Neural Network Modeling and Nonlinear Model Predictive Control for a Gas Fired Boiler Simulator

Abhinaya Joshi
ALSTOM Power Inc
Windsor, CT 06095

Xinsheng Lou
ALSTOM Power Inc
Windsor, CT 06095

Carl Neuschaefer
ALSTOM Power Inc
Windsor, CT 06095

Peter Luh
University of Connecticut
Storrs, CT 06269

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ABSTRACT

ALSTOM Power Plant Laboratories (PPL) has been working on power plant controls with optimization using dynamic process simulators. In the 2007 ISA POWID conference, a paper was presented on the application of linear model identification and linear model predictive control (LMPC) to steam/water system in ALSTOM's dynamic simulator for a gas-fired boiler (GFB). As continued research and development work into nonlinear model predictive control (NMPC) for power plants, a nonlinear auto-regressive with external variable (NARX) model was constructed. The model was based on an artificial neural network (ANN) and trained using data that was generated from the GFB simulator by using designed multi-level excitation signals. The NARX model was validated using additional test data and then used as the basis for the design of an NMPC controller. The controller was then connected to the GFB simulator via OPC connection to carry out control simulations. The controls performance of the NMPC is stable and comparable to the studies with LMPC. The simulation results show that the NMPC has potential to improve plant control particularly in rapid load changes for wide load range of operations.

1. INTRODUCTION

In fossil-fueled power plant boilers, steam temperature and drum-level controls are very important for plant safety, equipment life, generation efficiency, and following changing load demands. Due to the competitive deregulated market and environment regulations, control requirements have been tightened, requiring better control and optimization. Currently, conventional proportional-integralderivative (PID) controllers have given acceptable regulation performance in most standard operating conditions. By studying MPC, it is expected that even faster load ramping rates can be explored, in which power plant system and component constraints as well as optimization objectives could be explicitly addressed. MPC technology has been successfully implemented various industries, such as petrochemical, refineries, pulp and paper, etc. (Qin and Badgwell, 2003) for the past few decades. MPC in general uses linear process models as linear model identification is simpler and LMPC has well-established theory. However, linear models may be inadequate in boiler controls as the boiler is inherently nonlinear over the full load changing range. In this paper we present some results from an investigation of application of NMPC for power plant control. Theoretical background on linear MPC (LMPC) can be found in (Maine and Rawlings, 2000) and the applications can be found in surveys (e.g., Morari and Lee, 1999; and Qin and Badgwell, 2003). Similarly, NMPC theory and applications can be found in (Kouvarikatis and Cannon, 2004) and in surveys (e.g. Henson, 1998; and Qin and Badgwell, 2000).

Previous power plant applications of LMPC can be found in different areas of boiler control, such as, steam temperature (Hogg et al., 1994), pressure and power output (Lu and Hogg, 1997), and NOx control (Havlena and Findejs, 2005). In our previous work (Joshi et al, 2007), a linear MPC was designed and applied to a boiler simulator. Because of inherent nonlinearity in the boiler steam/water system, especially during load change conditions, LMPC may not be adequate and so NMPC is desired for control. There are very few NMPC works on power plant boilers found in the literature - one of them is based on physical models for nonlinear control (Prasad, et al, 2002). First principle based physical models can represent the process dynamic better, however, are very expensive to develop and usually complicated to use in control design. A good alternative is artificial neural networks that are powerful function approximators and useful for representing nonlinear models and controllers (Akesson and Toivonen, 2006). Neural nets have been widely used for modeling industrial processes (Irwin, et al, 1995) and NMPC design (Tian, et al., 2002; Tsai, et al., 2002). This work utilizes neural network based nonlinear autoregressive with external variable (NARX) structure for modeling of a boiler system.

Building on the results from previous application of LMPC, this work has been carried out to explore and develop NMPC based on a neural network model for the control of steam water circuit, i.e. superheated (SH) steam temperature, pressure, flow, and drum level, in a boiler simulator. The paper is organized as follows: Section 2 presents an overview of the boiler simulator, and details of nonlinear model identification and NMPC design. Section 3 presents the connection of the NMPC controller with the boiler simulator and the simulation test results. Finally, the conclusions and future directions are presented in section 4.

2. NONLINEAR MODEL IDENTIFICATION AND NMPC DESIGN

NMPC uses a nonlinear dynamic plant model and an optimization algorithm to calculate optimal control inputs so as to drive the plant outputs to their setpoints. Therefore, plant-model identification and optimization are two key ingredients of NMPC. This section presents a brief description of a boiler simulator, and details of the nonlinear plant model identification and dynamic optimization in the design of the NMPC controllers. A NMPC schematic is depicted in figure 2.1.

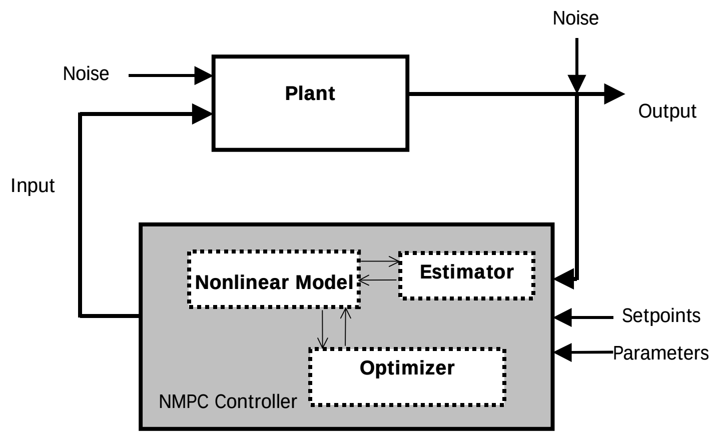

FIGURE 2.1. A NMPC SCHEMATIC

2.1. GAS FIRED BOILER SIMULATOR

A gas fired boiler (GFB) dynamic simulator has been used for data generation and control simulation. The simulator is inherently a nonlinear open-loop model. The boiler simulator represents the 'Plant' block in the MPC schematic depicted in figure 2.1. The boiler simulator model is depicted schematically in figure 2.1.1. The simulator is a drum-type gas-fired boiler model with two super-heater sections - low temperature superheater (LTSH) and high temperature superheater (HTSH). A de-superheater (DSH) spray is applied between the low temperature and the high temperature section for superheated steam temperature control. There is no turbine/generator unit in this simulator and therefore, a power load is represented simply by the amount of steam flow and the opening of a turbine throttle valve.

The superheat (SH) steam generation in the boiler is a multivariable, multistage, and nonlinear process. Further, drum level is an integrating process and because of swelling and shrinking phenomena that cause a temporary rise and fall of drum water level during load changes, drum level control can be more difficult.

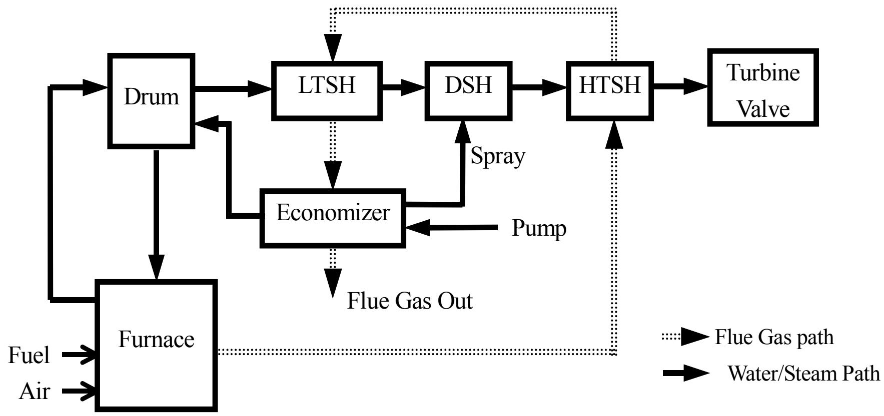

FIGURE 2.1.1. GFB BOILER SCHEMATIC

2.2 NEURAL NETWORK BASED NONLINEAR MODEL IDENTIFICATION

A plant model is an important component of the NMPC controller. This section presents the details of model identification of a neural network based nonlinear plant model. Considering the difficulties associated with drum level control, the model identification is also focused on the development of a plant model that can adequately characterize drum level dynamics. The resulting model becomes a part of the NMPC controller as depicted in Figure 2.1.

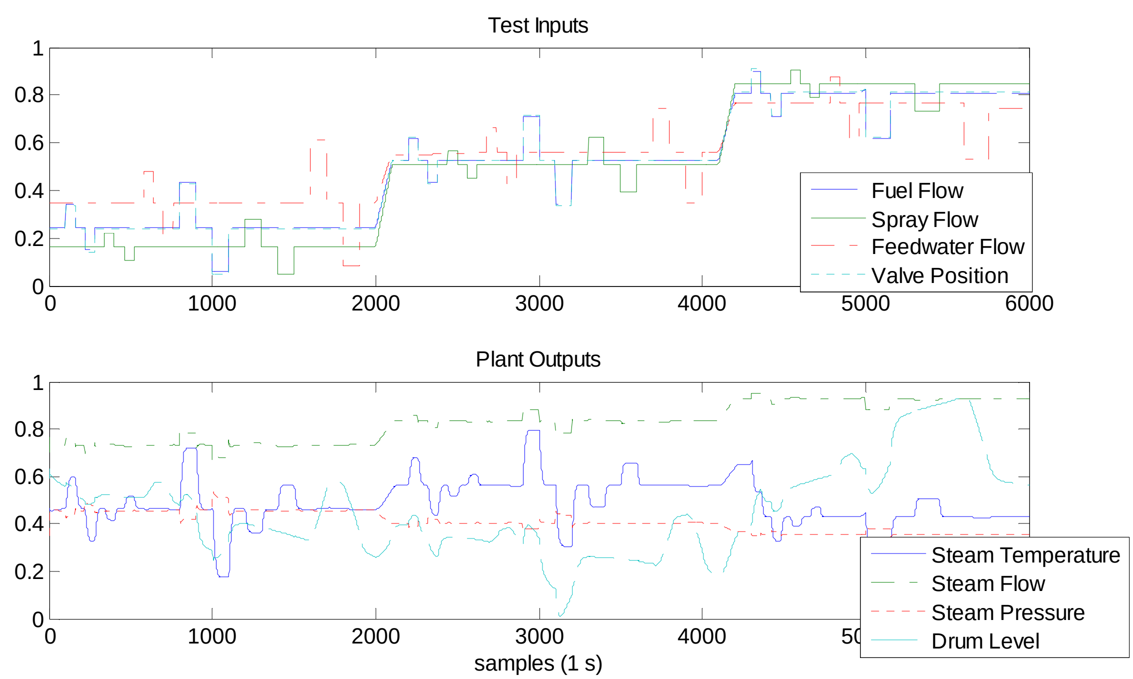

FIGURE 2.2.1. DYNAMIC TEST DATA FROM THE SIMULATOR

The control scheme, in this work, considers a fixed fuel/air ratio and consists of three manipulated variables or inputs (fuel flow, feedwater flow, and spray flow) and four controlled variables or outputs (SH steam temperature, pressure, flow, and drum-level). A few data sets generated by the GFB simulator using a carefully designed dynamic test sequence have been used for the modeling work. The data sets were obtained after a number of preliminary test runs on the simulator that were carried out to understand the input-output behavior, such as, rise time, settling time, etc. During each of the test runs, the simulator was excited with eight step changes for each input independently at three different load conditions - 70%, 85% and 100%, with continuous operation during load change. The dynamic tests have been conducted at three load conditions to investigate boiler nonlinear properties at different load conditions. A sample of the normalized input/ output dataset is shown in figure 2.2.1.

A dynamic neural network based nonlinear auto-regressive with external inputs (NARX) model, as depicted in Figure 2.2.2, has been identified for the boiler. The input vector to the NARX model includes present and past process inputs as well as outputs and the output vector is a one-step-ahead prediction of process outputs. This is a feedback network model where output predictions can be fed back for multi-step ahead prediction. Without the feedback the NARX model reduces to feed-forward neural network with input-output relationship given by

$$y_k = f_{NN}(x) = \sum_{i=1}^{Nh} w_{ki}^{o} \varphi_i \left(\sum_{j=1}^{Nx} w_{ij}^{h} x_j\right), \qquad (2.2.1)$$

where y_k is the k^{th} output; x_j is j^{th} input to the neural net (can be present/past inputs or outputs); w_{ki}^{o} and w_{ij}^{h} are weights for output and hidden nodes, respectively; φ(.) is the activation (here hyperbolic tangent) function; N_h and N_x are the number of hidden and input nodes, respectively; and f_{NN} represents the neural net model. During the training, the feedback path is disconnected and the model is trained with present and past inputs and outputs to one-step ahead outputs by using a back propagation algorithm. The range of past inputs (n) and outputs (m) are model parameters needed to be chosen based on process knowledge and modeling needs. When the model is appropriately trained, the feed back path is connected and the output prediction for time ‘k+1’ is fed back so that further prediction can be made for time ‘k+2’ and so on.

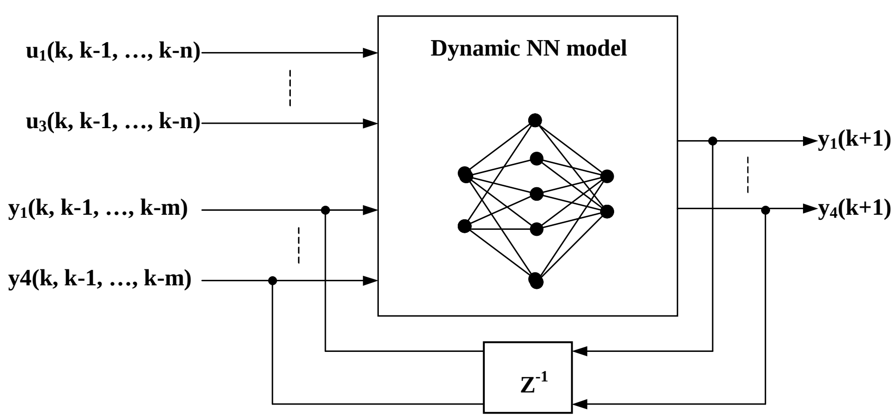

Figure 2.2.2. Nonlinear ARX model

In view of the fact that some of the outputs are independent of some of the inputs, e.g., drum level is affected only by feedwater flow and larger changes in fuel flow; the boiler model is identified in two parts. The first part (M1) is identified for three outputs (SH steam temperature, pressure, and flow) from fuel flow and spray flow inputs. The second part (M2) models the drum level output from feedwater flow input and the disturbance variable (turbine valve position) that reflects large fuel changes. Based on the data analysis it was found that output gain from fuel and spray flow to SH steam temperature, pressure, and flow changes at different power loads by as much as 20%. This suggests that M1 is close to linear at steady load condition. Further, nonlinearities in drum level arise primarily during load changes due to large changes in fuel flow that is reflected by turbine valve position. So M2 is linear from feedwater flow to drum level. As such, the identification of the boiler model in two parts makes the boiler model effectively linear at a constant load condition.

Different neural net structures, such as radial basis function (RBF), multi-layer perceptron (MLP), etc. were explored. NARX models with n=3 and m=3 with a number of hidden nodes = 10 (M1) and 5 (M2) gave good results with smaller network size and were selected for NMPC. The model size (order) is important because even though higher order models may give better prediction, they are computationally more (time) expensive which is critical in control applications. The resulting model can predict the outputs up to 20 time steps ahead with less than a 5% error. A plot of one-step-ahead predicted outputs against measured values is presented in Figure 2.2.3, where RMS values of one-step-ahead prediction errors were less than 0.4% for each of the outputs.

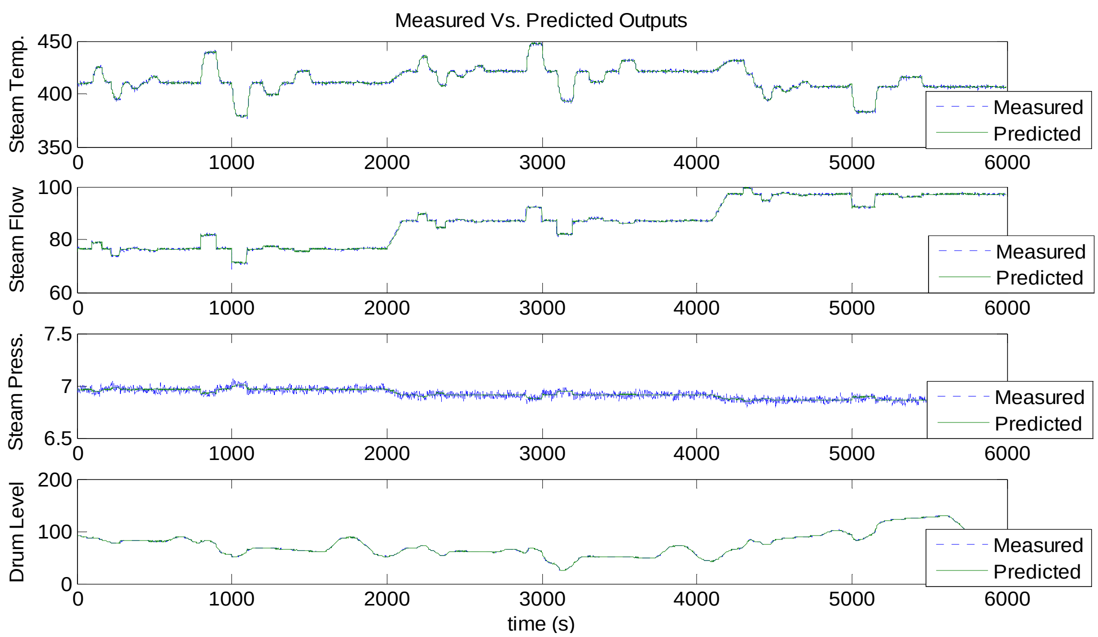

FIGURE 2.2.3. Measured Vs Predicted Outputs

2.3 NONLINEAR MODEL PREDICTIVE CONTROL DESIGN

The real-time dynamic optimization of output errors (control variations) and process inputs (control energy) is the next important component of MPC. At each control step in time, an objective function incorporating the output setpoint deviation, inputs and control moves is minimized in the presence of constraints on inputs, outputs, and input moves. The NARX model identified in the earlier section is used for predicting the future outputs. The MPC optimization problem with constraints is given by,

$$\min_{(u,\Delta u)} J, \quad \text{with } J=\sum_{k=1}^{Np-1}(\hat{y}_k-y_{s,k})^T Q(\hat{y}_k-y_{s,k})+\sum_{k=0}^{Nc-1}u_k{}^T R u_k \qquad (2.3.1)$$

subject to

$$\begin{aligned}&\hat{y}_{k+1}=f_{NARX}(u_{k,k\text{-}1,\ldots,k\text{-}n},y_{k,k\text{-}1,\ldots,k\text{-}m})\\&u_{min}\le u_k\le u_{max}\\&\Delta u_{min}\le\Delta u_k=u_k-u_{k-1}\le\Delta u_{max}\\&y_{min}\le\Delta y_k\le y_{max}\end{aligned},$$

where $\hat{y}$ is predicted output vector; y_s is output state setpoint vector; u is input vector; Δu is control move vector; Np and Nc (with Nc ≤ Np) are prediction and control horizons; Q (>0), R (≥0), and S (≥0) are symmetric weighting matrices; and f_{NARX} is the neural net NARX model.

In the present context, y is a vector of the boiler controlled variables or outputs (steam temperature, steam flow, steam pressure, and drum level) and u is a vector of manipulated variables or inputs (fuel flow, spray flow, and feedwater flow). The objective function in (2.3.1) gives the weighted sum of the squared output error over the prediction horizon and weighted sum of input and input moves applied over the control horizon. The optimization involved here, minimizes the objective function in the presence of bounded constraints on inputs, input moves, and outputs. The constraints on inputs and input moves are hard constraints, and are forced to be between the specified limits. The constraints on the outputs, on the other hand, are soft constraints and the violation of these constraints are allowed but are penalized.

The optimization problem (2.3.1) has been solved using a sequential quadratic programming (SQP) solver at every sampling interval. The SQP algorithm uses gradient (or Hessian) information of the cost function and the constraints to identify search direction in the course of finding a solution. Generally the optimization problem in NMPC tend to be non-convex, however, because of the way the boiler model has been identified (in two parts: M1 and M2) in this work the models are locally linear and the optimization problem is convex at any steady power load condition. As such, the SQP algorithm can give globally optimal solution at steady load condition and locally optimal solution during transients. The inputs corresponding to the next time interval from the solution matrix are used as the control inputs and the rest are discarded. This process is repeated for each control sample time interval. The input and output weights (Q and R), and control and prediction horizon (P and M respectively) in the dynamic optimization problem are tuning parameters. In this work, a MPC controller has been designed in MATLAB SIMULINK* with the optimization solver from the MATLAB Optimization Toolbox. The SIMULINK NMPC Controller is depicted in figure 2.3.1.

The MPC algorithm here uses a nonlinear NARX model and a quadratic cost function with bounded constraints. During the optimization, the gradient of the NARX model and eventually the gradient of the cost function and nonlinear constraints have been analytically computed; this significantly reduces the computation time (by about 60%). Without this the optimization algorithm would have calculated the gradients by using finite differencing, which is very time consuming. The results from the MPC control simulation are discussed in the next section.

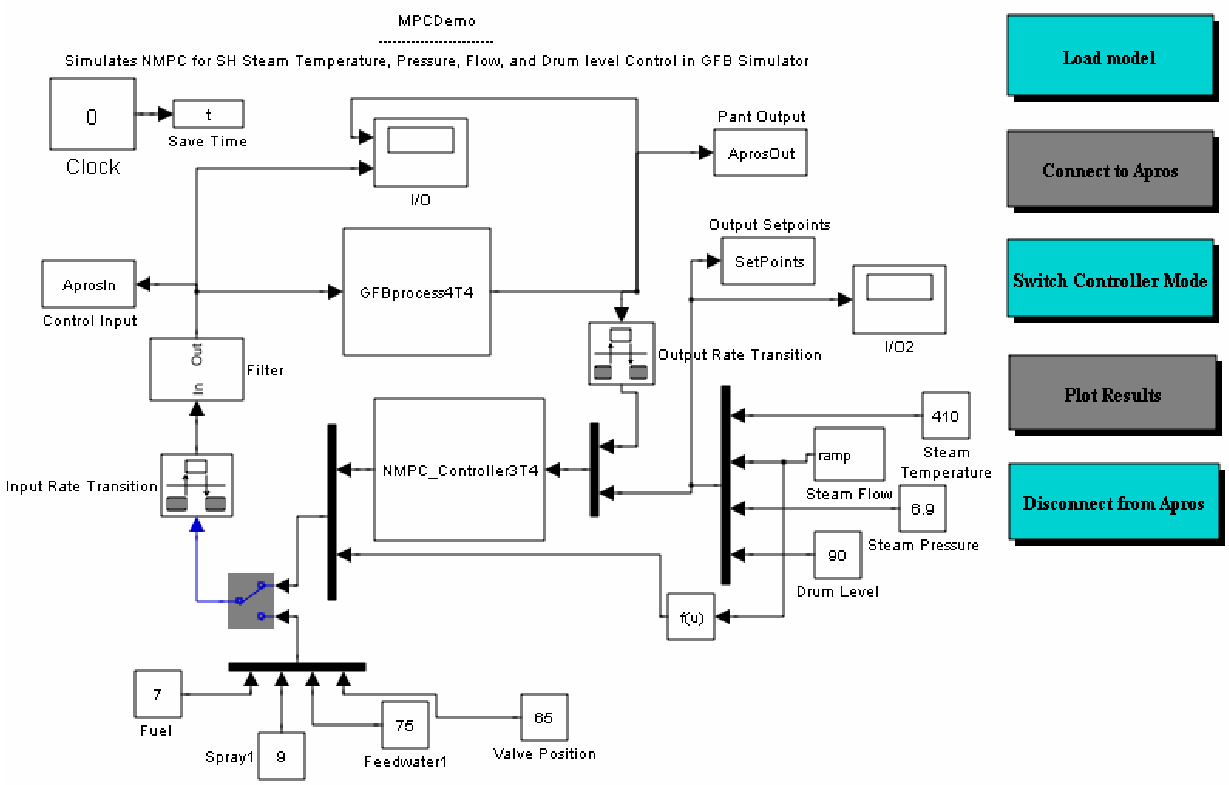

FIGURE 2.3.1. MATLAB SIMULINK® MODEL FOR MPC-GFB PROCESS SIMULATION

3. NMPC Simulation Test Results

The resulting NMPC controller has been tested for setpoint tracking in the presence of constraints and disturbances in a simulation environment. The NMPC controller developed in MATLAB

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* MATLAB SIMULINK is a registered product of The Mathworks, Inc., Natick, MA

SIMULINK® has been coupled with the GFB simulator by using an OPC connection using MATLAB OPC Toolbox. The OPC connection between the simulator and MATLAB is depicted in figure 3.1. The simulation has been carried out to control SH steam temperature, pressure, and drum-level during a load changing condition. Since the boiler simulator does not have the turbine and generator units, load changes have been simulated by making changes in turbine valve position and in steam flow demand. Turbine valve position has been used as a measured disturbance variable and it is changed as a function of the steam flow setpoint.

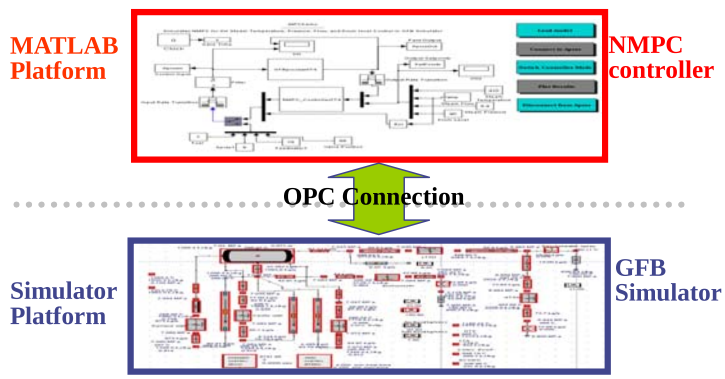

FIGURE 3.1. GFB SIMULATOR-OPC-MPC BLOCK DIAGRAM

A number of NMPC control simulations have been carried out on the GFB simulator with the identified models and tuning parameters. During the simulations, normally distributed, additive measurement noise, with zero mean and 1% variance has been introduced to each output. NMPC simulation results for this model are presented below together with LMPC simulation results. Both NMPC and LMPC control simulations were carried out for the following output setpoints: Steam temperature = 410 ^{o}C; steam flow = 70 - 100 Kg/S (two load conditions); steam pressure = 6.9 MPa; and drum-level = 90 cm. The input variables have following constraints: fuel (6 - 12) Kg/S; fuel rate (-0.5 - 0.5) Kg/S/sample; spray (6 - 20) Kg/S; spray rate (-0.5 – 0.5) Kg/S/sample; feedwater (50 - 110) Kg/S; feedwater rate (-2 - 2) Kg/S/sample. Similarly, the output variables have the following constraints: steam temperature (400 - 420) ^{o}C; steam flow (65 - 105) Kg/S; steam pressure (6.8 - 7.0) MPa; Drum level (70 - 110) cm. The controller-sampling rate is 1 s.

Figure 3.2 depicts a simulation result for the NMPC controller against GFB simulator. The prediction and the control horizon used for NMPC simulation are 20 s and 10 s, respectively. The weighting matrices Q and R have been selected to reflect the relative importance of the corresponding input and output variables. Similarly, figure 3.3 shows results for a LMPC control simulation. The parameters for LMPC are same as that of NMPC. The results show each output being driven to their setpoints. Tables 3.1 and 3.2 compare results for NMPC and LMPC simulations. Table 3.1 shows total inputs applied to the plant over the entire simulation time (800 s) using each of the controllers. Table 3.2 presents root mean square (RMS) output error over the simulation time (800 s) for NMPC and LMPC controllers.

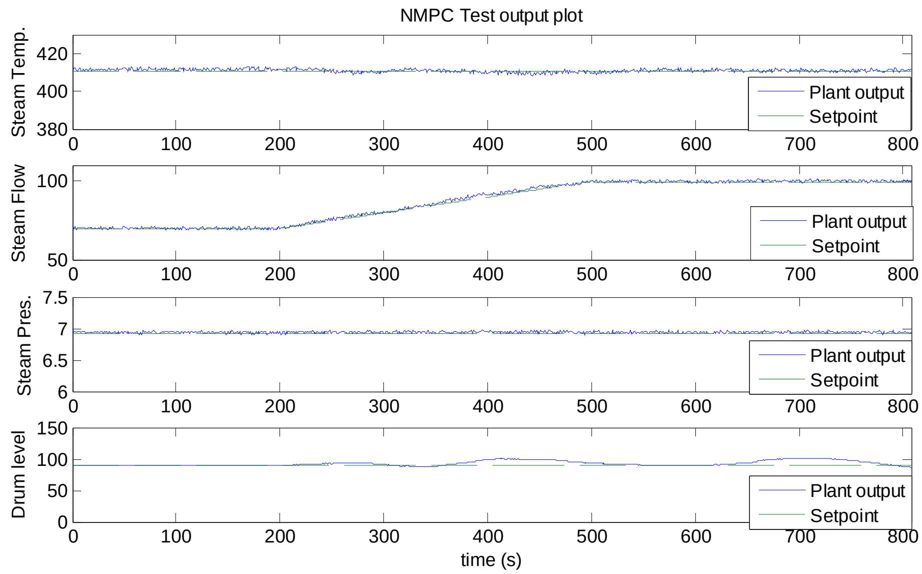

FIGURE 3.2. NMPC test results (Outputs) against the GFB simulator

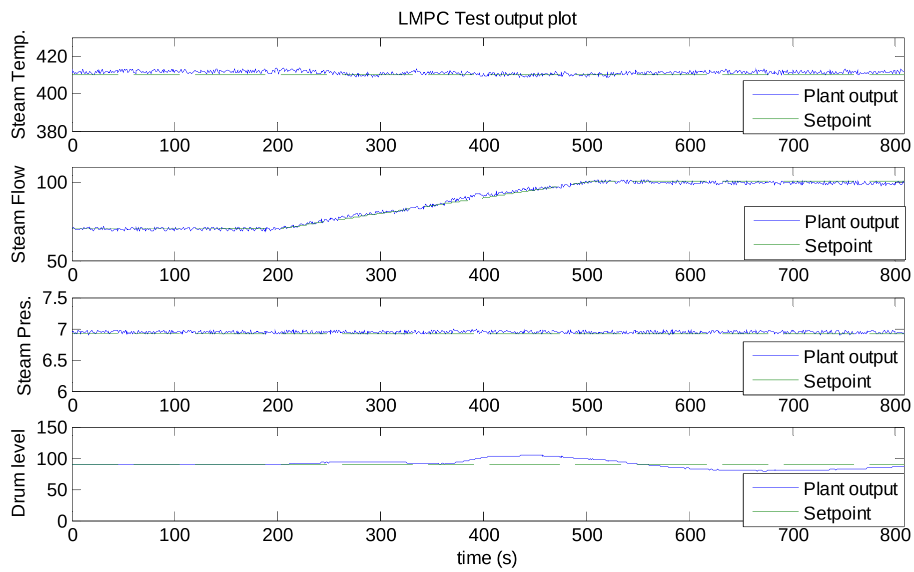

FIGURE 3.3. LMPC test results (Outputs) against the GFB simulator

TABLE 3.1. TOTAL INPUTS APPLIED TO THE PLANT

Controller\Total Input	Fuel Flow (Kg)	Spray Flow (Kg)
NMPC	7085.2	10861
LMPC	7097.6	10855

TABLE 3.2. TOTAL AND RMS OUTPUT DEVIATIONS FROM THE SETPOINTS

Output RMS Error	Temperature (^oC)	Steam Flow (Kg/S)	Steam Pressure (MPa)	Drum-Level (max. deviation from setpoint) (cm)
NMPC	0.776	0.95	0.015	9.03
LMPC	0.812	1.06	0.021	14.71

4. Conclusions

This paper presents the results of an investigation of the application of NMPC to a multivariable interactive boiler steam/water control system. The model has been identified in two pieces to avoid erroneous effects among boiler variables and then integrated to build a multivariable boiler model. The resulting nonlinear model is good at predicting multiple time-steps ahead. The gradient for the NARX model has been computed analytically to decrease the computation time of the nonlinear optimization problem in NMPC. Simulation results showed that the NMPC can control the GFB steam/water system at multiple load conditions with reasonably good performance. As NMPC controller, with its nonlinear model, is capable of handling nonlinear dynamics, it has potential to perform better in highly nonlinear processes. The experiences and results of this work are encouraging and the NMPC controller is being improved for performance and computational efficiency. A few alternative optimization algorithms are being explored. Future research will explore practical nonlinear modeling approaches for more complex architectures for clean fossil power generation plants.

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