COThermo interface. Thermodynamic property derivatives ($\frac{\partial\rho}{\partial P}, \frac{\partial h}{\partial P}$ and $\frac{\partial T_{sat}}{\partial P}$) were obtained using polynomial approximations of steam table obtained from NIST REFPROP V9.1.

From experience with the first principle model, it is determined that the main inputs to the drum boiler include the heat input, feedwater flowrate and steam flowrate and the outputs are drum level and drum pressure. The heat input is obtained from steady state calculations when the values of the drum pressure, volume of water in the loop and steam flowrate are specified (the values of the drum pressure, volume of water in the loop and steam flowrate used for the steady state calculations were obtained from Åström and Bell [3]). For complete coal-fired subcritical power plant, heat input will be replaced with coal flowrate and steam flowrate could be substituted with governor valve opening. The same input-output set up will be used for the NN model development.

The drum-boiler system is excited by perturbing the inputs in succession with a series of step changes of random heights (Fig. 4-6). Perturbation in each input is sustained for an hour resulting to a total test period of 3 hours (10800 seconds). When perturbing one input, the other inputs are maintained at their equilibrium value. Open loop conditions are assumed and control loops were therefore excluded from the model. The data is sampled every second giving a total 10800 data set over the entire test period. The resulting response of the output variables (drum pressure and drum level) during the course of the perturbation is shown in Fig.7-8.

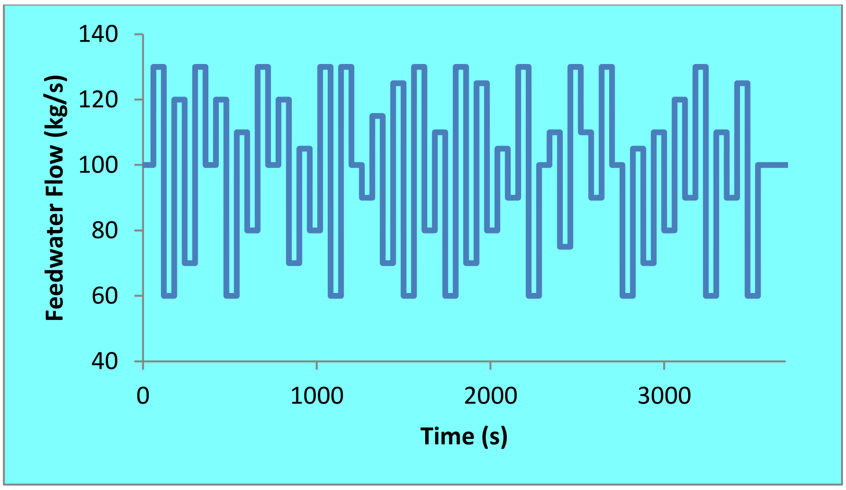

Figure 4 Perturbations in feedwater flowrate

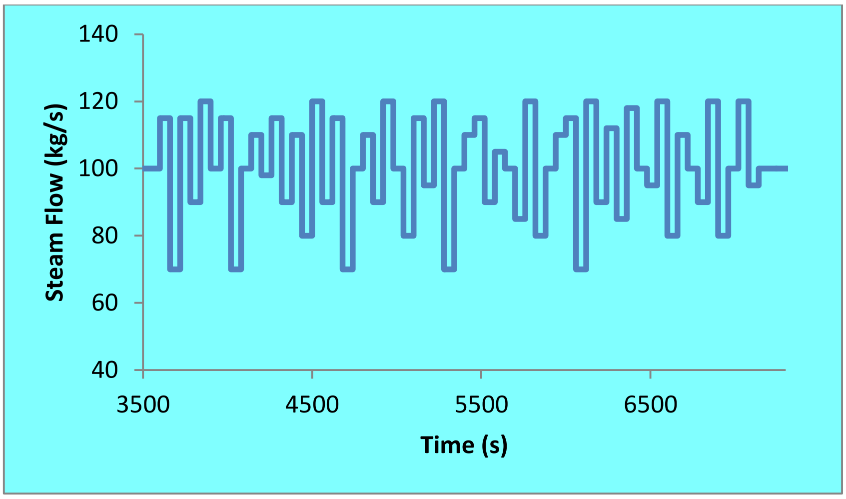

Figure 5 Perturbations in steam flowrate

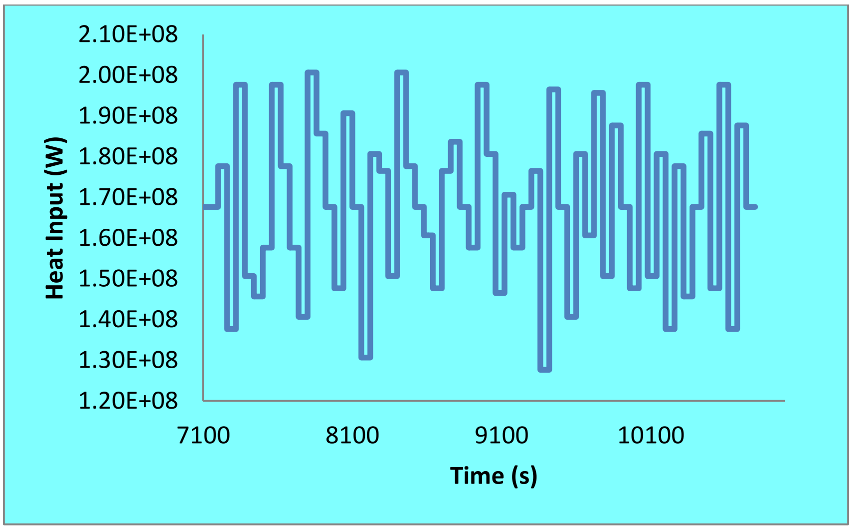

Figure 6 Perturbations in heat input

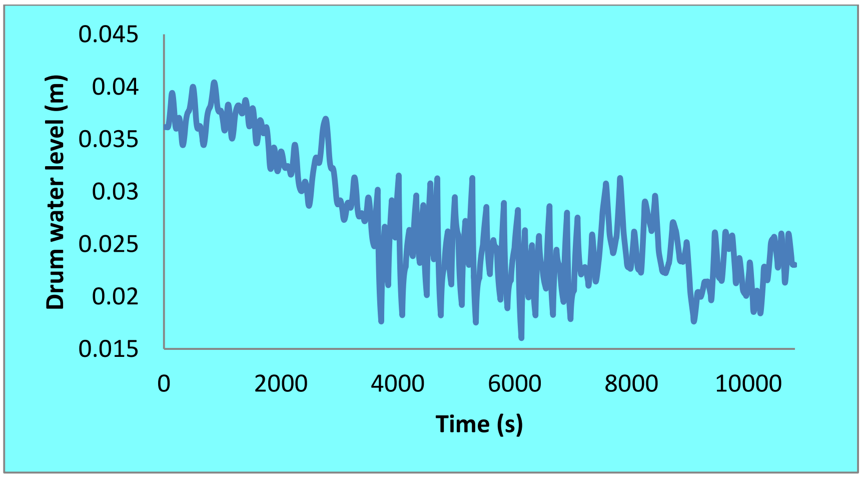

Figure 7 Drum level

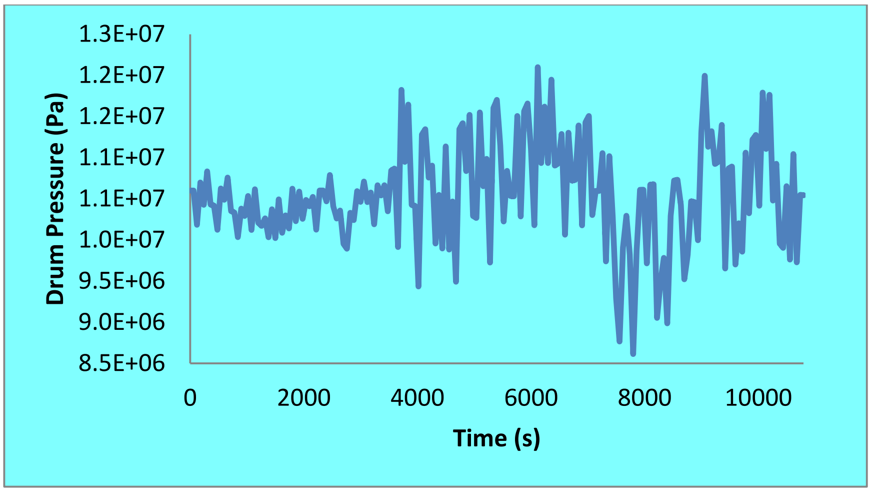

Figure 8 Drum pressure

4. Training

NN training is the process of obtaining optimal values for the adjustable parameters, weights and biases, necessary to achieve the best fit between input-output data. It is essentially a nonlinear optimization problem and the objective function involves minimization of an error function, typically mean absolute error (MAE), mean squared error (MSE), or sum of squared error (SSE) among others. The training task is accomplished using different optimization algorithm such as gradient descent, Levenberg-Marquardt, Bayesian regularization, scaled conjugate gradient among others. These algorithms are usually executed by performing the calculations backward through the network starting from the output layer. In MATLAB Neural Network Toolbox, the various optimization algorithms are implemented as training functions, namely *trainlm* function (Levenberg-Marquardt), *trainbr* function (Bayesian regularization), *trainscg* function (scaled conjugate gradient) etc.

For dynamic NN with a feedback loop such as NARX NN, training is complicated because some of the inputs (feedback) are also functions of the weights (Fig. 3). To avoid this complication, NARX NN is trained in open loop (without the feedback loop). This is based on series-parallel architecture where the actual output, rather than the estimated output fed back to the network, is used as the input. On this basis, the NARX NN is then purely feedforward network and can be trained as such. Details of this procedure can be found in Beale *et al*. [21]. After training, the *closeloop* function in MATLAB can be used to convert the NN from the series-parallel configuration (open loop) to close loop configuration for multi-step ahead predictions.

Prior to training, the available data (input and target vectors) is pre-processed to transform the data to more suitable form for NN training. This makes the learning process faster and efficient without the possibility of saturation of the sigmoid transfer function often used in the hidden layers [21]. Some training algorithm also requires particular pre-processing for optimal performance, e.g. data transformation to a form where their values fall into the interval [−1, 1] for *trainbr* algorithm. When the network is created, the pre-processing function becomes part of the network object, so that whenever the network is used, the data coming into the network is pre-processed in a similar way. The NN output is similarly post-processed to transform the output to the same form as the actual output. In this study, the *mapminmax* and *removeconstantrows* processing functions in MATLAB have been used. The *mapminmax* function transforms the data so that their values fall into the interval [−1, 1]. On the other hand, *removeconstantrows* functions removes the rows of the data vector that are constant (if any) since they will not provide useful information to the NN. Also, pre-processing for dynamic networks include shifting the data to initialize the TDL. In MATLAB, this is accomplished using *preparets* function. The function uses the network object to initialize the TDL by shifting the data accordingly to create the correct inputs and targets to use in training or simulating the network.

Commonly, overfitting occurs during NN training. This is a situation where the NN memorises the training examples including noises such that it is not able to generalize to new conditions. This can be avoided using either early stopping or regularization techniques. Early stopping technique was used in this study after exploring the two techniques; regularization technique gave poorer result. In early stopping method the available data is divided into three subsets, namely training, validation and testing sets. The error normally decreases during the initial phase of the training. Overfitting begins to set in when the validation error begins to increase. The optimal network weights and biases are obtained at the minimum validation set error before overfitting begins to set in.

5. Results and Discussion

5.1 Training Results

Based on the discussions above, a two-layer first order NARX NN dynamic model of the drum-boiler with three inputs (i.e. feedwater flowrate, steam flowrate and heat input) and two outputs (i.e. drum level and drum pressure) was developed in MATLAB using the simulation data from gPROMS ModelBuilder®(Fig. 4-8). There are 100 neurones in the hidden layer each utilizing sigmoid activation function while each of the two outer layer neurones utilize linear activation function. The Levenberg-Marquardt algorithm (*trainlm* training function in MATLAB) was used to obtain the optimal values of the adjustable parameters, weights and biases. The MSE performance function (Eq.2) was used to assess the network performance. In Eq. 2, z_i = the targets, y_i = network outputs and N = data size.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(z_i - y_i)^2 \rightarrow min \qquad (2)$$

As explained earlier, the early stopping technique used in this study involves simultaneous training, validation and testing. The training data comprised of 70% of the entire data while the validation and testing data were 15% each respectively of the entire data. The entire data was for 3 hours period (10,800 seconds) and division of the entire data set into the subsets (training, validation and testing sets) was done randomly (*dividerand* function in MATLAB was used for the purpose). Training is stopped at the lowest MSE for the validation set before the MSE starts to increase (Figure 9). Increase in MSE for the validation set after it reaches the minimum value is an indication of onset of overfitting. Network training should be stopped before onset of overfitting. This is the basis of the early stopping technique for network training. Also, there are no significant autocorrelations in the error distribution as can be seen in the error autocorrelation plot for the drum pressure and drum level predictions (Fig. 10-11). This suggests reliable estimate of the network parameters, weights and biases.

Figures 12 and 13 show the response of the network outputs, drum level and drum pressure, as the training progressed. Only the training set is involved in network training, the validation and testing set are not involved in training. The validation set gives an idea of when to stop training while the test set helps to show network performance on a ‘foreign’ data. The network predicted the drum level and drum pressure correctly based on the test data comparisons with the network data in Figures 12 and13.

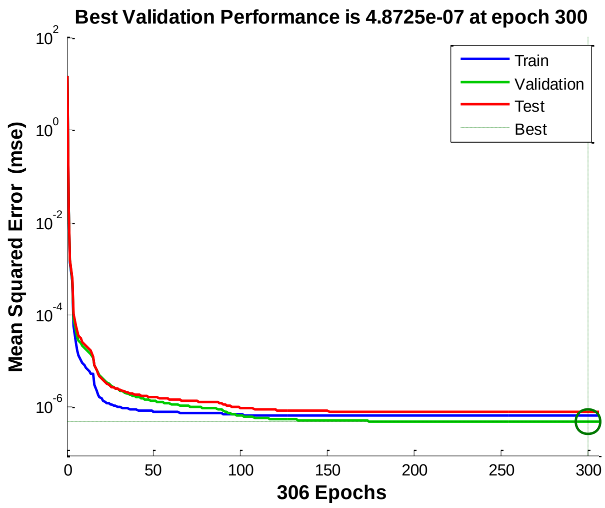

Figure 9 MSE for different training epochs

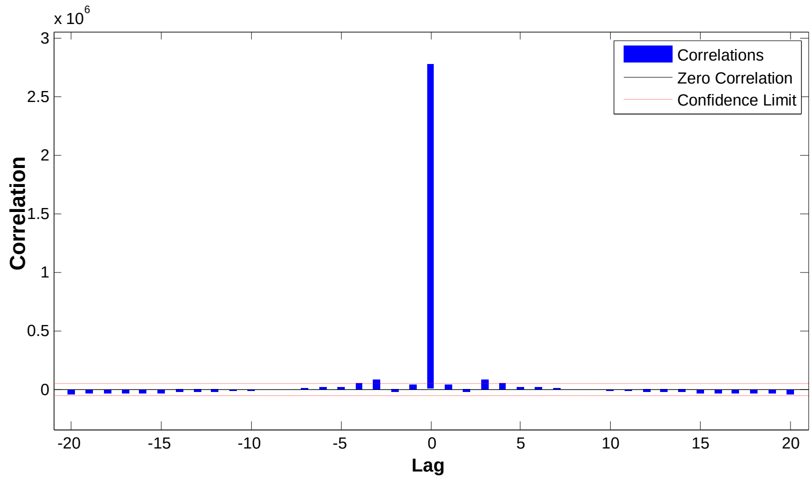

Figure 10 Drum pressure prediction error autocorrelation plot

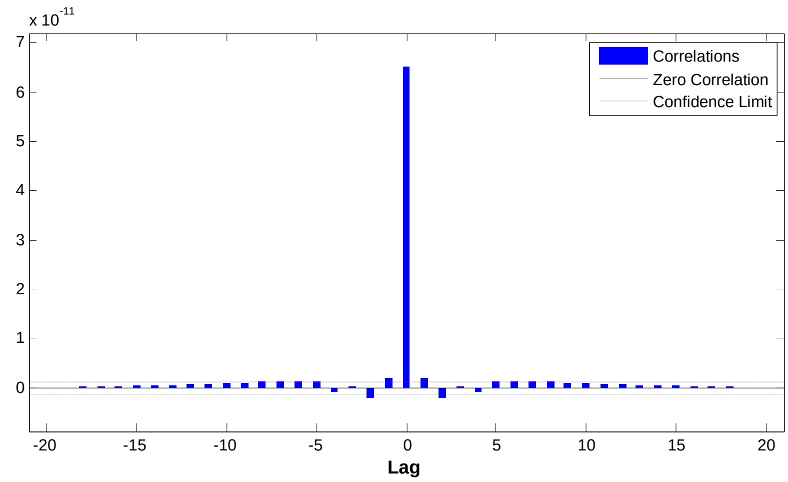

Figure 11 Drum level prediction error autocorrelation plot

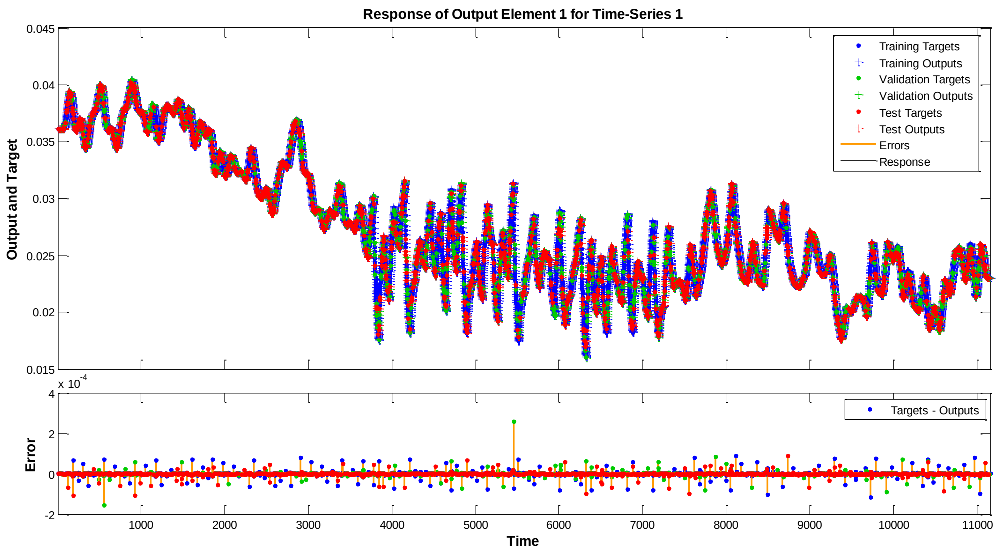

Figure 12 Drum level response

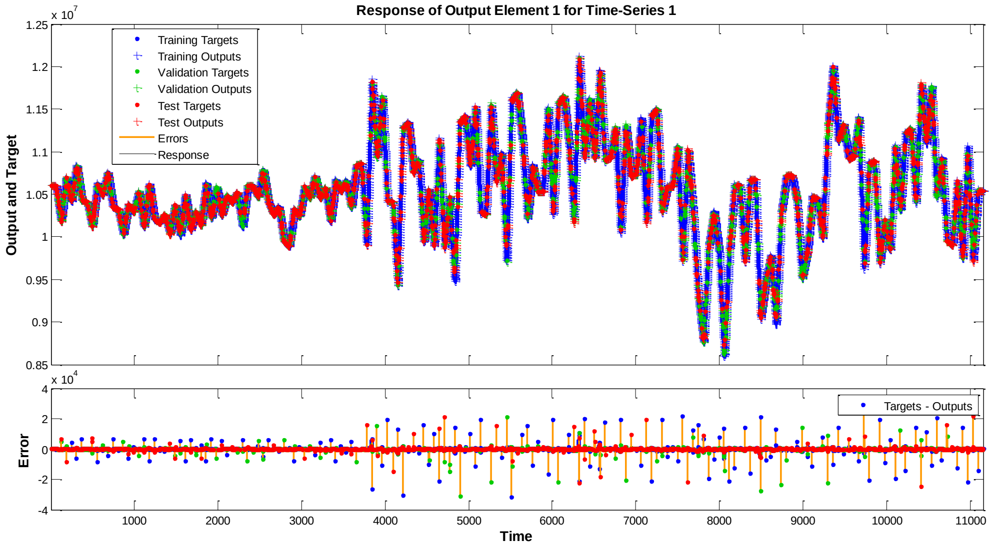

Figure 13 Drum pressure response

5.2 Step Change Test

In this section, step change test on each of the inputs is carried out and the drum pressure and level predictions of the detailed first principle model [3] and the NARX NN model are compared. The purpose of the tests is to determine if the NARX NN developed in this study is able to accurately predict the drum pressure and level when changes arise in any of the inputs.

During the first test, the feedwater flowrate was stepped up by 30 kg/s from 100 kg/s after 100 seconds of steady simulation. The steam flowrate and the heat input were respectively maintained at 100 kg/s and 167 MWth throughout the test. The drum pressure and level response during this test is shown in Fig. 14. In the second test, steam flowrate was stepped up by 10 kg/s from 100 kg/s after 100 seconds of steady simulation. The feedwater flowrate and the heat input were respectively maintained at 100 kg/s and 167 MWth throughout the test. The drum pressure and level response during this test is shown in Fig. 15. Finally, 10 MWth step change was implemented on the heat input from 167 MWth initial value. The feedwater and steam flowrate was maintained at 100 kg/s. The result of this test is shown in Fig. 16. From the tests, it can be seen that the NARX NN model developed in this study accurately predicted the drum pressure and level of the plant in the presence of sudden changes in the inputs.

6. Conclusions and Recommendations for future work

In this study, a first order NARX NN dynamic model of a drum-boiler for subcritical coal-fired power plant capable of predicting the drum pressure and drum level is presented. The model was developed based on a reference drum-boiler of a 160 MWe power plant in Sweden [3]. The results of the validation and testing showed good agreement. However, since the data used in developing the NARX NN dynamic model presented in this study is obtained from simulation of a first principle model, it must be noted that the performance of the NARX NN dynamic model is subject to the inherent deficiencies in the first principle model. It is therefore recommended that future study of the drum-boiler using NARX NN be based on actual plant data if available. Future studies are also expected to be extended to cover the entire coal-fired subcritical power plant.

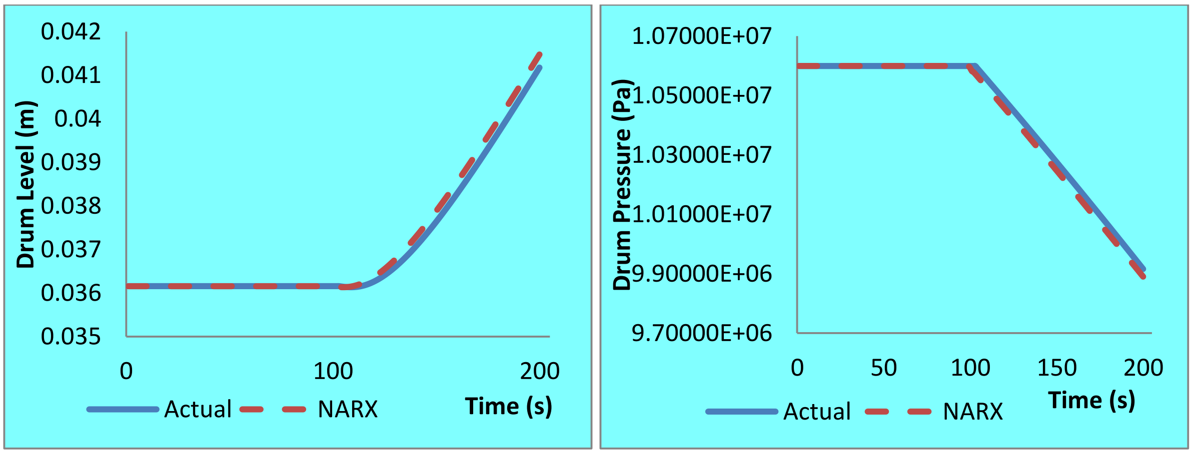

Figure 14 Drum pressure and level response to +30 kg/s step change in feedwater flowrate

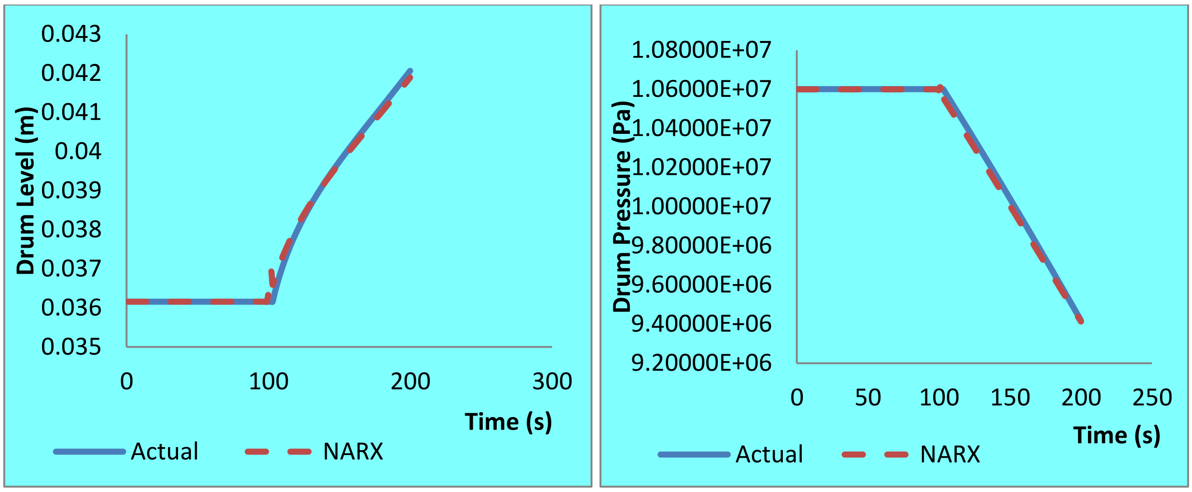

Figure 15 Drum Pressure and Level Response to +10 kg/s step change in Steam Flowrate

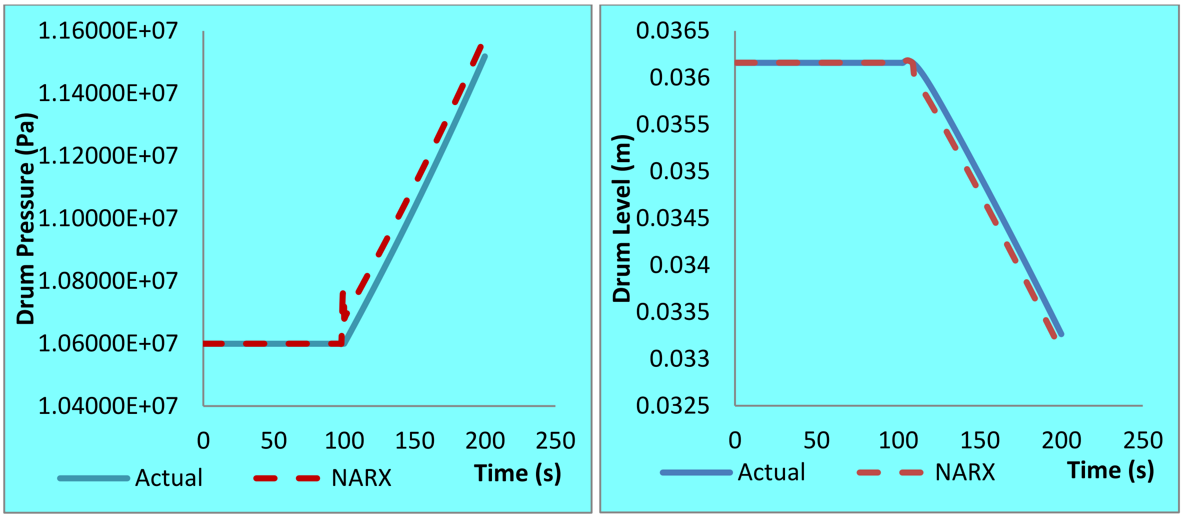

Figure 16 Drum Pressure and Level Response to +10 MWth step change in Heat Input

Acknowledgement

The authors are grateful to the Natural Environmental Research Council (NERC), Reference - NE/H013865/2, for financing this research. The financial support from EU FP7 (Reference: PIRSES-GA-2013-612230) is also acknowledged. Helpful discussions with Prof Jianhong Lyu at South East University, China are also acknowledged.

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