Modified Predictive Optimal Control Using Neural Network-based Combined Model for Large-Scale Power Plants

Kwang Y. Lee, *Fellow, IEEE*, Jin S. Heo, Jason A. Hoffman, Sung-Ho Kim, and Won-Hee Jung

***Abstract*--With a Neural Network-based Combined Model (NNCM) for a power plant, a Modified Predictive Optimal Control (MPOC) system can be developed based on predictive control algorithms and intelligent techniques. During the NNCM simulation, an On-Line Identification (OLID) system is updated every few steps to provide information from the model to the MPOC. Moreover, the MPOC will use the OLID as a test process to optimize the control actions, minimizing tracking-error. To search for the best control action, the MPOC utilizes a heuristic optimization technique, Particle Swam Optimization. With the proposed MPOC system the only input to the NNCM will be the unit load demand. Finally, major outputs of NNCM will be shown using the proposed approaches, validating the procedure as a means to design a control system for a new power plant.**

***Index Terms*-- Once-through type boiler, super-critical boiler, neural networks, modeling, modified predictive optimal control, particle swam optimization, power plant control, distributed large-scale power plant.**

I. Introduction

THE development of large capacity power plants requires new approaches for control. The fact that power plants are complex dynamic systems with significant uncertainties, has led to a departure from conventional control methods [1]. Specifically, for optimal power plant operation, many control algorithms have been introduced using intelligent techniques. In general, the challenge in optimizing power plant operation is to produce optimal control actions for minimizing load-tracking errors. The predictive control system can utilize an identification system to find the optimal control actions. For both predictive control and identification, the classic control algorithms provide the means to design a control system with a clearly defined mathematical model. However, while power plants are getting larger and more complex, conventional control methods, which minimize quadratic objective functions, have a large computational burden which precludes generating an optimal solution in real-time.

In conventional PID control systems, a single logic failure in a control loop can cause an entire system to go unstable. Moreover, under a changing environment, PID control systems have to properly tune gains and time constants continuously. As an evolution of conventional PID algorithms, intelligent control systems have been extensively studied in recent years. In order to produce optimal control action, neural network-based identifiers and heuristic optimization techniques have been used for handling non-model-based control system design and reducing the computational complexity in large-scale distributed systems.

As a practical approach, Model-based Predictive Controls (MPCs) which initially use open-loop optimal control, had attracted much attention until the introduction of Generalized Predictive Control (GPC). The GPC algorithm uses closed-loop optimal control within a moving horizon [2]. However, both approaches require a mathematical model and much computational time to find an optimal solution. By using intelligent techniques such as neural networks, fuzzy logic, and evolutionary algorithms, an intelligent predictive optimal control system was developed using neuro-fuzzy identification [3]-[5]. Without using a mathematical model, the intelligent identification system, by updating on-line, can provide plant information to the control system. Although intelligent predictive optimal control systems are designed without using models they require a great deal of time to find an optimal solution. In order to reduce the computation time, a new optimization technique is required to be embedded into the control system. This paper presents Particle Swarm Optimization (PSO) as a modern heuristic method for an on-line predictive optimal control system. The PSO algorithm is based on the analogy of a flock of birds and a school of fish [6]. It has been well known in many engineering applications that PSO techniques provide accurate solutions with fast convergence and simple implementation [6]-[9]. However, the performance of PSO in a predictive optimal control system is yet to be investigated.

Predictive control in general requires a repetitive simulation of the plant model. However, in practice, this is an impossible task for a large-scale plant. Therefore, the Neural Network Combined Model (NNCM) was developed to ease the simulation. The NNCM is made of a number of neural network models, each representing subsystems of the plant. Using NNCM, a Modified Predictive Optimal Control

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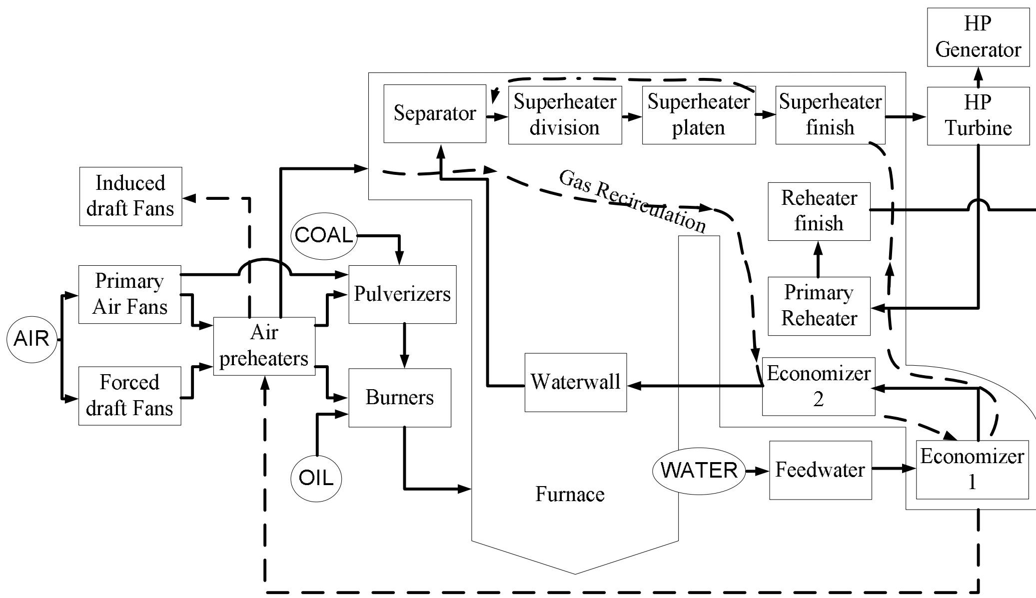


Fig. 1. A 500 MW once-through type boiler power plant.

(MPOC) system can be developed based on predictive control algorithms and intelligent techniques. During the NNCM simulation, an On-Line Identification (OLID) system is updated every few steps to provide information from the model to the MPOC. Moreover, the MPOC will use the OLID system as a virtual model to optimize the control actions, minimizing tracking-error. To search for the best control action the MPOC utilizes a heuristic optimization technique, Particle Swarm Optmization (PSO). Since the NNCM requires external inputs other than the control action, an External Neural Network (ENN) is developed to provide the external data, such as the feedwater inputs and the sprays for the superheaters and reheaters. With the proposed MPOC and ENN systems the only input to the NNCM will be the unit load demand. Finally, major outputs of NNCM will be shown using the proposed approaches. Thus the proposed approaches provide the means to design a control system for a new power plant.

Following the introduction, the 500 MW once-through type super-critical boiler power plant is described in Section II. Section III describes the development of the Modified Predictive Optimal Control systems. Section IV shows simulation results to demonstrate the feasibility of the proposed approach. The final section draws some conclusions and presents future works.

II. Once-Trough Type Boiler Power Plant

A. *Description of Power Plant*

The power plant under investigation is a 500 MW coal-pulverized once-through type boiler-turbine-generator unit. The controlled once-through type boiler is capable of delivering steam at a pressure of 35 MPa and a temperature of 595°C. Two forced draft fans supply air to the burner and furnace, two primary fans provide air to the pulverizers, and two induced draft fans are controlled to maintain furnace pressure at a desired value. Economizers are arranged before and after a Selective Catalytic Reduction (SCR) to improve denitrification and net efficiency. The superheater consists of three parts, division, platen, and finish. The steam is reheated after the High Pressure (HP) turbine using the primary reheater and the reheater finish. There is a separator on top of the furnace which supplies high pressure steam to the superheater division. The waterwall is around furnace vertically and spirally. Flue gas is supplied to the furnace through the pulverizers and burners. 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. A depiction of the power plant is shown in Fig 1.

Each subsystem inside the furnace 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. The model, which is based on the ANN, uses the predefined control action as feedforward control.

B. *Neural Network-based Combined Power Plant Model*

Each subsystem of the boiler depicted in Fig. 1 was modeled using a NN. By combining the models of the individual subsystems the NN-based Combined Model (NNCM) was developed. To reduce the complexity and provide better information the primary air, forced draft fan, induced draft fan, and air preheater are clustered into a single subsystem, called air systems. The waterwall and furnace are also clustered into the furnace/waterwall subsystem. The resulting sixteen subsystems will be connected with corresponding subsystem inputs and outputs; in addition, there are several external inputs for air, water, coal, oil, and control actions. Fig. 2 shows the NNCM.

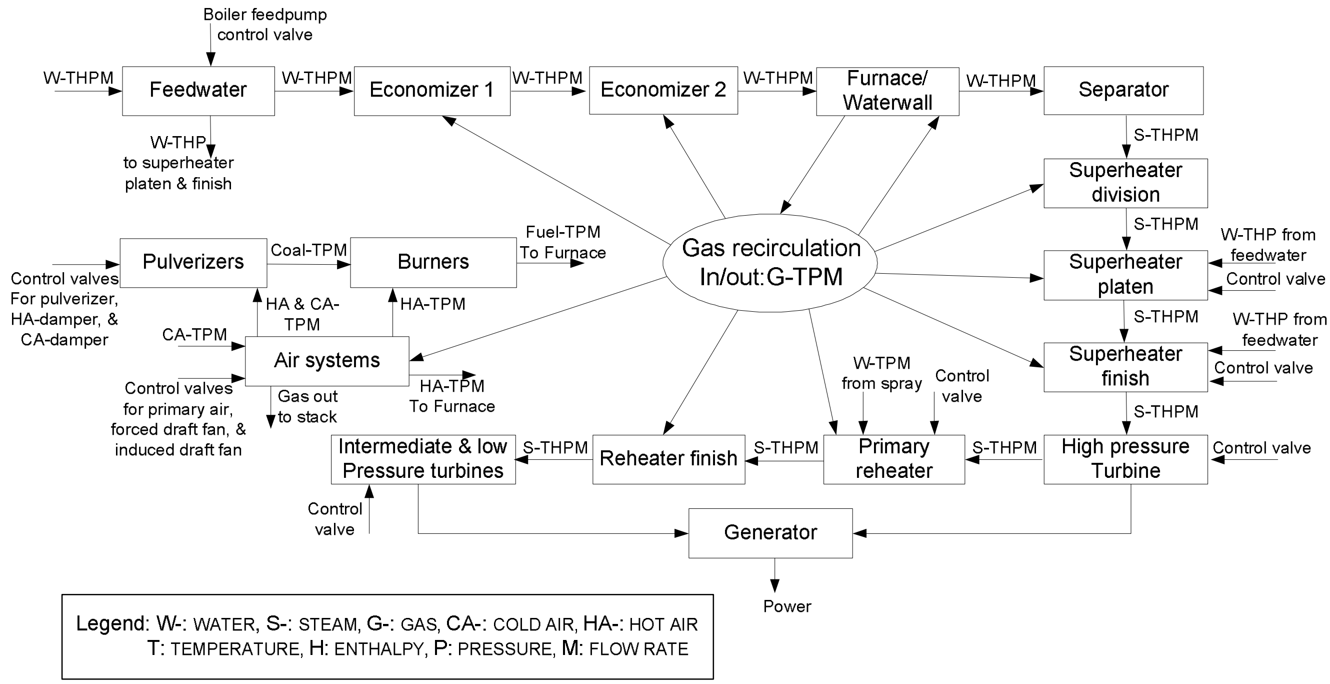


Fig. 2. NN-based Combined Model.

III. Development of Modified Predictive Optimal Control Systems

A. Modified Predictive Optimal Control (MPOC) System

General Predictive Optimal Control (POC) calculates a sequence of future control inputs on a prediction horizon [2]. For large-scale power plants, the calculation of a long range of the input sequence demands an extraordinary amount of computations and therefore requires a long time to produce results. The period of prediction time makes it difficult to apply POC directly in real-time applications.

In a similar manner the proposed MPOC system will calculate future control inputs. However, instead of a long range of the input sequence, the set of control inputs will be produced only for the next time step (one-step ahead prediction). This approach will reduce calculation time to allow for real time applications. Fig. 3 shows the overall structure of the control system.

From the Unit Load Demand (ULD) the MPOC calculates feedforward control action and the External NN (ENN) system generates external inputs. The feedforward control is used by the On-Line Identification System (OLID) system as initial candidate control inputs. The OLID system estimates outputs from the control action, and feeds them to the MPOC. The MPOC then updates the control values and returns them to the OLID. This process is repeated for a given number of iterations before the optimal control action and external inputs are sent to the NNCM.

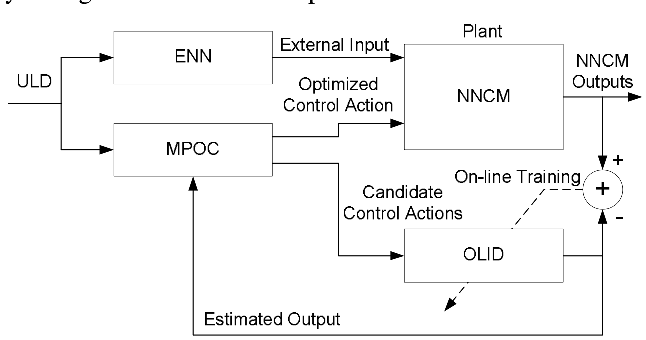


Fig. 3. Structure of the MPOC.

B. On-line Identification (OLID) System

The OLID is used in the MPOC as a simplified model of the NNCM to estimate the outputs that would be generated by a set of control inputs. The OLID system is made up of 4 NNs which use control values to estimate set-points the NNCM would produce. Because the OLID has many fewer NNs and they are decoupled, the OLID system considerably reduces calculation time. Morover, by using the OLID as a test process for the MPOC, the OLID allows for the stability of the NNCM to be preserved.

There are eleven stages in the NNCM where steam properties are changed. Each of these stages corresponds to the output of a different subsystem. The OLID approximates the output of each of these subsystems using control values as inputs. For each subsystem the OLID provides three set point values: temperature, pressure, and enthalpy, for a total of thirty three set points. There are thirteen control inputs used to drive the outputs of the plant to the desired set-points. This gives a total of thirteen inputs and thirty three outputs. Because of the large number of inputs and outputs, training a NN of this size requires a large amount of memory. For this reason the inputs and outputs were divided into four smaller networks that would require less memory for training and produce more accurate results. The order in which the inputs and outputs are grouped is important. The outputs must depend upon the inputs they are grouped with, otherwise the

NN cannot accurately predict the correct outputs. Table I shows how the control inputs and outputs are separated for the OLID. Each output represents temperature, pressure, and enthalpy. Before the OLID can be implemented the NNs must be trained off-line with a wide range of data. Data from the same ULD used to train the NNCM subsystems is also used for off-line training of the OLID networks.

TABLE I
DIVISION OF INPUTS AND OUTPUTS FOR OLID

	Control Inputs	Outputs
On-line ID#1	feedwater (u1,u2)	feedwater
On-line ID#2	pulverizers (u3,u4,u5), induced draft fan a (u6), forced draft fan (u7), induced draft fan b (u8)	economizer 1, economizer 2, furnace, superheater division
On-line ID#3	primary air fan(u9), superheater platen spray (u10), final superheater spray (u11)	superheater platen, superheater finish
On-line ID#4	high pressure turbine valve (u12), reheater spray (u13)	high pressure turbine, primary reheater, final reheater, intermediate pressure turbine

When in run mode, the OLID system shown in Fig. 4, uses the optimized control inputs from the MPOC to generate estimated outputs. The estimated outputs are compared with the NNCM outputs and the error is fed back to the OLID. Using this error the weights of each NN are updated every 5th data point for more accurate results. In search mode the estimated outputs are fed to the MPOC where candidate control actions are calculated and given to the OLID. The OLID returns a new set of estimated outputs to the MPOC, where the process continues for the given number of iterations. When the MPOC has completed all iterations, the OLID returns to run mode, and the optimized control actions are sent to the NNCM.

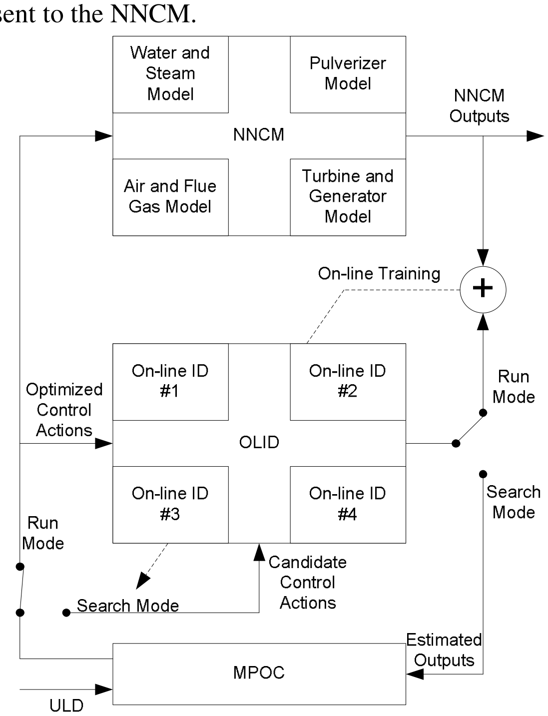


Fig. 4. Block diagram of the On-line Identification System (OLID).

C. External Neural Network (ENN) System

The boiler system of the power plant consists of 28 inputs that originate from external sources. The water provided to the feedwater system (Eu1, Eu2), the air inputs to the air gas system (Eu3, Eu4), the water for the reheater spray (Eu5, Eu6), and all control inputs are generated from other processes in the power plant. The MPOC calculates the 13 control inputs, but another process is required to provide the 15 external inputs to the NNCM.

It was determined that the external inputs were dependant on the ULD. Therefore the external inputs to the NNCM can be accurately estimated using NNs with the ULD as the input. For this section a recurrent NN is also used because of its ability to capture the dynamic behavior of the inputs.

There are a total of six non-constant external inputs which are labeled Eu1 through Eu6 in Fig. 5. To improve the accuracy of the NNs the time varying external inputs were divided into three groups, each group corresponding to a single NN. The first NN has two outputs, the second has three outputs and the third has a single output. The remaining external inputs are constant for the whole operating range of the power plant. They are simply supplied to the NNCM from prior knowledge of their values.

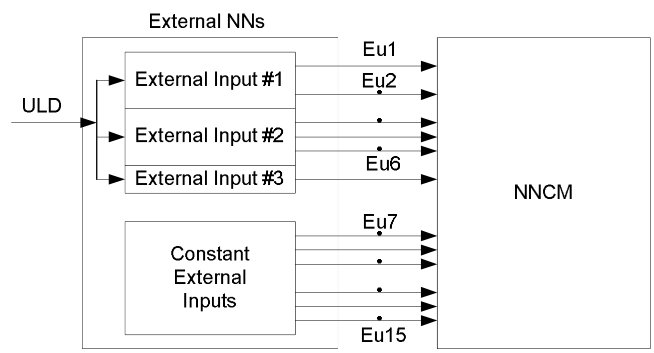


Fig. 5. Structure of the External NN system.

D. Modified Predictive Optimal Control (MPOC)

The MPOC can be developed using the proposed OLID, ENN, and NNCM. This design will preserve the stability of the NNCM while minimizing the tracking-error. Based on the ULD, the MPOC uses a mapping function to find the feedforward control actions from a lookup table. The solution space the MPOC uses to search for the optimal control inputs is then defined. Multiobjective optimization by Particle Swarm Optimization (PSO) is then used to find the control action that will produce the most desirable outputs. Fig. 6 shows the three procedures of the MPOC.

1) Mapping Function: Because the training ULD covers a wide range of operation, the control inputs for the training ULD are used as a feedforward control for the MPOC. To find the feedforward control inputs that correspond to the correct power output, a mapping function that relates the new ULD with the training ULD must be used. The training ULD can be approximated as a straight line from 100% to 50% and therefore a linear relationship can be used to estimate the feedforward control inputs based upon the power demand at

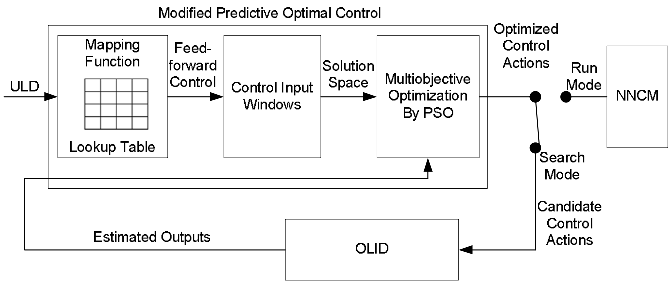


Fig. 6. Block diagram of the MPOC.

any point. The mapping function uses a new ULD to find feedforward control inputs corresponding to the same power output from the lookup table. The feedforward control inputs are then used as a starting point for the PSO search.

2) Solution Space: Before PSO begins searching for the optimal control inputs, a solution space is needed as a boundary for the search. In order to generate the solution space, the control input windows use the feedforward control input as the center of the solution space or boundary gap. The boundary gap, used to restrict the range of the solution space, expands the search window as the ULD increases from 50% to 75%, and decreases the search window as the ULD moves from 75% to 100%. The varying limiting function restrains the optimized controls from departing too far from the feedforward control, which is the center of the solution space. A plot of the boundary function is shown in Fig. 7. The boundary gap size for all control inputs is measured in percent of the total range for that control input.

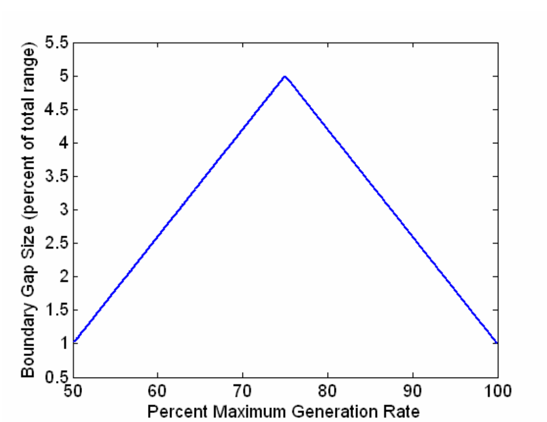


Fig. 7. Function used to constrain the solution space for the PSO.

3) Multiobjective Optimization Using PSO: The operation of PSO for a single step of the NNCM is outlined in Fig. 8. Using the solution space from the control input windows, PSO provides candidate control inputs to the OLID. The OLID estimates the outputs that would be generated by the candidate control inputs and feeds them to PSO. The estimated outputs are compared with the given set-points and an error is calculated. This error is used in the cost function shown below, where some control inputs are weighted to give them a higher priority than others:

$$Cost = \sum_{i=0}^{11} a_i\left(T_i - ET_i\right)^2 + b_i\left(P_i - EP_i\right)^2 + c_i\left(H_i - EH_i\right)^2 \quad (1)$$

In (1) *Cost* is the value which is to be minimized, i ranges from one to eleven because there are eleven subsystems for which set-points are generated, a_i, b_i, and c_i are weights that can be adjusted for multiobjective optimization, T_i, P_i, and H_i are known set-points of subsystem i for temperature, pressure, and enthalpy, respectively, and, ET_i, EP_i, and EH_i are the respective outputs of subsystem i estimated by the OLID system. By weighting the differences between the set-points and the outputs of the OLID, PSO can simultaneously optimize the set of control inputs for multiple criteria. The PSO algorithm uses the cost function (1) to update the control values which are again used as inputs to the OLID. This procedure is repeated for the given number of iterations before the optimal control values are used as inputs to the NNCM. For the next time step the ULD is used to find the feedforward control and solution space. These parameters are given to PSO and the process is repeated.

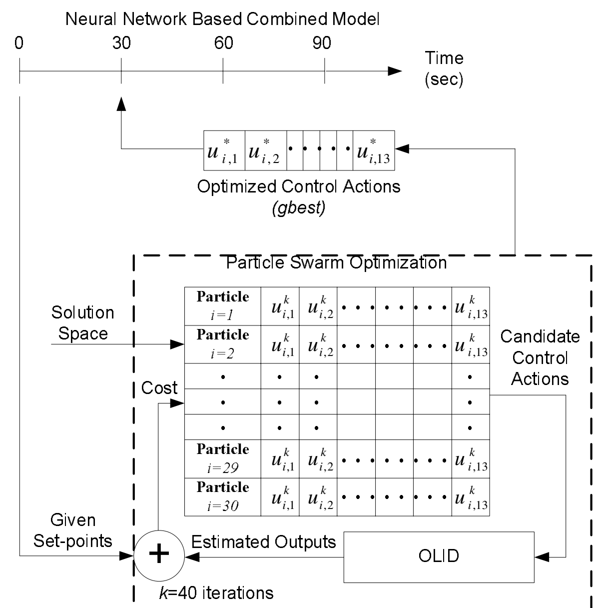


Fig. 8. Operation of the PSO section of the MPOC.

IV. Simulation Results

A. *Modified Predictive Optimal Control (MPOC)*

For validation of Neural Network-based Combined Model (NNCM), a new Unit Load Demand (ULD) is applied to the MPOC. For validation purposes the new ULD should allow the plant to reach steady-state for several different power demands. Once steady-state has been reached the ULD should maintain that value for at least 30 minutes. A ULD with these characteristics replicates a typical ULD that would be seen in real applications. Fig. 9 shows the ULD that was used to validate the NNCM. The ULD begins at 100% and decreases to 65% then increases to 80% and finally back to 100% of the MGR. In the decreasing section in Fig. 9, the ULD is changing at a rate of 3 MW/minute, in the increasing sections the rate of change is 2 MW/minute.

The results of the MPOC simulation for the new ULD are shown in the following subsections. The four subsections correspond to the four processes involved in the MPOC simulation: On-line identification (OLID), External Neural Network (ENN), Modified Predictive Optimal Control

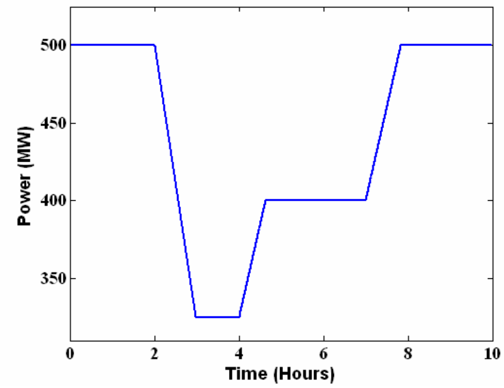
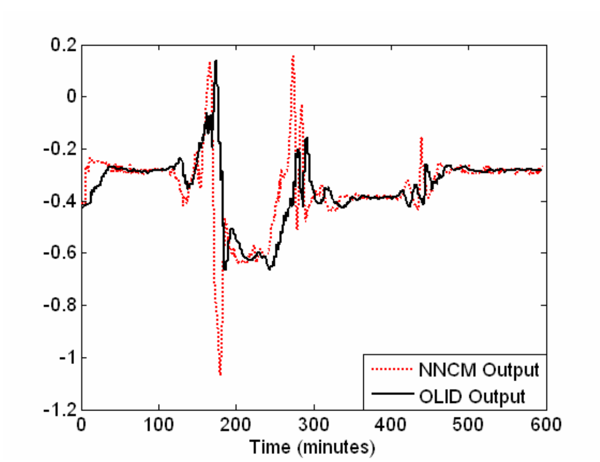


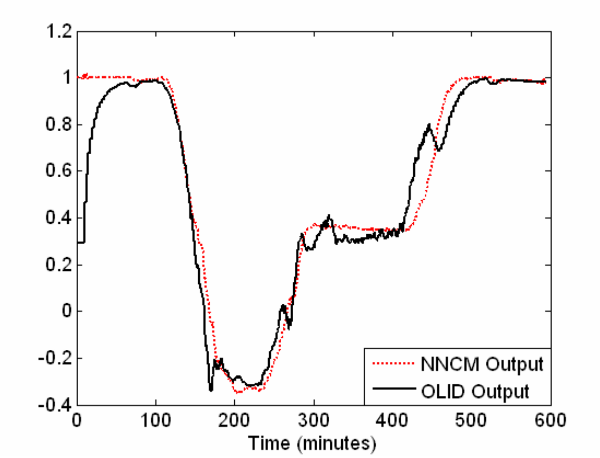
Fig. 9. New ULD used for validation of the NNCM.

(MPOC), and Neural Network-based Combined Model (NNCM).

1) On-line Identification (OLID): Fig. 10 shows selected outputs of the OLID system. Fig 10 (a) shows the superheater finish steam temperature. Fig. 10 (b) shows the primary reheater steam pressure. The OLID data is prescaled so that



(a) Superheater finish steam temperature



(b) Primary reheater steam pressure

Fig. 10. On-line identification result and target values for two outputs.

the range is between -1 and 1. By observing the differences between the estimated outputs of OLID and the outputs of NNCM, the accuracy of the OLID can be seen. The OLID generates the estimated outputs very well by continuous updates.

2) External Neural Networks (ENN): The water temperature output of the ENN for the primary reheater spray is shown in Fig. 11. By comparing outputs of the ENN with filtered data from the plant simulator, the ENN generates

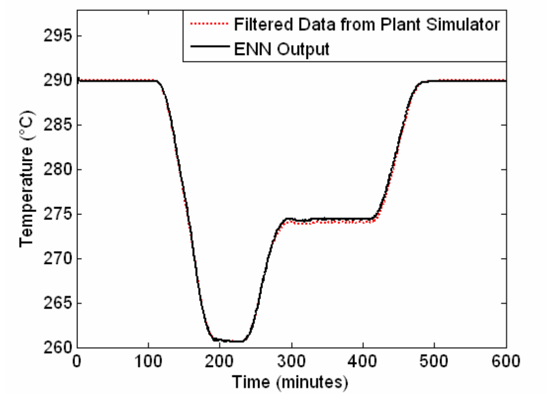


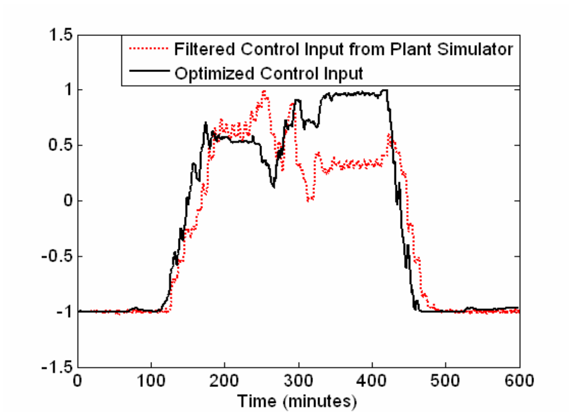
Fig. 11. Water temperature for primary reheater spray.

external inputs appropriately to produce power and operate the NNCM simulation.

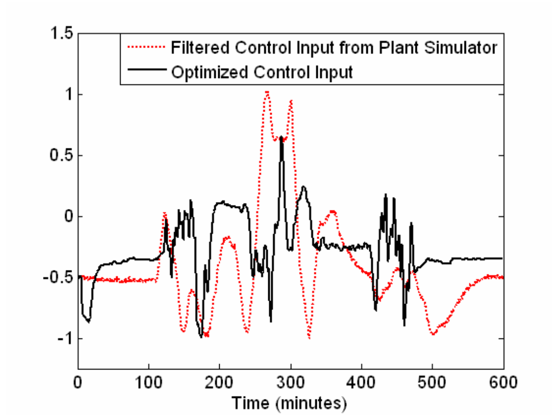
3) Modified Predictive Optimal Control (MPOC): Sample control inputs, found using PSO, are shown in Fig. 12. Fig. 12 (a) shows the primary reheater spray control, and Fig. 12 (b) shows the superheater platen spray control. It is obvious that the MPOC generates control inputs that are quite different from the filtered control input from the plant simulator.

4) Neural Network Combined Model (NNCM) with MPOC: The results from major outputs of the NNCM are shown in Fig. 13: the total power output, the superheater finish steam temperature, the final reheater steam temperature, and the division superheater steam pressure. Observing the error between the simulation data and the NNCM output gives a good idea of the accuracy of the MPOC. The primary goal of following the ULD has been achieved by the MPOC, while maintaining the secondary objectives of keeping the pressure and temperatures within the operating windows.

With the proposed Neural-Network based combined model, the Modified Predictive Optimal Control system generates the optimal control action very efficiently. Since the PID-based plant simulator has many control loops, the failure of a single loop could adversely effect the operation of the rest of the system. Moreover, under a changing environment, PID control systems have to properly tune gains and time constants continuously. However, the MPOC generates optimal control action by minimizing load-tracking error without consideration of complicated control loops or adjusting of gains and time constants. The MPOC also preserves stability by predicting the outputs of the plant using the OLID, while PID control uses the actual error from the real plant. Therefore the MPOC can be used as an advanced



(a) Primary reheater spray control



(b) Superheater platen spray control

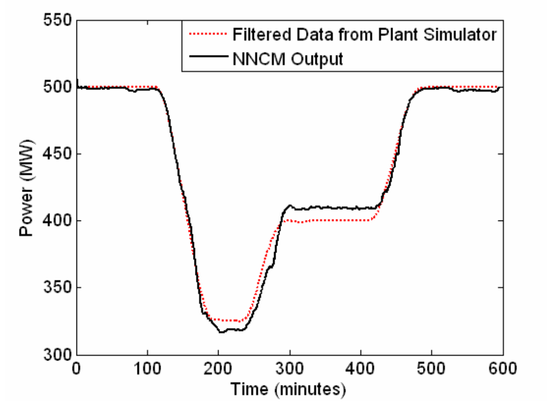
Fig. 12. Superheater platen spray control.

control methodology for use in real applications.

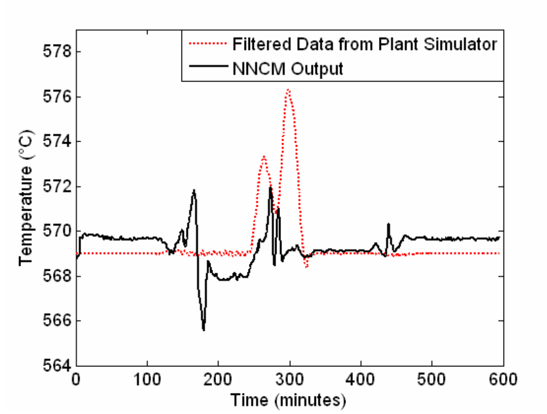
V. Conclusion

Using the NN-based Combined Model (NNCM), a Modified Predictive Optimal Control (MPOC) system is developed. The MPOC consists of an On-line Identification (OLID) system, and an External Neural Network (ENN). The On-line Identification (OLID) system allows stability to be preserved during the search for optimal control inputs. The External Neural Network (ENN) provides external inputs to the NNCM using the given unit load demand. The proposed approach provides a means to efficiently search for optimal control inputs during on-line operation. The simulation results show that the proposed MPOC follows the set-points and power outputs, and therefore can be applied in real time to large scale power plants.

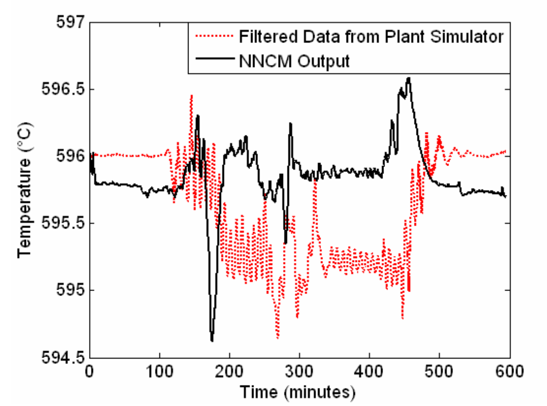
For future work, with the developed NNCM and MPOC, a reference governor will be developed to provide optimal set-points and optimal feedforward control inputs for the MPOC. Moreover, applicability to larger capacity power plants such as an Ultra Super Critical (USC) boiler power plant will be investigated.



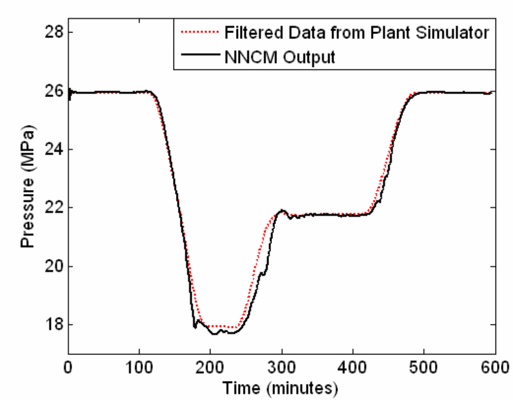
(a) Total power output



(b) Superheater finish steam temperature



(c) Final reheater steam temperature



(c) Superheater division steam pressure

Fig. 13. Results of the NNCM compared with data from simulator.

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