DEVELOPMENT OF A HYBRID SIMULATOR OF A FOSSIL FUEL STEAM POWER PLANT

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Abstract

Considering the extensive applications and also importance of simulators with flexible abilities such as link speed, reliable topology and accessible for all necessary data and tests, this paper addresses a method which have these advantages including a structure which can be updated for several behaviors of processes. Here we present an advanced power plant simulator based on a combination of mechanistic equations and neural networks and wavelet models to achieve a high performance response. The hybrid modeling approach is applied to the complex dynamics of a fossil fuel steam power plant which have previously developed via SIMULINK and OOP. Since most of high order simulators consume much time to analyze a behavior and also their development is very time consuming, this article tries to present a hybrid simulator to overcome these problems. Comparisons of the hybrid simulator and the original one is also presented.

1 Introduction

With improving computer hardware and numerical methods, simulation and simulators have been received attention in the literature. Since power plants are complicated systems, their simulators and also simulation time are important issues for engineers [4].
In this paper, the development of a hybrid model of a fossil fuel steam power plant using artificial neural networks and its combination with wavelets (i.e. called wavenets) [9] is presented. The basic system under study here is a typical power plant developed in SIMULINK environment based on "Object Oriented Programming" (OOP) and C-programming language, and created a new toolbox for constructing simulators. An important feature of this environment is building the "Dynamic Link Library" (DLL) of m-files and c-files of the block diagrams of this simulator using Visual C++ program linked with the MATLAB. Here, one needs to produce new MATLAB S-functions to construct an intelligent library [10],[11].
The developed simulator is able to use all MATLAB toolboxes for training, testing and other research studies. One may also invokes neural network and wavelet toolboxes for the development of the hybrid models of the system within this simulator.
Several parts of the basic power plant such as boiler, steam turbine, condenser, feed water system, furnace, steam generator, superheater, attemperator, reheater and air preheater can be modeled with neural networks. Such models would be so useful for decreasing the time of simulation and can be easily modified and developed for real power plants. Besides, due to the capability of general neural networks and also wavenets, reliable and accurate models based on the real data and under practical conditions can be developed and employed in the simulator.
In this paper, after the above general introduction, the concept of hybrid modeling is explained. Then, various components of a fossil fuel steam power plant are introduced. The study will be followed by hybrid modeling of the power plant and simulation results of the new developments.

2 Hybrid Modeling

In science and engineering there are two fundamentally different philosophies that form the basis of modeling, namely the mechanistic and empirical approaches. A mechanistic model structure is developed on the basis of a detailed understanding of the generic underlying mechanisms, or laws, that governs the system behavior. While system parameters may be identified using empirical data. An empirical model, on the other hand, is derived on the basis of the specific observed behavior of the system. Its structure is often a generic black box that cannot be directly interpreted in terms of the system mechanisms.
However, it may also be developed on the basis of empirical knowledge, including measured process data, and the experience of process operators and engineers. Often, neither of these two approaches are attractive. If the system mechanisms are only partially understood, the development of a mechanistic model structure may not be feasible. This may, however, also be the case for an empirical model, because of a lack of process data and difficulties to incorporate the available system knowledge in this approach.

This is because engineering knowledge is incompatible with many empirical model representations, like black boxes.
In practice, most models are based on an unbalanced combination of mechanistic and empirical knowledge. For example, in a mainly mechanistic approach certain aspects of the system that are not sufficiently well understood may be described by empirical correlations in the model. Also, in a dominantly empirical approach, some mechanistic understanding is often useful to make certain structural choices, like the model order, or non-linearities.

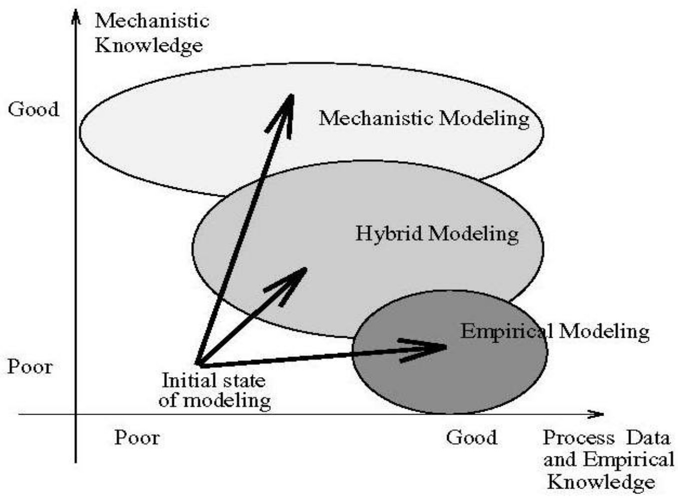

Figure 1: Illustration of different modeling paradigms [6]

Moreover, at early stages in the model development, an empirical model will often be useful as a starting point for gaining more knowledge and eventually designing a mechanistic model. Different modeling paradigms are visualized in Fig.1, projected onto the “mechanistic” and “empirical” axes. A typical situation is illustrated, where the initial state of the model development is characterized by a lack of both empirical and mechanistic knowledge [7].
With the empirical approach, one will collect more data, and end up in a state with more data and perhaps some improved mechanistic knowledge. With the mechanistic approach, on the other hand, one will end up with significantly improved mechanistic knowledge and perhaps some more data. The “in between" region and path corresponding to hybrid models (semi-empirical models, semi-mechanistic models, or models with a balanced utilization of empirical and mechanistic knowledge) is often approached in an ad. hoc. manner, or avoided. A major reason for this may be that powerful frameworks and software tools for such problems are lacking. The main objective of this papers is to develop and study a framework that we believe may be useful for solving such hybrid modeling problems. It is our assumption that resources in many cases can be saved by choosing the hybrid approach [6].

3 Steam Power Plant Components

A typical fossil fuel steam power plant contains four main parts:

- Boiler
- Turbine
- Condenser
- Feed Water System

In our basic simulator the above subsystems are accessible in both open loop and closed loop situations. So we are able to get data from each variable of the plant under various conditions. But it is assumed that the measured parameters are in the normal behavior of the plant. No start up and/or shut down stages are considered here. The subsystems of each part of the plant have been introduced as the following.

3.1 Boiler

The boiler contains the following components:

- Furnace
- Drum and Riser
- Superheater
- Reheater

The order of the dynamic mechanistic equations of the open loop boiler, without PID controllers and actuators is 14 with 22 output and 14 input variable including 42 algebraic equations as it shown in Fig.2. For more details of mechanistic and thermodynamics equations, one may see [10].

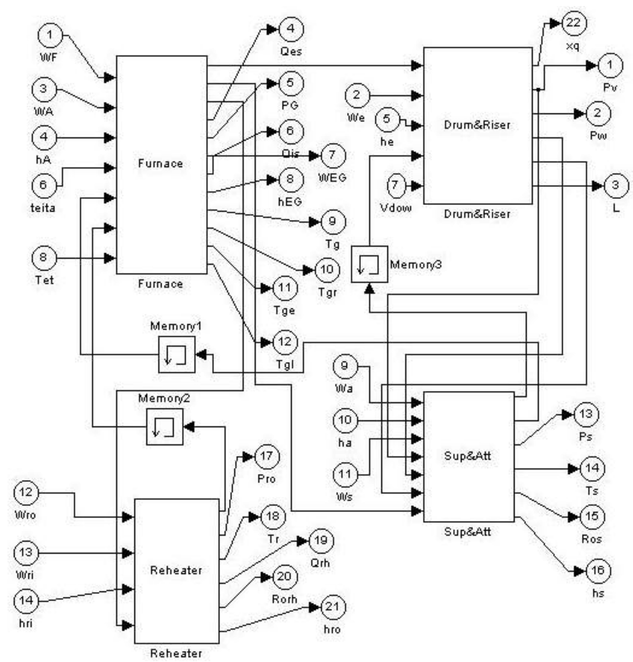

Figure 2: Block diagram of boiler configuration

Each subsystem of the boiler is constructed via MATLAB S-functions compiled with MEX-functions. These blocks use DLL files and can be incorporated in an intelligent or expert simulator.

According to the practical situations [2],[5],[8] not all the inputs are subject to considerable deviations, and it is only necessary to deal with the manipulated variables which are used to control the system. The reduced set of variables is shown in Table 1.

INPUTS			
Notation	***Variable Name***	***Unit***	***Nominal Value***
W_F	fuel flow to furnace	Kg/Sec	16.3584
W_e	water flow to drum	Kg/Sec	12
W_A	air flow to furnace	Kg/Sec	84.8824
θ	tilt angle	Rad	0.88041
W_a	water flow to attemporator	Kg/Sec	0
OUTPUTS			
Notation	***Variable Name***		***Unit***
L	level of drum water		m
P_G	air furnace pressure		Pa
P_S	Superheater steam pressure		Pa
T_S	Superheater steam temperature		ºK
T_r	reheater steam temperature		ºK

Table 1: Manipulated variables of the boiler

As seen in Table 1, there are five fundamental inputs in the boiler to be changed to produce the necessary information for training the neural networks. This is performed by applying changes to the manipulated variables of Fig.2. These inputs have deviations around their nominal value (see Table 1). The range of these changes can be found by measuring the input deviations in the closed loop system, and is suggested in Table 2.

Deviations in Inputs	
ΔW_F	[-0.01,+0.01] Kg/Sec
ΔW_e	[-0.5,+0.5] Kg/Sec
ΔW_A	[-0.015,+0.080] Kg/Sec
$\Delta\theta$	[-0.0011,+0.0015] rad
ΔW_a	[0,+1] Kg/Sec

Table 2: Input changes of the boiler

Any change in the input is applied after every 50 seconds, for 500 seconds with a normal random distribution and the solution method is (ode4) Runge Kutta with Δt=0.01 second fixed step. The resulting outputs are shown in Fig.3.

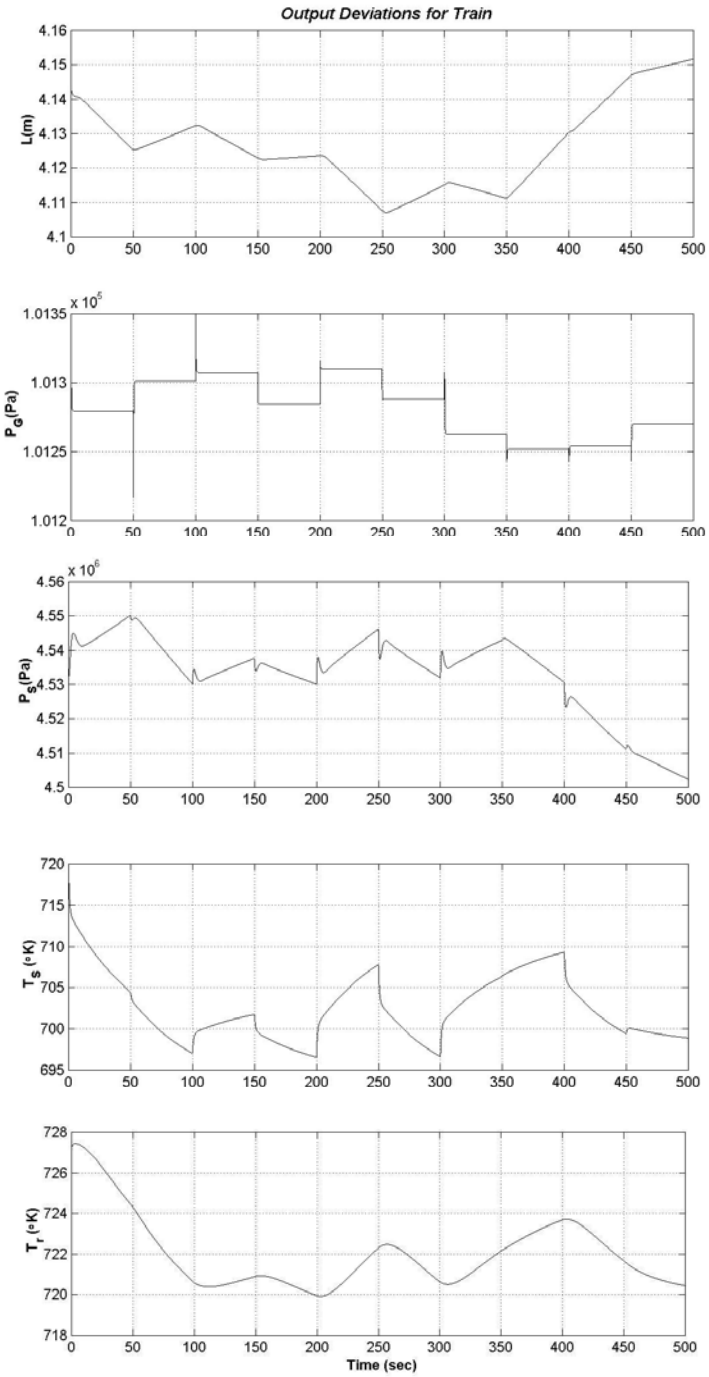

Figure 3: Output changes of the boiler for the input variation of Table 2

3.2 Turbine

The components of turbine of the simulator are:

- High Pressure (HP)
- Intermediate Pressure (IP)
- Low Pressure (LP)

The order of the dynamic equations of the open loop turbine (without PID controllers and actuators) is 10 with 11 outputs and 11 inputs and 32 algebraic equations as shown in Fig. 4

(see [10] for details of equations). The manipulated variables are shown in Table 3.

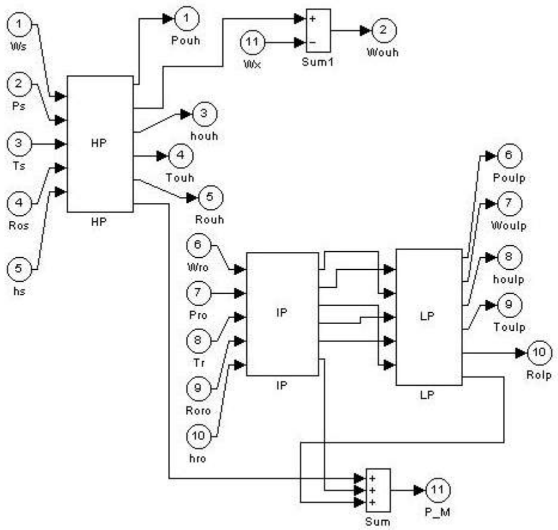

Figure 4: Block diagram of Turbine Configuration

INPUTS			
Notation	***Variable Name***	***Unit***	***Nominal Value***
W_S	Steam flow to HP	Kg/Sec	12
P_S	Steam pressure of HP	Pa	$4.5251*10^6$
T_S	Steam temperature of HP	ºK	717.72
ρ_{os}	Steam density of HP	Kg/m^3	13.662
h_S	Steam enthalpy of HP	J/Kg	$3.3117*10^6$
W_{ro}	Steam flow to IP	Kg/Sec	10.459
P_{ro}	Steam pressure of IP	Pa	$1.3034*10^6$
T_r	steam temperature of IP	ºK	727.25
ρ_{or}	Steam density of IP	Kg/m^3	3.8835
h_{ro}	Steam enthalpy of IP	J/Kg	$3.3334*10^6$
OUTPUTS			
Notation	***Variable Name***		***Unit***
P_m	turbine power output		W
ω	turbine speed		p.u.

Table 3: Manipulated variables of turbine

The ten input variables of the turbine are due to the change to get necessary output information. Their changes in closed loop system are presented in Table 4 for neural network training.

The changes in inputs, apply after every 50 second, for 500 second with a normal random distribution and the solution method is (ode4) Runge Kutta with $\Delta t=0.1$ second tolerance. We should note that in practice not all the inputs are to considerable change in close loop system, but here we apply the changes to all inputs to get rich data for training.

The measured output due to the ten inputs changes is shown in Fig.5. As it is shown in Table 3, the angular velocity (ω) is also another output, but because of the simple dynamic of the generator in the simulator we do not need to model this component.

Deviations in Inputs			
Variable	***Changes***	***Variable***	***Changes***
ΔW_S	[-4,+1] Kg/Sec	ΔW_{ro}	[-3,+1] Kg/Sec
ΔP_S	$[-10^4,+10^4]$ Pa	ΔP_{ro}	$[-10^4,+10^4]$ Pa
ΔT_S	[-4,+4] ºK	ΔT_r	[-2,+2] ºK
$\Delta \rho_{os}$	[-0.02,+0.02] Kg/m^3	$\Delta \rho_{or}$	[-0.03,+0.03] Kg/m^3
Δh_S	$[-10^3,+10^3]$ J/Kg	Δh_{ro}	$[-3*10^3,+3*10^3]$ J/Kg

Table 4: Input changes of turbine

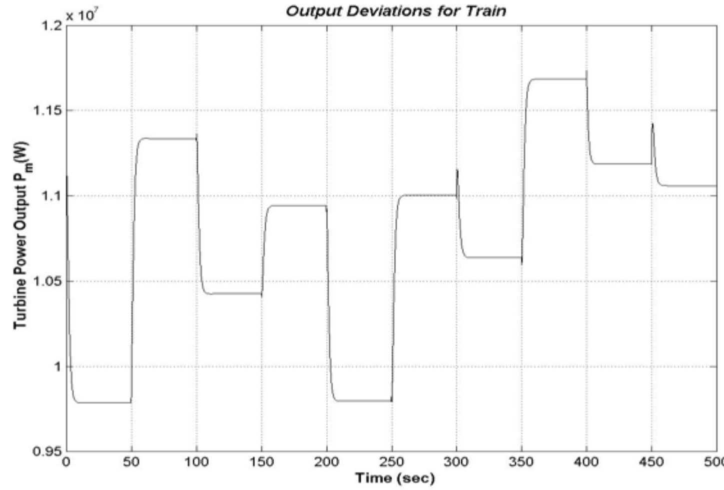

Figure 5: Output changes of the turbine

3.3 Condensor, Feed Water System and Generator

The other components of the simulator such as condenser, feed water system, generator, pumps, valves, economiser, deaerator, actuators and the others have simple dynamics and are represented via simple algebraic equations. Therefore, we do not need to find any new model for these parts. So the combination of mechanistic equations for the components with simple dynamics and the neural network modeling for the complex parts of the plant will build a hybrid model with high performances.

4 Developing Hybrid and Neural Network Models

Because of the complexity of the boiler and the turbine dynamics, we try to develop accurate neural networks (NN) models for these components in the simulator. The numbers of inputs and outputs of the boiler regarding their sampling time, are ten data sequences with 500,000 samples in each series that should be used to train a neural network and with 5 input and 5 output. Such a training with a proper error index takes tremendous time and may not be practically useful. To avoid this problem, we use an extrapolation method for every 5 sample. Also, to simplify the modeling we can use five different neural networks for each output. This allows us to have a smaller error and it does not take much training time for the networks. The past inputs of the last two sampling times are also taken as the inputs of the neural networks model of the boiler. Thus, for each of the boiler's output variables y_k, the inputs of the network will be y_{k-1}, y_{k-2}, u_1, u_2, u_3, u_4 and u_5.

The networks considered here is a three hidden layer (Multi Layer Perceptron) MLP network. The number of the neurons in each layer is chosen by trial and error to get the best numbers. The functions used in the layers are tan-sigmoid for the first and second layers, and pure linear for the output layer (see Fig.6).

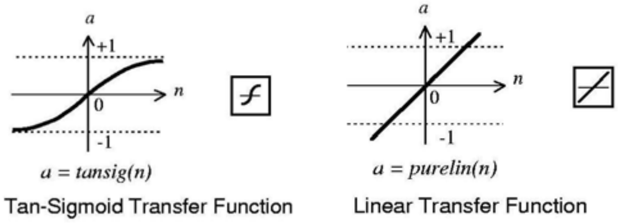

Figure 6: Normalized Tan-Sigmoid and Linear Function used in Neural Network [3]

The termination error is 10^{-6} and the number of neurons for each output is shown in Table 5.

Number and Types of the Neurons to Train Boiler Variable with MLP Network			
Variable	***Layer Number 1 (Tan-Sigmoid)***	***Layer Number 2 (Tan-Sigmoid)***	***Layer Number 3 (Pure Linear)***
L	2-Neurons	4-Neurons	1-Neuron
P_G	2-Neurons	2-Neurons	1-Neuron
P_S	1-Neuron	2-Neurons	1-Neuron
T_S	2-Neurons	3-Neurons	1-Neuron
T_r	2-Neurons	3-Neurons	1-Neuron

Table 5: Number of neurons for the boiler modeling

For the turbine system we use Pm_{k-1}, Pm_{k-2}, u_1, u_2, …, u_{10} to train the network. The layers used in this case are:

- *Layer Number 1 (Tan-Sigmoid), 1-Neuron*
- *Layer Number 2 (Tan-Sigmoid), 2-Neurons*
- *Layer Number 3 (Pure Linear), 1-Neuron*

MLP networks with backpropagation learning algorithm were developed for the boiler system [3]. Due to the special nature of the turbine system, wavenet networks showed better approximation features and thus used here. For a detail explanation of the wavenets and their properties see [9].

5 The Hybrid Simulator and Closed Loop Responses

Having developed NN models of the turbine and boiler systems which cover the most complex part of the power plant simulator, and constructing the rest of the simulator components using the mechanistic model formulations, the hybrid simulator is built by combining the two parts of our developments. In fact, to get familiar with the mechanistic parts of the simpler elements of the simulator, one may see [10], [11]. The closed loop systems (with controllers, valves and etc.) in this new simulator is studied to show the performance of the new developments.

The testing signals are applied to the closed loop boiler system which contains the boiler, two valves and six PID controllers and closed loop turbine system containing three valves, generator and a PID controller [10],[11]. We apply different disturbances based on the real environment and actual conditions [2],[5],[8] to test the performance of the hybrid simulator by changing the setpoints as follows:

Test 1: Reduce in p_s and p_g by 10% in 200 seconds (fig.7)
Test 2: Increase in level of drum water by 10% (fig.8)
***Test 3*:** Reduce in temperature of superheater by 7ºk (fig.9)
***Test 4*:** Reduce in temperature of reheater by 3ºk (fig.10)
***Test 5*:** Reduce turbine power by 10% in 200 seconds(fig.11)

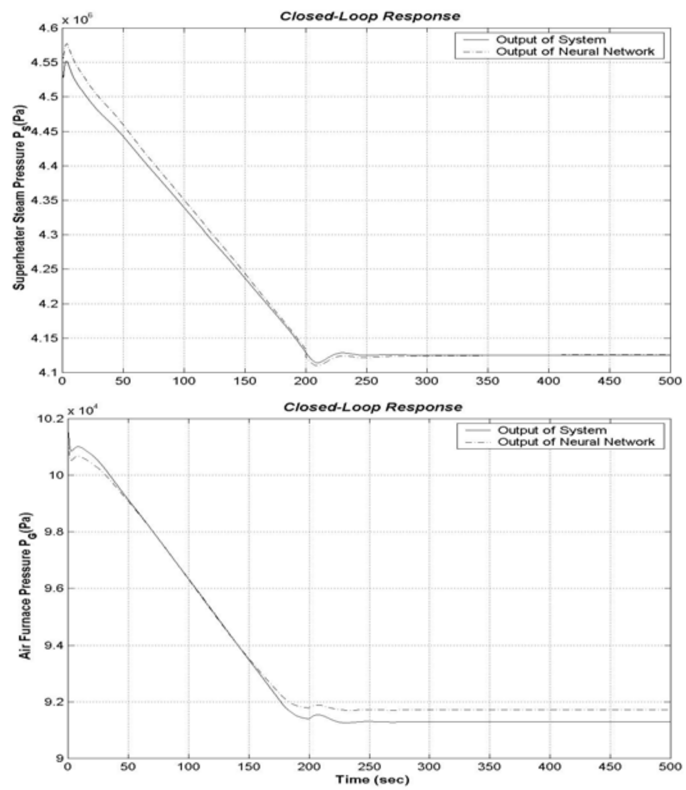

Figure 7: Reduce in P_S (top) and P_G (bottom) by 10% in 200 seconds

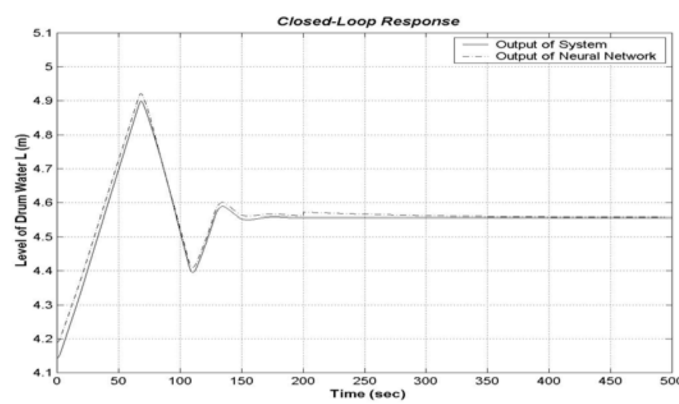

Figure 8: Increase in level of drum water by 10%

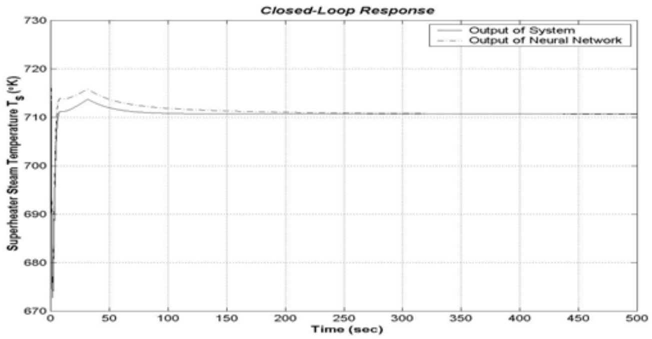

Figure 9: Reduce in Temperature of Superheater by 7ºK

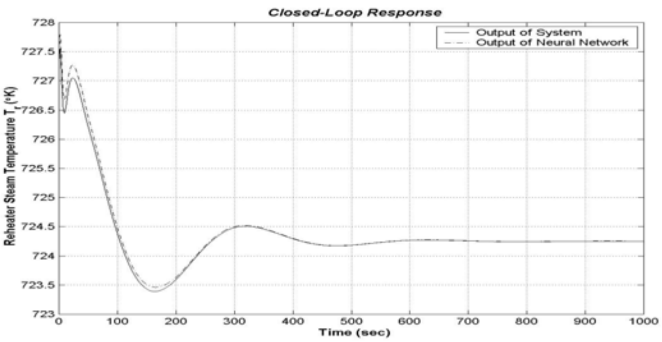

Figure 10: Reduce in Temperature of Reheater by 3ºK

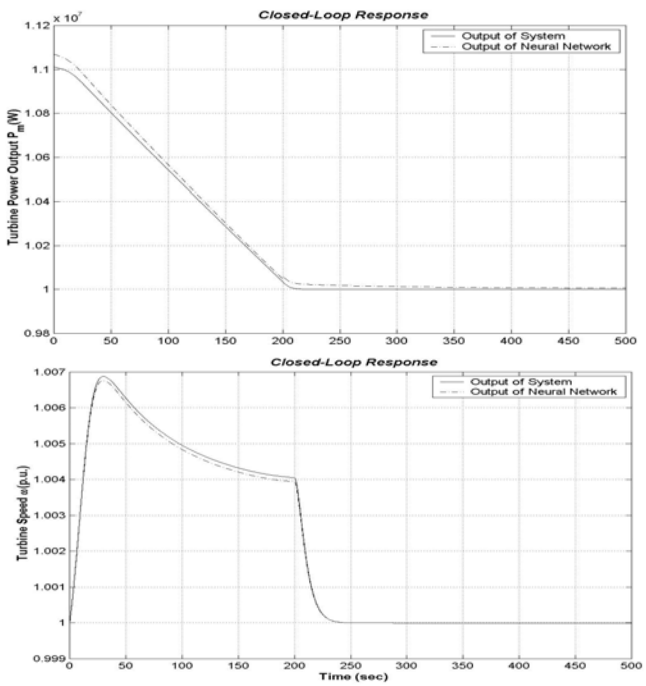

Figure 11: Reduce turbine power by 10% in 200 seconds; output power (top) and turbine speed (bottom)

To compare the results of the basic simulator and estimated outputs by the hybrid simulator, we use the normalized root mean square error [1]:

$$\varepsilon = \sqrt{\frac{\sum_i (x_i - \hat{x}_i)^2}{\sum_i x_i^2}}$$

where $\hat{x}$ is the output vector of hybrid simulator and x is the output vector of the basic simulator. This error is computed for all of the boiler and turbine outputs. The results is shown in Table 6.

Output Normalized Root Mean Square Errors			
L	0.0281	T_S	0.0207
P_G	0.0759	T_r	0.0377
P_S	0.0452	P_m	0.00023
	ω	0.0000715	

Table 6: Output Errors

As we can see in Table 6, the minimum errors occurs in variables P_m and ω of turbine, because the training method of these parts is based on wavenet structure. The wavelet which is used in this case is One-Dimensional-Daubechies-Type-Wavelet [9]. Beside of the good performance one can see in the hybrid simulator, the simulation time is also a great importance. The simulation times decrease from about 10 minutes for 500 seconds simulation to 10-20 seconds for each part of the simulator.

6 Conclusions

In this article, a new development of a hybrid simulator of a fossil fuel power plant was addressed. The idea was to model some complex and time consuming parts of the power plant using NN's and wavenets. Then combined these parts with some simple mechanistic formulations to build the hybrid simulator. Some advantages of this hybrid simulator is its flexibility in re-newing the models of the complex parts and the accuracy that it will have due to the possibility of the development of NN models based on the real and updated data of a true power plant. Besides, the simulation time will be considerably reduced and allows a faster decision making process. The great potential of wavenet models were proved very well in this study. For additional works, we are able to add some noise sources to simulate the various behaviors of the plant and also to extend the hybrid simulator to cover the start up and shut down equations which are very complicated.

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