Fuel 151 (2015) 139–145

Contents lists available at ScienceDirect

Fuel

journal homepage: www.elsevier.com/locate/fuel

Neural network approach for predicting drum pressure and level in coal-fired subcritical power plant

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HIGHLIGHTS

- Dynamic modelling of coal-fired subcritical boiler based on Neural Networks (NN).
- Dynamics of drum level and drum pressure predicted with NN.
- First principle model for subcritical coal-fired boiler used to generate data for NN training.
- NN model predictions in good agreement with actual outputs of the drum-boiler.

ARTICLE INFO

Article history:
Received 5 October 2014
Received in revised form 11 January 2015
Accepted 27 January 2015
Available online 8 February 2015

Keywords:
NARX neural networks
Subcritical coal-fired power plant
Drum-boiler
gPROMS modelling and simulation

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).

1. 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.

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 nonlinear models still have to be reduced in model order and then linearized [5]. The performance of linear models usually deteriorates

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http://dx.doi.org/10.1016/j.fuel.2015.01.091
0016-2361/

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].

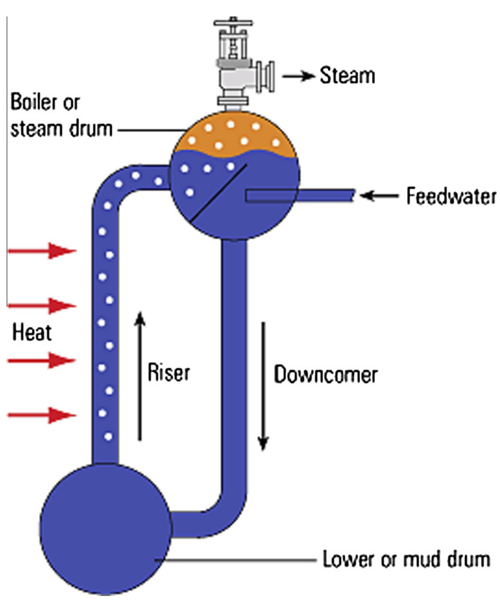

Fig. 1. Drum-boiler (∗) illustrations and text are taken from the Spirax Sarco website 'Steam Engineering Tutorials' at <http://www.spiraxsarco.com/resources/steam-engineering-tutorials.asp>. Illustrations and text are copyright, remains the intellectual property of Spirax Sarco, and have been used with their full permission.

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) was 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 of 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.

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, $(u_1(t), u_2(t), u_3(t) \ldots u_k(t))$, 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 ($w_{1,} w_2, w_3 \ldots w_k$) 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:

$$y(t) = f\big(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)\big) \tag{1}$$

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 $(y(t-1), y(t-2), \ldots, y(t-n_y))$ and previous values of an independent (exogenous) input signal $(u(t-1), u(t-2), \ldots, u(t-n_u))$. 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.