Neural Network Modeling for ALSTOM Gasifier

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Abstract. Neural Network Model Based Predictive Control (MPC) has become a good choice of control strategy in many cases especially in the process industry because it could face non linearities and cross coupling variables [6], being modeling the first step to achieve this end. The model of a gasifier, provided by ALSTOM Power Technology Centre, is of an industrial standard and has been validated against a set of real data from test facilities. This makes the challenge all the more relevant to practicing engineers. The paper sets out the specifications and describes the design and performance of neural networks modeling and presents a neural network approach to model the ALSTOM Benchmark Challenge gasifier. This is a complex non-linear process, with a high degree of cross coupling of the variables, manual control is difficult.

1 Introduction

Power generation is responsible for a significant part of the total emissions of solid, liquid and gaseous pollutants all around the world. Due to a predicted higher long-term availability of solid fuels, in particular coal, compared to oil and natural gas, solid fuels will play an important part in future energy supply.

As a result of this, Integrated Gasification Combined Cycle (IGCC) power plants, combining gasification with a gas and steam cycle, are being developed around the world.

Low emission power generation techniques are being developed around the world to provide environmentally clean and efficient power. To this scope, ALSTOM has carried out researches on the combustion of pulverized coal using an Integrated Gasification Combined Cycle (IGCC) power plant.

The operation of this Pilot Integrated plant (PIP) is based upon the Air Blown Gasification Cycle (ABGC). First, limestone is added to the pulverized coal to minimize sulphur originated from the coal.

Then, the mixture is fluidized in a stream of air and steam and conveyed into the gasifier. As a result, a low calorific value fuel gas is produced by the reaction between the air and steam and the carbon and volatiles from the coal. The limestone, ash and unreacted carbon are removed as bed material from the base of the gasifier or elutriated to avoid carrying it out of the top of the gasifier as fines with the product gas.

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In 1997 the ALSTOM Power Technology Centre issued an open challenge to the UK academic control community, which addressed the control of a Gasifier plant. The 'Challenge information pack' included three linear models (derived from ALSTOM's comprehensive non-linear model of the system), together with a detailed specification comprising output limits, control input constraints and disturbance tests [1] and [2].

The second round of the challenge was issued in June 2002 (see reference [3]), and extends the original study by providing participants with the full non-linear model of a gasifier in MATLAB\SIMULINK shown in Figure 1.

It includes an expanded specification to incorporate set point changes and coal quality disturbances.

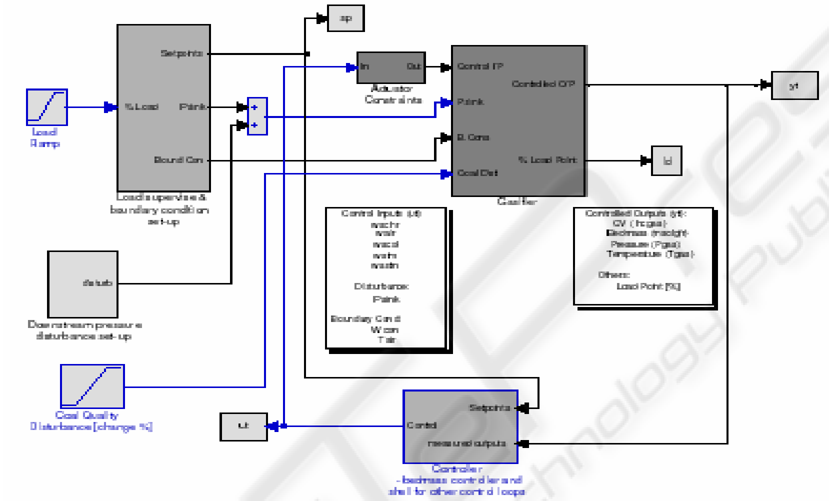

Fig. 1. MATLAB/SIMULINK model plant.

In this paper a practical design procedure of Neural Networks Dynamical Modeling is studied and applied to a simulated non linear plant of gasifier.

The rest of this paper is organized as follows. Section 2 discusses modeling using neural network and included a short summary about the gasifier. Also are explained in section 2 data acquisition for identification and the simulation results obtained after the neural model have determined, and finally in section 3 some conclusions are drawn from work.

2 Modeling Using Neyral Network

Neural networks have found widespread application to solving modeling and global optimization problems, and have been used for control of power systems. For further control design using Model Based Predictive Control, we require to find a non linear model for this purpose.

2.1 Plant Description

A schematic of the plant is shown in Figure 2. The gasifier is a non-linear, multivariable component, having five controllable inputs (coal, limestone, air, steam and char extraction) and four outputs (pressure, temperature, bed-mass and gas quality) with a high degree of cross coupling between them.

Note that as limestone is used to absorb sulphur in the coal its flow rate must be set to a fixed ratio of coal flow, nominally 1:10 limestone to coal. This leaves effectively a four-input four-output regulation problem for the control design [4].

Other non-control inputs for the model include boundary conditions (to allow maneuvers to different operating points), a disturbance input (PSINK) which represents pressure disturbances, and a coal quality input.

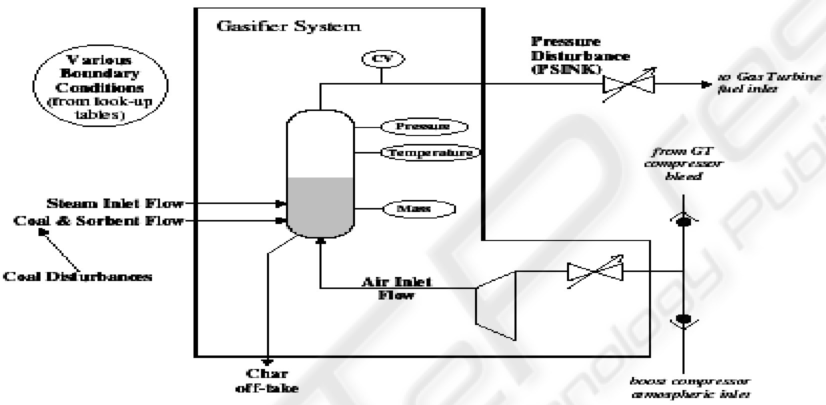

Fig. 2. Gasifier Schematics.

The controllable inputs then are:

- Char extraction flow - WCHR (kg s-1)
- Air mass flow - WAIR (kg s-1)
- Coal flow - WCOL (kg s-1)
- Steam mass flow - WSTM (kg s-1)

The controlled outputs are:

- Fuel gas calorific value - CVGAS (J kg-1)
- Bed mass - MASS (kg)
- Fuel gas pressure - PGAS (N m-2)
- Fuel gas temperature - TGAS (K)

2.2 Data acquisition for the identification

The set of data to the training process and validation process were collected from the model of the plant given by ALSTOM, after knowing the dynamics of the system and after several testing process using a random signal as inputs within the measure of the range of each input.

The type of input has suggested for the identification and validation of the model is the PRS (Pseudo-random Signal), this is used for the design of experiments of identification [5].

We will consider variations on every input of the gasifier. Figure 3 and 4 shows the PRS inputs and the output for this signal respectively, where the dot line represents their mean values shown in Table 1. This PRS takes randomic values, within 10% range of the 100% load case for the gasifier, as inputs to the model plant and with the result output data we got the set to train the network.

Table 1. Input and output var and its mean values.

Inputs	Values (kg/s)	Outputs	Values
WCHR	0.9	CVGAS (J/kg)	4.36e+6
WAIR	17.42	MASS (kg)	10000
WCOL	8.55	PGAS(N/m^2)	2.0e+6
WSTM	2.70	TGAS (K)	1223.2
WLS	0.85		

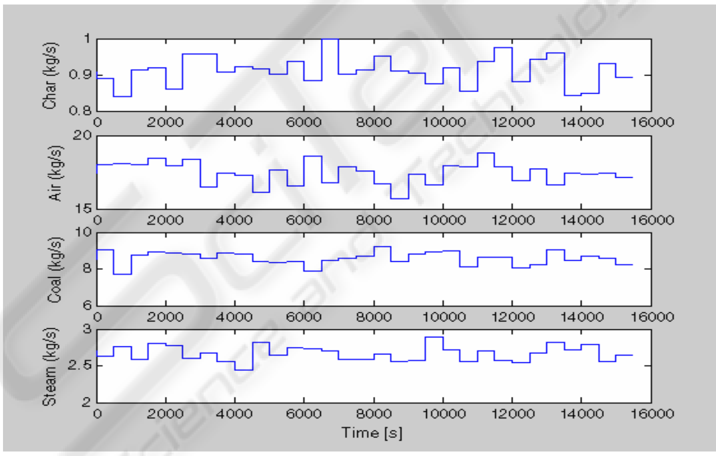

Fig. 3. Simulated PRS input.

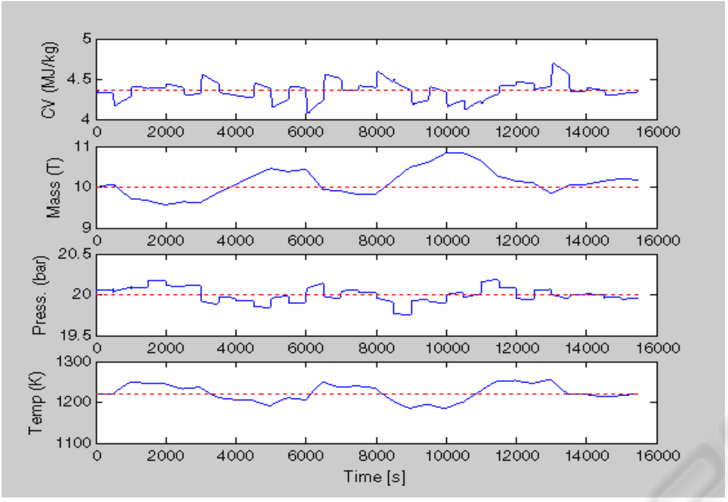

Fig. 4. Simulated output for a PRS input.

As explained above limestone must be set to a fixed ratio of the coal flow, nominally 1:10. This leaves effectively a four-input four-output regulation problem for model design which simplifies the quantity of data needed to train the neural network on the identification process.

2.3 Plant Identification

At first we need to define which kind of neural network we will use. As we move into the neural network field we find that one of the most common network used in this field to approximate a nonlinear continues function is the two layers perceptron [8], being the first layer function sigmoid and the second layer function lineal as shown in the Figure 5.

The number of units of the output layer is limited to the number of outputs, in this case four and the number of units of the hidden layer can not be less than the number of output units because they would be linearly dependent. After several tests we found four units were a good choice.

Also as inputs we added one delayed output following observable states black box equation showed below [7]:

Ec.1 Generalized model type input-output:

$$y(k+1) = h\{y(k), y(k-1),...y(k-n), u(k), u(k-1),..u(k-m)\} \quad \textbf{(1)}$$

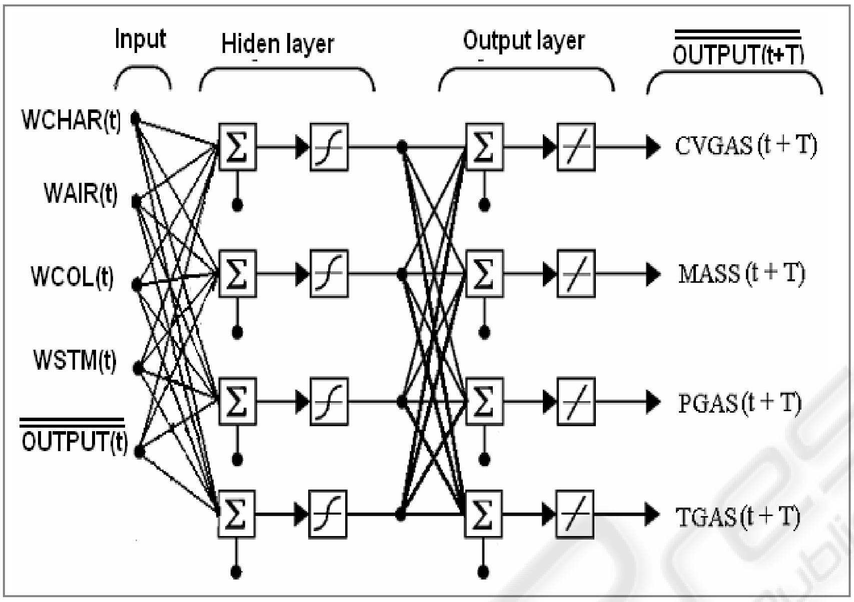

Fig. 5. Neural network schematics

We have included in our testing process more past output data using a delayed network and organizing a past data set [8], but experimentally it did not improve the performance of the network. As the simple network performance good enough, we leave the attempts of using delayed networks.

This set of data collected were used for training and validating the neural network, this is divided in two parts, first part for training and second one for validating. In order to avoid square error function to minimize, as a priority, greater module signals we have normalized all signals as in their original values these would have more effect on the total value of the error. Normalization is hardly recommended by some training algorithms [8].

Figures 6 shows simulated outputs when the neural network model if feed with training data. In this figure we can distinguish two lines, the first one is a red dot line referred to the output when PRS inputs signal were applied to the SIMULINK plant model; the continues blue line refers to the simulated output of the network.

Same as above Figure 7 shows simulated outputs when validating data were applied to the network.

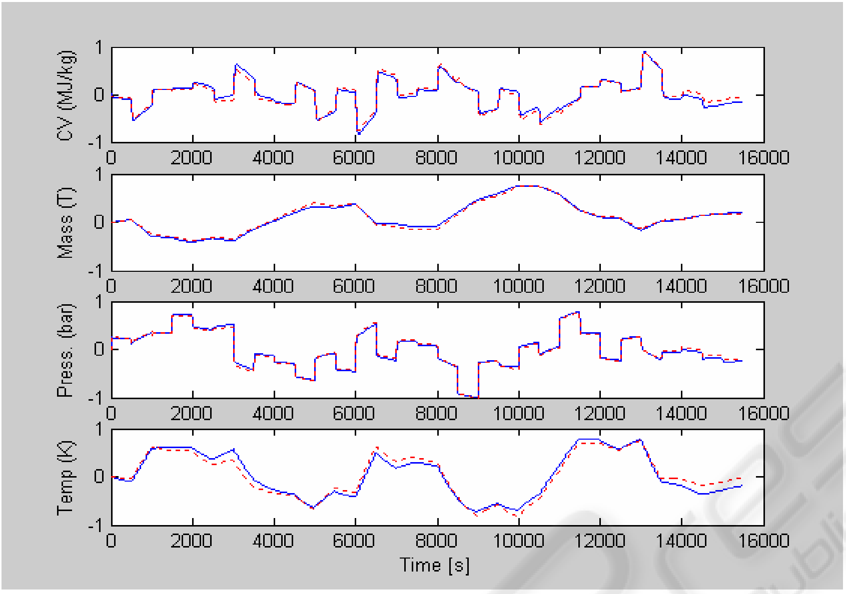

Fig. 6. Simulated output for training data.

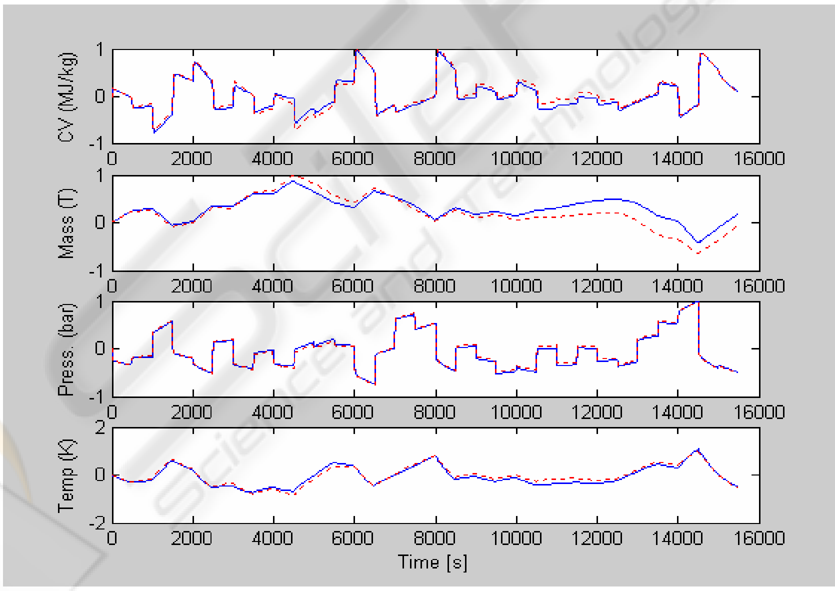

Fig. 7. Simulated output for validating data.

Table 2. Mean Square Error

		Training simulation	Validating simulation
MSE	9.4413e-005	0.0025456	0.069403

Table 2 shows the Mean Square Error (MSE) for: the training process, the simulation with the information of training and the simulation with other information for validation. MSE are low for the simulation of neuronal network with the same data using in the training, while using other data, column of validation, the MSE is greater. This is because when simulating using training data set we do not use delayed output as input to the network; and when simulating using validating data, this set of data is completely new for the network so it tries to follow what it have learned from the training process.

3 Conclusions

The present paper consists on a first study of the Gasifiers Modeling by empirical methods, specifically the based on Neural Networks:

– The theoretical study of the gasification has allowed us to know the principles of this complex process.
  From the system's point of view, we conclude that the Gasifier plants are a platform for the development of the methodologies of advanced control.

– The theoretical study on neural networks has allowed us to familiarize with this technology so useful and applicable to so diverse problems. In specific, the application of this technology to the empirical modeling of dynamical systems can be very much suitable in case of systems with highly non linearity.

– The simulated ALSTOM Gasifier offers us an important tool for the application of methodologies of modeling, allowing us to extract conclusions before the application to the real system.

– For the case of variations of maximum 10 % in the inputs, was not found difficulties in training the net. It is important that information would be representative of the behavior of the system in the whole operation range.

– With the employment of Neural Network to the simulator, the familiarization has been obtained as much by the Neural Network Toolbox of Matlab, as by the methodology of application of static networks for a dynamical process type black box, defined by its inputs and outputs.

– Some architectures were proved and a network type perceptron with two layers, the first one of sigmoid and linear the second one has been chosen as firstly attempt for the application of the methodology.

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