Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Controller Design for a 1000 MW Ultra Super Critical Once-through Boiler Power Plant

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Abstract: A large-scale 1000 MW once-through type ultra super-critical boiler power plant, requires investigation for the development of an analyzable model for use in the development of an intelligent control system. Using data from the power plant, a model is realized using dynamically recurrent neural networks. For proper operation, the plant must be broken into smaller subsystems that are each modeled by a separate neural network. Modified predictive optimal control is then used to drive the plant to desired states. Due to the computational intensity of modified predictive optimal control, it was rendered unviable by the computation time required for each time step of the controller. As an alternative, a reference governor was implemented along with a PID feedback control system that utilizes intelligent gain tuning.

1. INTRODUCTION

Ultra super-critical (USC) boiler power plants are currently being developed to increase the efficiency of standard fossil fuel power plants. The modelling and control of a large-scale 1000 MW once-through type ultra super-critical boiler power plant is investigated here. Larger more complicated power plants require more sophisticated methods to streamline the modelling process as well as more sophisticated control schemes that can be used to further enhance plant efficiency.

The development of large capacity power plants requires new approaches to analyze plant dynamics for control purposes. In practice, many utility companies utilize simulation programs, such as Modular Modelling Systems (Leavesley*, et al*., 1996) or their own simulation tools for modelling. However, it is a challenge to extend current models to model larger capacity plants, and to design new models without component specifications. To design a control system for a power plant, a model must be developed in advance. Recently, the study of Neural Networks (NN) has become important in designing system identification and control systems in the power systems area. With system data, the NN can be trained to approximate highly nonlinear functions. Since the NN strongly depends on the input/output data but not on the physical structure of the system, it is flexible and can easily be adapted to different types of power plants.

Accurately modelling such a system with a single NN is theoretically possible, but it was discovered that in practice, the training of such a network was not practical. Instead, the individual subsystems of the power plant were modelled with separate NN that were combined to form the power plant model. This type of approach is covered in detail in (Lee, *et al.*,2007a). Only the higher level details will be covered to show the differences required to deal with a new power plant.

It was desired to use a modified predictive optimal control scheme with this plant to track unit load demand in order to provide adaptive control that optimized certain functions of the power plant. This scheme was developed successfully, but turned out to be more computationally intensive than desired for an actual controller. To overcome this difficulty, a reference governor was developed to provide feed forward controls in conjunction with a simple PID feedback control system that utilizes intelligent gain tuning. Both approaches are presented with a focus on the reference governor and intelligent gain tuning.

2. 1000 MW USC POWER PLANT

In this report, the USC boiler power plant consists of four processes which are air/flue gas, pulverizer, water/steam, and turbine/generator. However, for modelling purposes, the number of detailed subsystems will be nineteen. Fig. 1 shows the 1000 MW USC boiler power plant. Most blocks are subsystems, which will be represented by a NN-based subsystem model. The proposed scheme will be applicable to other types of plants, including nuclear and fuel cell plants.

The power plant under investigation is a 1000 MW coal-pulverized, once-through type, boiler-turbine-generator unit. There are three economizers used to raise the temperature of water entering the boiler from the feedwater system. Two forced draft fans and two primary air fans provide air to the air preheater. The air preheater in turn provides heated air to the pulverizers, burners, and furnace. The primary air fans

978-1-1234-7890-2/08/$20.00 © 2008 IFAC

10.3182/20080706-5-KR-1001.3464

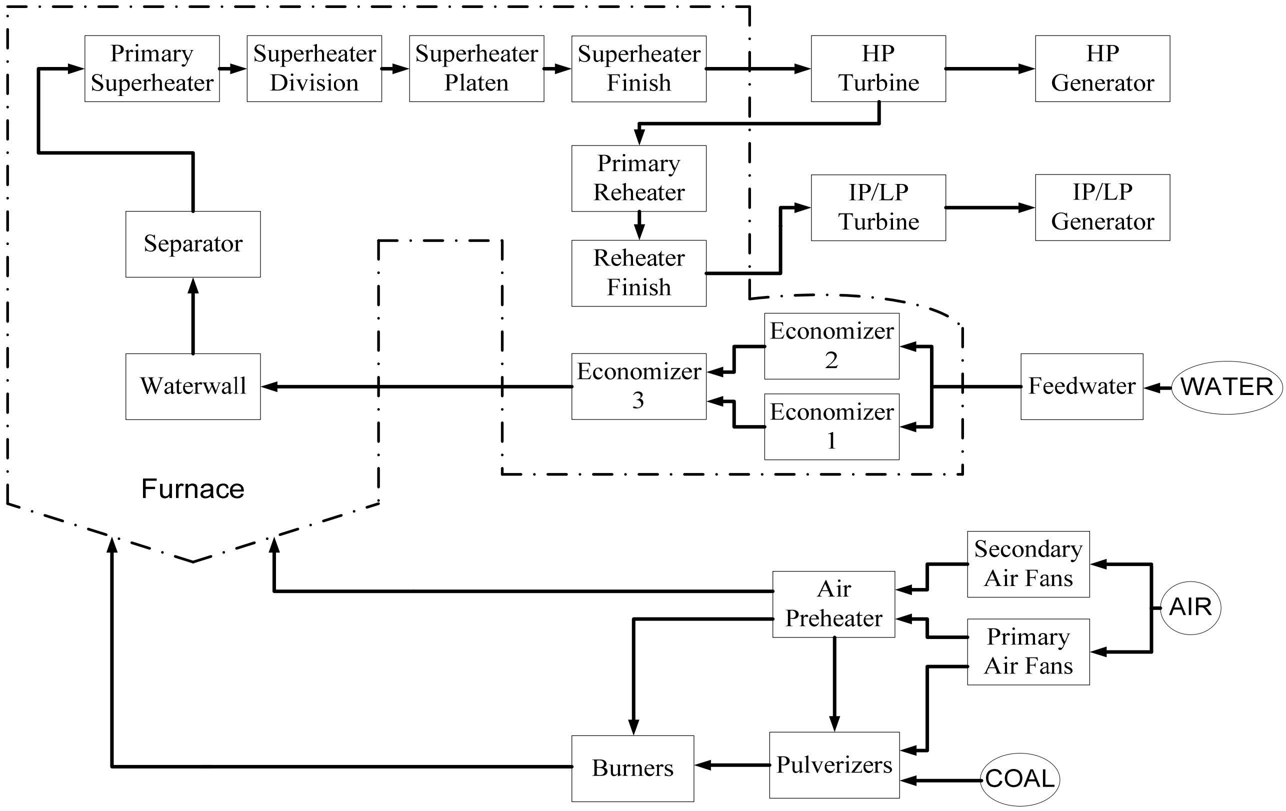

Figure 1. 1000 MW USC Power Plant.

also provide cold air to the pulverizers. The fuel is provided to the furnace through the pulverizers and burners. Furnace pressure is maintained at the desired value by controlling two induced draft fans. The waterwall surrounds the furnace vertically and spirally. Flue gas exiting the furnace travels through the superheaters and reheaters, economizers, and air preheater to raise the temperature of the steam, water or air, respectively. There is a separator on top of the furnace which supplies high pressure steam to the primary superheater and reduces the impurities in the steam. The superheater consists of four parts, primary, division, platen, and finish. The reheaters reheat the steam after the High Pressure (HP) turbine using the primary reheater and the reheater finish. Finally, the turbine generates power from the tandem compound triple turbines, which consist of three parts: a HP turbine, an Intermediate Pressure (IP) turbine, and Low Pressure (LP) turbine.

The model will be focused on boiler, turbine, and generator parts. Each subsystem has common inputs and outputs: mass flow rate, temperature, pressure, and enthalpy of fluid. In addition to these inputs, there are control variables involved in driving each subsystem to the desired state, which are listed in Table 1. The proposed model, which is based on the NN, will use the predefined control action as feedforward control. The four process models which are broken up further into subsystems are shown in Table 2. With the proposed approach, the utility company is able to investigate the dynamic characteristics of power plants with different capacities.

Table 1. Control actions

Control Number	Control Description	Associated Subsystem
u_{c1}	primary air fan control	primary air subsystem
u_{c2}	forced draft fan control	secondary air subsystem
u_{c3}	induced draft fan control	gas recirculation subsystem
u_{c4}	hot primary air damper control	pulverizer/burner subsystem
u_{c5}	cold primary air damper control	pulverizer/burner subsystem
u_{c6}	coal feeder control	pulverizer/burner subsystem
u_{c7}	feedwater pump control	feedwater subsystem
u_{c8}	superheater division spray control	feedwater subsystem
u_{c9}	superheater platen spray control	feedwater subsystem
u_{c10}	high pressure turbine valve control	high pressure turbine subsystem
u_{c11}	superheater damper control	gas recirculation subsystem
u_{c12}	reheater damper control	gas recirculation subsystem

Table 2. Process models and subsystems

Water & steam model	Air & flue gas model	Pulverizer model	Turbine & Generator model
Feedwater	Primary Air	Pulverizer/ Burner	Intermediate/Low pressure turbine
Economizer1			
Economizer2			
Economizer3	Secondary Air		
Waterwall/Furnace			
Separator			
Primary Superheater	Air preheater		High pressure turbine
Superheater Division			
Superheater platen			
Superheater Finish	Gas recirculation		
Primary Reheater			
Reheater Finish			

3. NEURAL NETWORK COMBINED MODEL

A neural network (Ku and Lee, 1995) representing each subsystem is trained many times with different numbers of hidden neurons. The cost function for each training, which is the Mean Squared Error (MSE) between the neural network output and the target values, is compared with the others for different numbers of neurons. The number of hidden neurons with the smallest MSE is set as that subsystems hidden neuron number. The optimal number of neurons depends on the number of inputs and outputs of each subsystem as well as the input/output data pattern; therefore, some subsystems with few inputs and outputs require more hidden neurons to achieve the best performance. The resulting hidden neurons for each subsystem are shown in Table 3. The gas recirculation system was split into two separate networks because there were six inputs and thirty-two outputs. Each NN of the two gas recirculation networks uses the six inputs to generate half of the outputs. Gas 1 delivers outputs to the division superheater, the platen superheater, the primary superheater, the final superheater, the primary reheater, and the final reheater. Gas 2 delivers outputs to the primary reheater, the economizers 1, 2, and 3, and the air preheater. A neural network with six inputs and thirty-two outputs will cause the computer to run out of memory when training. The final result is referred to as the neural network combined model (NNCM).

4. MODIFIED PREDICTIVE OPTIMAL CONTROL

Modified predictive optimal control has already been used successfully in (Lee, et *al.*, 2007b), and was the method expected to be used to control this power plant. This particular instance of predictive optimal control uses recurrent neural networks (RNNs) to implement an online identifier that models plant behaviour. Particle swarm is used in conjunction with this identifier to test the validity of the

Table 3. Control actions

Subsystem	Inputs	Outputs	Hidden Neurons
Pulverizers/ Burners	11	3	19
Primary Air	2	4	17
Secondary Air	2	2	21
Separator	4	4	11
High Pressure Turbine	5	5	21
Intermediate Pressure Turbine	4	4	25
Platen Superheater	10	4	21
Primary Superheater	7	4	23
Primary Reheater	7	4	25
Air Preheater	7	9	17
Division Superheater	10	4	23
Economizer1	7	4	23
Economizer2	7	4	25
Economizer3	11	4	21
Feedwater	5	11	17
Final Reheater	7	4	25
Final Superheater	7	4	9
Furnace	10	7	17
Gas1	6	16	21
Gas2	6	16	15

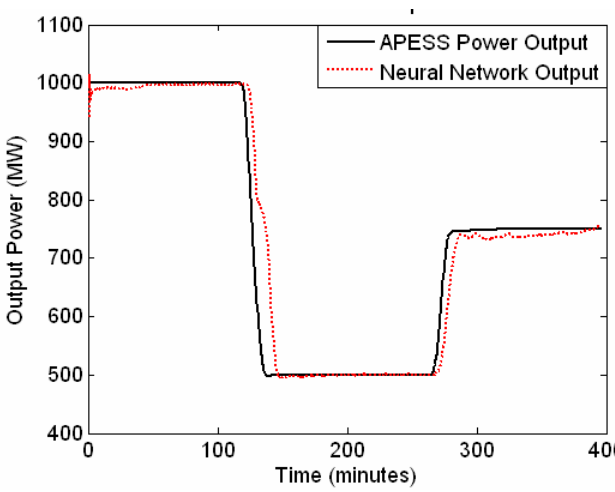

Fig. 2. MPOC (Neural Network Output) tracking power demand (APESS Power Output).

next control action to see if it moves the power plant to the desired states. This is different from standard predictive control which evaluates further than just the next time step. This was done to reduce overall calculation time. Unfortunately, the proposed method still did not achieve quick enough results to be used real-time for this application. Figs. 2 and 3 show the designed control system successfully tracking the desired performance. The online identifier (Ghezelayagh & Lee, 2005) is updated so that it can

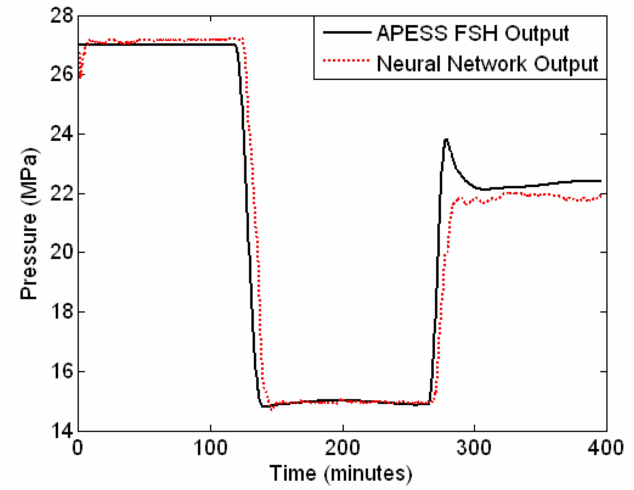

Fig. 3. MPOC (Neural Network Output) tracking pressure demand (APESS Power Output).

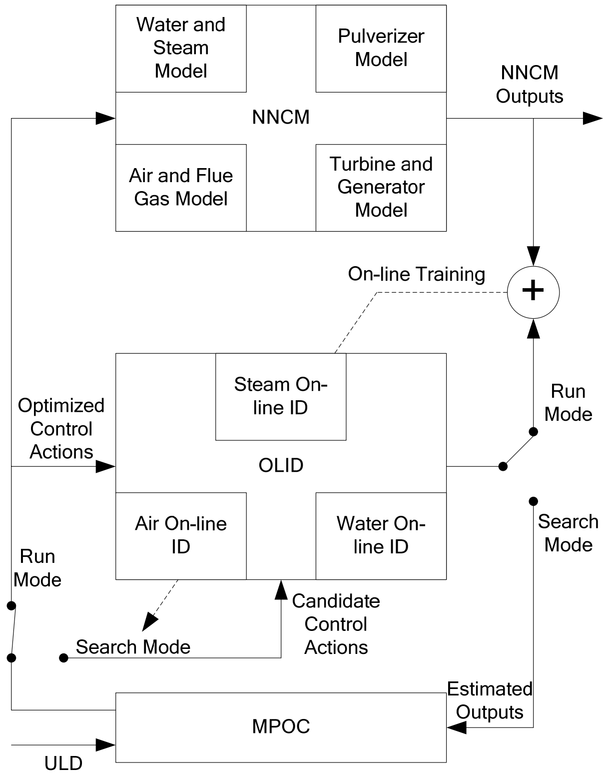

Fig. 4. Scheme for online identifier with MPOC.

accurately model current plant behaviour and can be used by MPOC to search for the next control action. Fig. 4. details the online identifier because the same scheme is used for an online identifier in the second control approach.

4.1 Calculation Time Issue

The trouble with calculating control actions with MPOC, is that the control signal was desired to be updates at least every 0.25 seconds. It was acceptable, while running in Matlab, for the algorithm to generate an update every second, but the final speed as closer to 1.5 seconds. While the speed could have been easily decreased through the use of parallel processing, it was decided against adding this level of complexity to the controller.

5. REFERENCE GOVERNOR AND GAIN TUNING

Since the MPOC did not generate control actions quickly enough, an older method was modified to work with this process. Using a two stage system, a reference governor can provide feedforward control actions as well as setpoints for a feedback controler, and the feedback controller provides the

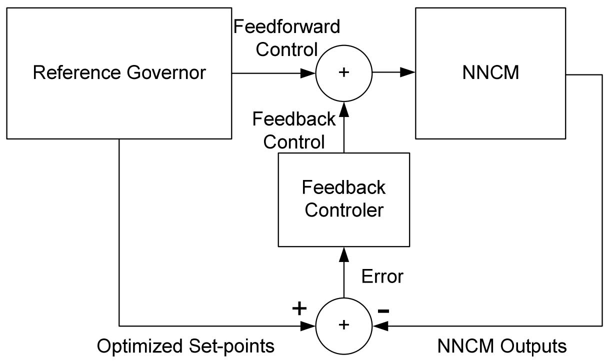

Fig. 5. Overall control scheme for reference governor and feedback control.

Table 4. Set points

Set-Points/Demands
Throttle Pressure Demand
Feedwater Demand
Coal Flow Demand
Final Superheater Temperature Demand
Final Reheater Temperature Demand
Furnace Gas Pressure Demand
Pulverizer Temperature Demand
Air Flow Demand
MW Demand

Table 5. Control actions and coupled set points

Controls	Associated Set-points/Demands
Primary Air Fan	Coal Flow Demand
Secondary Air Fan	Air Flow Demand
Feedwater Pump	Feedwater Demand
Spray 2	Final Superheater Temperature Demand
Spray 3	Throttle Pressure Demand
HP Turbine Valve	MW Demand
Induced Draft Fan	Furnace Gas Pressure Demand Air Flow Demand
Reheater Damper	Final Reheater Temperature Demand
Superheater Damper	Final Reheater Temperature Demand
Hot Air Damper	Pulverizer Temperature Demand
Cold Air Damper	Pulverizer Temperature Demand
Coal Feeder	Coal Flow Demand

actual control actions to the plant, or in this case, the NNCM. This method is visualized in Fig. 5. For this to work, it was required to determine what set points would be used and which control actions would be coupled to these set points. The results are shown in Tables 4 and 5.

5.1 Calculation Time Issue

The reference governor with gain tuning bypasses the issue of how quickly the control signal can be updated, because both the reference governor and gain tuner work offline, and simply provide updates to the controller as required. While the reference governor and gain tuner are searching for their next results, the controller can be set any feasible sample period achievable by the hardware, as only PID control loops must be calculated.

5.2 Reference Governor

Using a reference governor for providing feedforward control actions and set points has been shown many times such as in (Garduno-Ramirez & Lee, 2001). As done in previous work, a steady state model (Heo & Lee, 2005) of the system was trained using a static neural network, and then a heuristic search method was used to find the feed forward control actions and corresponding set points that would optimize a cost function made of weighted objectives.

For this application, four of the five set points are actually held constant regardless of unit load demand, and can therefore be eliminated from the neural network, as their values will never be changing. These set points are Final Superheater Temperature Demand, Final Reheater Temperature Demand, Furnace Gas Pressure Demand, and Pulverizer Temperature Demand.

Interestingly, this approach worked poorly at first. With the high order of this system, the search algorithm was able to find numerous candidate control actions and set points that equally satisfied the provided cost function. This was very undesirable as ideally, the cost function should be set up so that a single set of control actions and set points provide an optimal solution, or the reference governor will not know which set to choose. Using a scheme where different control actions have the same fitness is very noisy and inefficient. To cope with this problem, the concept of using nominal control actions was introduced. The nominal control actions are simply what the conventional control actions would be for a given unit load demand if a more sophisticated control scheme was not in place. The cost function was then modified so that it would optimize specific goals, and then choose the candidate control actions that were closest to the nominal control actions. This modification served to fix the problem and provided good performance. The result was the following cost function (1).

$$\begin{aligned} f(u) = \alpha_1 \left|ULD - PowerOut\right| + \ldots \\ \alpha_2 \left|CoalFlow\right| + \alpha_3 \left|u - u_{nom}\right| \end{aligned} \quad (1)$$

Where the variables are as follows:

$\alpha_1, \alpha_2, \alpha_3$: Multi-objective weights

ULD: unit load demand

PowerOut: actual power output

CoalFlow: control that determines how much coal is used as fuel

u: feedforward (ff) control actions

u_{nom}: nominal feed forward control actions (what the power plant would do without optimization)

There is a disadvantage to using this approach because it assumes that the nominal control actions are available. In this case, these nominal control actions were available from earlier in the power plants design process. If this is not the case, a simple control system would have to be developed to create these control actions, which may be more work than desired to use this particular approach.

5.3 Intelligent Gain Tuning

Intelligent gain tuning is done using an online identifier and a heuristic search. The online identifier is similar to the one used for MPOC, but different in that it has outputs that are used for feedback control. The heuristic search tries different gain values and then simulates the system with these gain values and the online identifier. It continues to experiment with different gain values until it finds the set of gains that reduce the error between the set points and the plant outputs.

It is very similar to MPOC except that instead of choosing the control values, it is choosing the gain values. This change is made because the gain values do not have to be updated all of the time, while control values do. For gain tuning, a large window size can be chosen for which to tune the gains. This window could range from the size of a few minutes to multiple hours, depending on how often it is desired the gains be tuned. The gain tuning has exactly the time of the window to search for the next set of gains. Once the window time has passed, the gain tuner reports the best set of gains it has found to the control system, which is then updated with these new gain values. Then the gain tuner starts searching again for the best set of gains for the next window. This process is repeated indefinitely.

The window size was chosen to be twenty minutes. This is not the only window size that can be used, but it was the smallest window size that had smooth operation. Smaller window sizes can change the gains too often, which causes the system to become noisy and if the window size was small enough, could actually lead to unstable operation. This is not the case for a window size of twenty minutes though. The power plant is obviously running for longer than one window size, so its operation must be split into multiple windows. With a window size T, and total operational time of Tf, the operation is split into N = T/Tf windows, with end at T0, T1,.. TN. This is shown in Fig. 6. After an optimization window ends is when the gain values are updated.

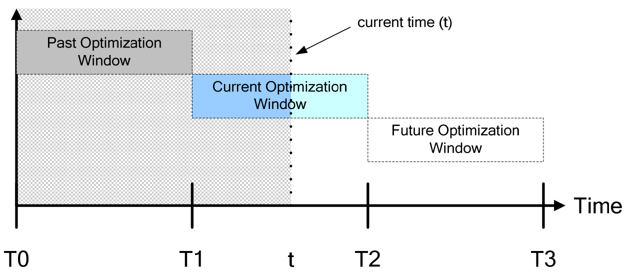

Fig. 6. Window operation.

The algorithm works by searching three different gain matrices, one for the proportional control, integral control, and derivative control. It takes the possible gain matrices and simulates the system for the next twenty minutes (the current window size) with those gain values. It repeats this simulation for different possible combinations of gains and then evaluates the gains by choosing which gain has the smallest total error for set point tracking, using the following cost function, where setpoint$_n$ is the nth desired set point, and output$_n$ is the nth actual plant output of that setpoint:

$$y = \sum_{n=1}^{9} \sum_{t=t_o}^{t_f} \left| setpoint_n - output_n \right| \qquad (2)$$

An online identifier, as with MPOC, is continually updated and used for the simulation of the different gain values. It only needs to be updated once every window, so a large window size means the online identifier has to be updated less. Shown in Fig. 7 are the results of using the reference governor to vary the power plant from 1000 MW to 600 MW to 800 MW. Only the setpoints which actually change are shown, as the rest simply remain constant.

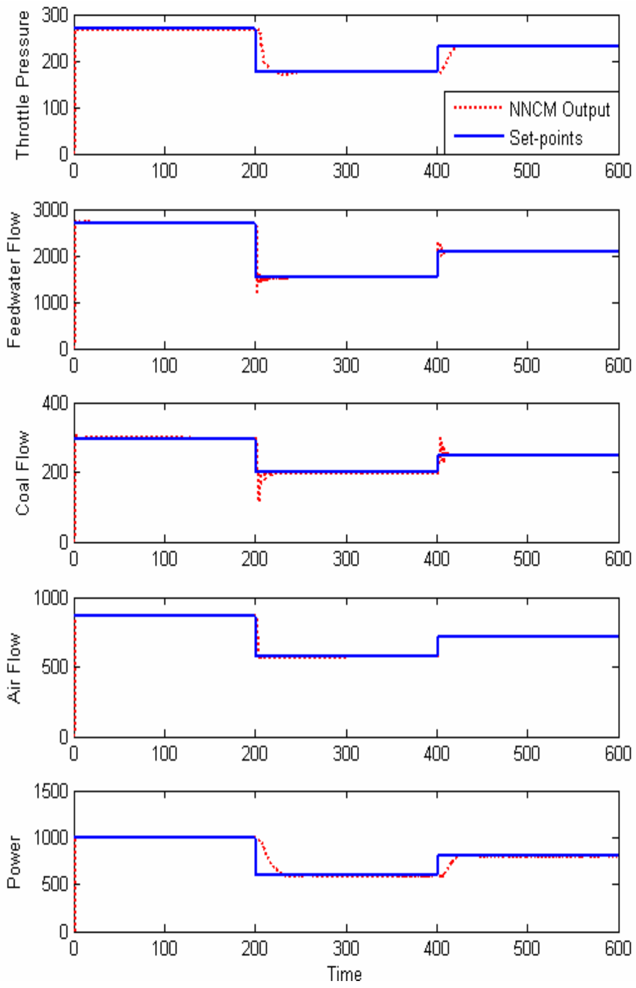

Fig. 7. Set point tracking of reference governor with gain tuning.

6. CONCLUSIONS

While MPOC was desired for its adaptive capabilities and the ability to optimize a cost function, it turned out to be too calculation intensive to implement in a real time controller. Instead, a reference governor with intelligent gain tuning was implemented. To get the reference governor to work, it had to favour control actions that were closer to the nominal control actions over others. If specialized hardware was used for the OLID, mainly, the neural network calculations, MPOC might become a viable option as well.

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