

Design of MPC for Superheated Steam Temperature Control in a Coal-fired Thermal Power Plant

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Abstract

A superheater is a vital part of the steam generation process in the boiler-turbine system. Reliable control of temperature in the superheated steam temperature system is essential to guarantee efficiency and high load-following capability in the operation of coal-fired Thermal power plant. The PI and PID controllers are extensively used in cascade control of secondary superheated steam temperature process. The design and implementation of a Model Predictive Control (MPC) strategy for the superheated steam temperature regulation in a thermal power plant is presented. A FOPTD model is derived from the dynamic model of the superheater. This model is required by the MPC algorithm to calculate the future control inputs. A new MPC controller is designed and its performance is tested through simulation studies. Compared with the superheater steam temperature control using a conventional PID controller, the steam temperature controlled by the MPC controller is found to be more stable. The stable steam temperature leads to energy saving and efficient plant operation, as verified by the simulation results.

Keywords: FOPTD model, MPC, PID, steam temperature control, superheater (SH), ITAE

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1. Introduction

Thermal energy is the vital source of electric power generation in India. More than 60% of total electric power is generated by steam plants in India. Steam power plant operates on Rankin cycle. The main parts of thermal power plant are boiler, generator, turbine and their auxiliaries. Steam produced in boiler at certain temperatures and pressure, supplied to turbine which is coupled to the generator. The generator converts mechanical energy into electrical energy. Continuous process in a power plant and power station are difficult systems characterized by nonlinearity, uncertainty, and load disturbance. The superheater is an essential part of the steam generation process in the boiler-turbine system where steam is superheated before entering the turbine that drives the generator. Generation of steam from the superheater is a nonlinear process and the pressure and the temperature in the superheater are very high. Hence steam temperature control at the super heater (SH) outlet is one of the most vital and challenging control tasks in a thermal power plant [1].

This temperature control process is achieved by monitoring the spray of water in a super heater. The complexity occurs at the peak nonlinear characteristics of the SH, the extended time delays occurs due to thermal process, and perturbations caused by the flue gases [2, 3]. In a Thermal power plant, the growth in steam temperature will yields to increment in power plant efficiency. The plant can operate at a high temperature only when it is maintained at a stable level. Maintaining the constant steam temperature increases, the lifetime of the boiler and steam turbine while reducing thermal stresses [3]. In order to decrease CO₂ emissions, power generation from alternate renewable energy sources has grown incomparably over the past five years, forcing changes in the operating requirements of conventional power plants [4]. Although a power plant is initially designed to operate at its base load, it needs to be efficient, flexible, and capable of handling changes in load demand and variations in power generation profiles from renewable energy [3]. This, in turn, makes it more difficult to maintain the steam temperature at a constant value. The most popularly used controller in power plants is PID controller because of its acceptable degree of control performance, technology maturity, simplicity, operation security, and robustness [5]. However, owing to new challenges in load

demand and the transients, performance of the PID controller is far from being optimal [6]. This motivates the development of other type of controllers, such as model Predictive controllers.

Model Predictive Control (MPC) defines a class of control algorithms that calculates control inputs based on the predicted behavior of process outputs over a time horizon. In MPC algorithm, future control inputs are calculated in order to reduce the difference between the predicted control outputs and the set point values over the prediction horizon. Only the first element of the calculated sequence of the control inputs is applied to the calculation process. This process is repeated at consequent sampling times with prediction horizons of the same length, but shifted one step forward. This process is known as the principle of a receding horizon [7].

Different predictive control algorithms have been developed over time. The Model Predictive Heuristic Control (MPHC) algorithm was first developed by Richalet et al., [8], which was followed later by a number of other such algorithms, including Dynamic Matrix Control (DMC), Quadratic Dynamic Matrix Control (QDMC) [9], Generalized Predictive Control (GPC) [10], and Shell Multivariable Optimizing Controller (SMOC) [11]. All these algorithms make use of linear process models to predict the future moves of the control variables. It has been confirmed that the predictions made through the linear model are helpful in calculating the next values for the control variables.

A DMC controller was developed in [2] for superheater steam temperature control and tested in a power plant simulator and in a field operating coal-fired thermal power plant having a drum boiler. Simulation tests shown that the DMC controller outperformed the conventional PID controllers. A successful implementation of a DMC control strategy is reported in [12] for steam temperature regulation, in which the controller was tested in a power plant simulator operating with a once-through boiler. Sanchez et al., [13] designed a fuzzy controller and a DMC to regulate the steam temperature in a 300 MW power plant.

Clarke et al., [10] designed a MPC algorithm, which became popular both in industry applications, as well as in academic studies [15]. The main feature of the MPC algorithm is that it can be used with unstable and non– minimum phase plants [16]. In [17], the MPC controller shows good performance against the existing PID controller for regulating the superheated steam temperature in a thermal power plant having a once through boiler. For this reason, MPC is chosen for addressing the new challenges faced by superheater steam temperature control with uncertain load demand profiles.

The rest of the paper is organized as follows: The description of the steam generation process is given in Section 2. Superheater steam temperature control circuit is demonstrated in Section 3. The mathematical model of a superheater is derived in Section 4. System identification is described in Section 5. System identification using Transfer function approach is described in Section 6. System identification using Frequency response approach is described in Section 7. Zeigler-Nichols tuning method is demonstrated in Section 8. MPC design is given in Section 9. Finally, conclusion is drawn in Section 10.

2. Mathematical Model of A Superheater

The behaviour of five state variables of superheater can be well described by five nonlinear partial differential equations by applying the energy equation, Newton's equation, and heat transfer equation, and principle of continuity [1].

The Reduced energy equation for flue gas is given by:

$$\frac{C_2 \rho_2 F_2}{\alpha_{S_2} O_2} \left[u_2 \frac{\partial T_2}{\partial x} + \frac{\partial T_2}{\partial t} \right] + (T_2 - T_S) = 0 \quad (1)$$

The Heat transfer equation from burned gases to steam via the wall is given by:

$$\frac{\partial T_S}{\partial t} - \frac{T_1 - T_S}{c_{S_1} G} - \frac{T_2 - T_S}{c_{S_2} G} = 0 \quad (2)$$

The continuity equation for steam is given by:

$$\frac{1}{F \rho_1} \left\{ F u_1 \left(\frac{\partial \rho_1}{\partial p_1} \frac{\partial p_1}{\partial x} + \frac{\partial \rho_1}{\partial T_1} \frac{\partial T_1}{\partial x} \right) + u_1 \rho_1 \left(\frac{\partial F}{\partial p_1} \frac{\partial p_1}{\partial x} + \frac{\partial F}{\partial T_1} \frac{\partial T_1}{\partial x} \right) + \rho_1 \left(\frac{\partial F}{\partial p_1} \frac{\partial p_1}{\partial t} + \frac{\partial F}{\partial T_1} \frac{\partial T_1}{\partial t} + F \left(\frac{\partial \rho_1}{\partial p_1} \frac{\partial p_1}{\partial t} + \frac{\partial \rho_1}{\partial T_1} \frac{\partial T_1}{\partial t} \right) \right\} + \frac{\partial u_1}{\partial x} = 0 \quad (3)$$

The Newton's equation for steam is given by [1]:

$$\frac{\partial p_1}{\partial x} + \rho_1 u_1 \frac{\partial u_1}{\partial x} + \rho_1 \frac{\partial u_1}{\partial t} + \rho_1 g \sin(\theta) + \frac{\rho_1 \lambda_1 u_1 |u_1|}{2d_n} = 0 \quad (4)$$

Energy equation for steam is given by:

$$\begin{aligned} & \frac{\partial}{\partial t} \left\{ \rho_1 (c_1 T_1 + \frac{u_1^2}{2}) \right\} + \frac{\partial}{\partial x} \left\{ \rho_1 u_1 (c_1 T_1 + \frac{u_1^2}{2}) \right\} \\ & + \frac{\partial}{\partial x} \{ c_1 u_1 \} + \frac{\partial}{\partial x} \{ \rho_1 u_1 g \cdot z \} - \alpha_{1s} O_1 (T_s - T_1) \frac{1}{F} = 0 \end{aligned} \quad (5)$$

Table 1. Relevant parameters for superheater dynamic model

Parameters	Description
$T_1(x,t)$	Steam temperature
$T_2(x,t)$	Flue gas temperature
$T_s(x,t)$	Temperature of the wall of the heat exchanging surface of the superheater
$P_1(x,t)$	Pressure of steam
$u_1(x,t)$	Velocity of steam
$P_2(0,t)=P_2(x,t)=P_2(L,t)$	pressure of flue gas
$u_2(0,t)=u_2(x,t)=u_2(L,t)$	Velocity of flue gas
X	the space variable along the active length of the wall of the heat exchanging surface of the superheater
T	Time
$c_1 = c_1(P,T)$	heat capacity of steam at constant pressure, $J \cdot kg^{-1}K^{-1}$
$c_2 = c_2(P,T)$	heat capacity of flue gas at constant pressure, $J \cdot kg^{-1}K^{-1}$
c_s	heat capacity of superheater's wall material, $J \cdot kg^{-1}K^{-1}$
dn	diameter of pipeline, m
$F_1 = F_1(x)$	steam pass cross Section, m^2
$F_2 = F_2(x)$	flue gas channel cross Section, m^2
g	acceleration of gravity, $m \cdot s^{-2}$
$G = G(x)$	weight of wall per unit of length in x direction, $kg \cdot m^{-1}$
L	active length of the wall, m
$O_1 = O_1(x)$	surface of wall per unit of length in x direction for steam, m
$O_2 = O_2(x)$	surface of wall per unit of length in x direction for flue gas, m
$z = z(x)$	ground elevation of the superheater, m
$\alpha S_1 \cdot K^{-1}$	heat transfer coefficient between wall and steam, $J \cdot m^{-2} \cdot s^{-1} K^{-1}$
αS_2	heat transfer coefficient between the wall and flue gas, $J \cdot m^{-2} \cdot s^{-1} K^{-1}$
$\lambda_1(x)$	steam friction coefficient, 1
θ	superheater's constructional gradient, 1
$\rho_1 = \rho_1(P,T)$	density of steam, $kg \cdot m^{-3}$
$\rho_2 = \rho_2(P,T)$	density of flue gas, $kg \cdot m^{-3}$

3. System Identification

Modeling is representation of physical system in mathematical form. The order of the system is expressed based on the mathematical equation of the physical system. There are different models like integrating process, integrating with dead time process, first order process, first order with dead time process, second order process and second order with dead time process. First order with dead time and second order with dead time process models are

extensively used to analyze many real time systems. System identification of the first order plus dead time process is to determine the model parameters like system gain, dead time and time constant. Different methods are available for determining the model parameters of the FOPTD model. The two common and effective methods of FOPTD identification are transfer function identification algorithm and frequency response method system identification algorithm [12].

4. Transfer Function Identification Algorithms

The FOPTD model with delay is given by [12]:

$$G_p(s) = \frac{ke^{-Ls}}{Ts+1} \quad (6)$$

The first order derivative of $G_p(s)$ with respect to s is given by:

$$\frac{G_p'(s)}{G_p(s)} = -L - \frac{T}{1+Ts} \quad (7)$$

$$\frac{G_p''(s)}{G_p(s)} - \left(\frac{G_p'(s)}{G_p(s)}\right)^2 = \frac{T^2}{1+Ts^2} \quad (8)$$

Evaluating at $s=0$ results in:

$$T^2 = \frac{G_p''(0)}{G_p(0)} - T_{ar}^2 \quad (9)$$

$$T_{ar} = -\frac{G_p'(0)}{G_p(0)} = L + T \quad (10)$$

The identified FOPTD model using transfer function approach is given by:

$$G_p(s) = \frac{0.8247}{65.7709s+1} e^{-47.8911s} \quad (11)$$

5. Frequency Response Based System Identification Algorithm

The first order plus dead time model for a given plant is represented by:

$$G_p(s) = \frac{K}{Ts+1} e^{-Ls} \quad (12)$$

Where, K is the process gain, T is the time constant, L is the dead time.

The frequency response of a first order model is given by:

$$G(j\omega) = \frac{K}{Tj\omega+1} e^{-j\omega L} \quad (13)$$

The ultimate gain K_c is obtained at the crossover frequency ω_c . ω_c is determined from the first intersection of a Nyquist plot with the negative part of the real axis. The resulting equations are (8):

$$\begin{cases} \frac{K(\cos\omega_c L - \omega_c T \sin\omega_c L)}{1+\omega_c^2 T^2} = -\frac{1}{K_c} \\ \sin\omega_c L + \omega_c T \cos\omega_c L = 0 \end{cases} \quad (14)$$

Where k is gain of the system and it can be calculated directly from the given transfer function. The two variables $x_1 = L$ and $x_2 = T$ is defined as [12]:

$$\begin{cases} f_1(x_1, x_2) = k K_c (\cos \omega_c x_1 - \omega_c x_2 \sin \omega_c x_1) + 1 + \omega_c^2 x_2^2 = 0 \\ f_2(x_1, x_2) = \sin \omega_c x_1 + \omega_c x_2 \sin \omega_c x_1 = 0 \end{cases} \quad (15)$$

The Jacobian matrix J is denoted as:

$$J = \begin{bmatrix} \partial f_1 / \partial x_1 & \partial f_1 / \partial x_2 \\ \partial f_2 / \partial x_1 & \partial f_2 / \partial x_2 \end{bmatrix} \quad (16)$$

The Jacobian matrix is calculated as:

$$J = \begin{bmatrix} -k K_c \omega_c \sin \omega_c x_1 - k K_c \omega_c^2 x_2 \cos \omega_c x_1 & 2 \omega_c^2 x_2 - k K_c \omega_c \sin \omega_c x_1 \\ \omega_c \sin \omega_c x_1 - \omega_c^2 x_2 \sin \omega_c x_1 & \omega_c \cos \omega_c x_1 \end{bmatrix} \quad (17)$$

The first order plus dead time model thus identified using frequency response method [9] is given by:

$$G_p(s) = \frac{0.8247}{174s+1} e^{-37s} \quad (18)$$

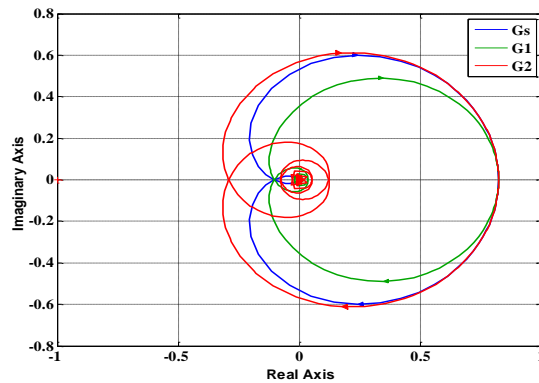


Figure 1. Nyquist diagrams

Gs: Nyquist diagrams for the plant

G1: Nyquist diagram for the identified first order plus dead time model using frequency response method

G2: Nyquist diagram for the identified first order plus dead time model using transfer function based fitting.

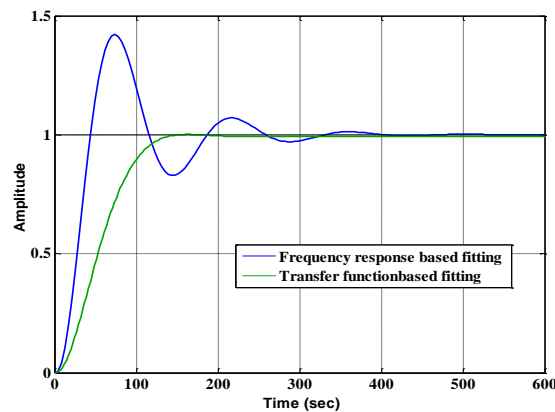


Figure 2. Closed Loop step responses

The simulation results are shown in Figure 2. From the responses it can be seen that although the PID controller designed with the transfer function identification algorithm looks better, but it does not exhibit the overshoot characteristics of Ziegler–Nichol’s tuning method, mostly due to the inaccurately identified parameters of an First order plus dead time model. Hence FOPTD parameters identified by frequency response based approach is used for tuning of controllers for supeheater steam temperature control.

6. Zeigler-Nichol’s Method

Zeigler and Nichol’s proposed a tuning formula in early 1942. The tuning formula is obtained when the plant model is given by a first order plus dead time model and it is given by [12]:

$$G(s) = \exp(-sL) * \frac{K}{Ts+1} \tag{19}$$

Table 2. Zeigler-Nichol’s tuning formula

Controller type	From step response		
	K_p	T_i	T_d
PI	$0.9/a$	$3L$	
PID	$1.2/a$	$2L$	$L/2$

Where $a = KL/T$

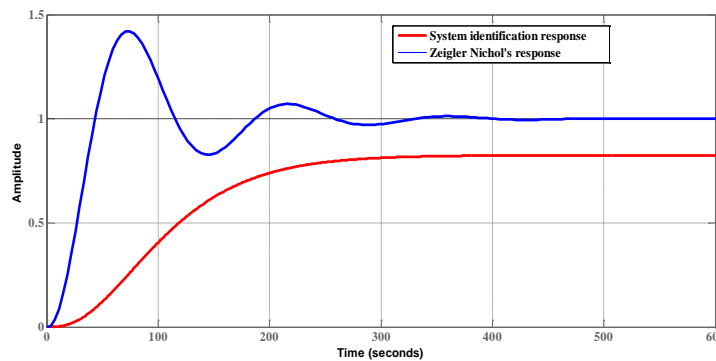


Figure 3. Response of PID controller tuned using Zeigler Nichol’s method

7. Design of Model Predictive Controller

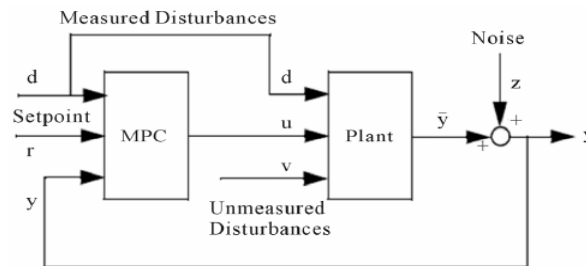


Figure 4. Block diagram of MPC

7.1. Prediction of State and Output Variables

Assume sampling instant as k_i , $k_i > 0$. The state variable vector $x(k_i)$ provides the current plant information. The future control trajectory is given by [7]:

$$\Delta u(k_i), \Delta u(k_i + 1), \dots, \Delta u(k_i + N_c - 1) \tag{20}$$

Where N_c is called the control horizon.

With $x(k_i)$, the future state variables are predicted for N_p number of samples, where N_p is called the prediction horizon. N_p is also the length of the optimization window. The future state variables is given by:

$$x(k_i + 1|k_i), x(k_i + 2|k_i), \dots, x(k_i + m|k_i), \dots, x(k_i + N_p|k_i) \quad (21)$$

Where $x(k_i + m|k_i)$ the predicted state variable at $k_i + m$ with given current plant information $x(k_i)$.

The control horizon N_c is chosen to be less than (or equal to) the prediction horizon N_p . Based on the state-space model (A, B, C), the future state variables are calculated sequentially using the set of future control parameters [9].

$$\begin{aligned} x(k_i + 1|k_i) &= Ax(k_i) + B\Delta u(k_i) \\ x(k_i + 2|k_i) &= Ax(k_i + 1|k_i) + B\Delta u(k_i + 1) \\ &= A^2 x(k_i) + AB\Delta u(k_i) + B\Delta u(k_i + 1) \\ &\vdots \\ x(k_i + N_p|k_i) &= A^{N_p} x(k_i) + A^{N_p-1} B\Delta u(k_i) + A^{N_p-2} B\Delta u(k_i + 1) \\ &\quad + \dots + A^{N_p-N_c} B\Delta u(k_i + N_c - 1) \end{aligned} \quad (22)$$

From the predicted state variables, the predicted output variables are given by:

$$\begin{aligned} y(k_i + 1|k_i) &= CAx(k_i) + CB\Delta u(k_i) \\ y(k_i + 2|k_i) &= CA^2 x(k_i) + CAB\Delta u(k_i) + CB\Delta u(k_i + 1) \\ y(k_i + 3|k_i) &= CA^3 x(k_i) + CA^2 B\Delta u(k_i) + CAB\Delta u(k_i + 1) \\ &\quad + CB\Delta u(k_i + 2) \\ &\vdots \\ y(k_i + N_p|k_i) &= CA^{N_p} x(k_i) + CA^{N_p-1} B\Delta u(k_i) + CA^{N_p-2} B\Delta u(k_i + 1) \\ &\quad + \dots + CA^{N_p-N_c} B\Delta u(k_i + 2) \end{aligned} \quad (23)$$

Variables information $x(k_i)$ and the future control movement $\Delta u(k_i + j)$, where $j = 0, 1, \dots, N_c - 1$.

$$Y = [y(k_i + 1|k_i) \ y(k_i + 2|k_i) \ y(k_i + 3|k_i) \ \dots \ y(k_i + N_p|k_i)]^T \quad (24)$$

$$\Delta U = [\Delta u(k_i) \ \Delta u(k_i + 1) \ \Delta u(k_i + 2) \ \dots \ \Delta u(k_i + N_c - 1)]^T \quad (25)$$

$$Y = Fx(k_i) + \Phi\Delta U \quad (26)$$

Where,

$$F = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \vdots \\ CA^{N_p} \end{bmatrix}; \Phi = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2 B & CAB & CB & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ CA^{N_p-1} B & CA^{N_p-2} B & CA^{N_p-3} B & \dots & CA^{N_p-N_c} B \end{bmatrix} \quad (27)$$

7.2. Optimization

For a set point signal $r(k_i)$ at sample time k_i , within a prediction horizon the objective of the predictive control system is to bring the predicted output as close as possible to the set point signal, where we assume that the set point signal remains constant in the optimization window. This objective is then translated into a design to find the 'best' control parameter vector ΔU such that an error function between the set-point and the predicted output is minimized. The data vector that contains the set point information is assumed as [7]:

$$R_s^T = \overbrace{[1 \ 1 \ \dots \ 1]}^{N_p} r(k_i) \quad (28)$$

The cost function J that reflects the control objective is given by:

$$J = (R_s - Y)^T (R_s - Y) + \Delta U^T \bar{R} \Delta U \quad (29)$$

The first term is linked to the objective of minimizing the errors between the predicted output and the set point signal while the second term reflects the consideration given to the size of ΔU when the objective function J is made to be as small as possible. $\bar{R} = r_w I_{N_c \times N_c}$ ($r_w \geq 0$), r_w is used as a tuning parameter for the desired closed loop performance. To find the optimal ΔU that will minimize J, J is expressed as [8]:

$$J = (R_s - Fx(k_i))^T (R_s - Fx(k_i)) - 2\Delta U^T \phi^T (R_s - Fx(k_i)) + \Delta U^T (\phi^T \phi + \bar{R}) \Delta U \quad (30)$$

The first derivative of the cost function J is denoted as:

$$\frac{\partial J}{\partial \Delta U} = -2\phi^T (R_s - Fx(k_i)) + 2(\phi^T \phi + \bar{R}) \Delta U \quad (31)$$

The necessary condition of the minimum J is obtained as:

$$\frac{\partial J}{\partial \Delta U} = 0 \quad (32)$$

The optimal solution for the control signal is given as:

$$\Delta U = (\phi^T \phi + \bar{R})^{-1} \phi^T (R_s - Fx(k_i)) \quad (33)$$

Assume that $(\phi^T \phi + \bar{R})^{-1}$ exists. The matrix $(\phi^T \phi + \bar{R})^{-1}$ is called the Hessian matrix. R_s is expressed as:

$$R_s = \overbrace{[1 \ 1 \ \dots \ 1]^T}^{N_p} r(k_i) = \bar{R}_s r(k_i) \quad (34)$$

Where,

$$\bar{R}_s = \overbrace{[1 \ 1 \ \dots \ 1]^T}^{N_p} \quad (35)$$

The optimal solution of the control signal is given as:

$$\Delta U = (\phi^T \phi + \bar{R})^{-1} \phi^T (\bar{R}_s r(k_i) - Fx(k_i)) \quad (36)$$

The following parameters of the MPC for superheater steam temperature system were found to give the best performance.

1. Prediction horizon $N=20$
2. control horizon $N_u = 4$
3. control weight $\lambda = 300$
4. output weight $\delta = 1$

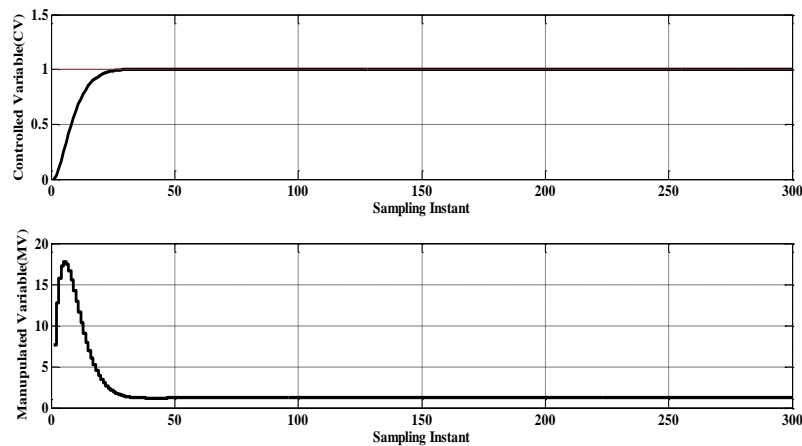


Figure 5. Response of MPC for Superheated steam temperature system

Table 3. Comparison of performance indices

Performance Indices	PID controller	MPC Controller
Rise time	33.2197	13.9
Settling Time	307.5812	23.3867
Settling Min	0.8279	0.9011
Settling Max	1.4200	1.0011
Overshoot	42.0017	0.1112
Undershoot	0	0
Peak	1.4200	1.0011
Peaktime	74.5434	36
ITAE	4691	58.0269

8. Conclusion

This paper has established that MPC technique for temperature control of superheated steam temperature system. Using the dynamical model of superheater, we presented the FOPTD model identification using Frequency response method and transfer function method. Based on the FOPTD model derived using frequency response function approach, it was shown that MPC for superheated steam temperature control has least value of ITAE. Compared with PID controller MPC has obtained good setpoint tracking with very less overshoot for superheater steam temperature control.

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