

ANN Controller Design for Lime Kiln Process

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Abstract

The lime kiln is a very complex multivariable process with severe non linearities, high degree of coupling and frequent disturbances. In this paper a 2x2 lime kiln process with two manipulated variables namely the fuel gas flowrate, and the percent opening of the induced draft damper and two controlled variables namely front end temperature and back end temperature has been considered. After its decoupling, artificial neural network (ANN) controllers have been designed to control the front end temperature. The performance of ANN controllers have been compared with that of conventional controllers.

Keywords: lime kiln, decoupling, neural network, PI controller

1. Introduction

Limekiln is essentially a long rotating cylinder with single or two layer refractory and insulation inside the kiln and is slightly inclined to the horizontal as shown in Figure 1. The task of the kiln is to convert lime mud (CaCO_3) into lime (CaO) by the calcination process. This conversion process is endothermic, requiring large amount of heat to be supplied to the kiln [1]. The prime goal of lime kiln is to produce good quality lime for which maintenance of the front end temperature i.e temperature of hot lime is essential [2]. The chemical equation of this reaction is:

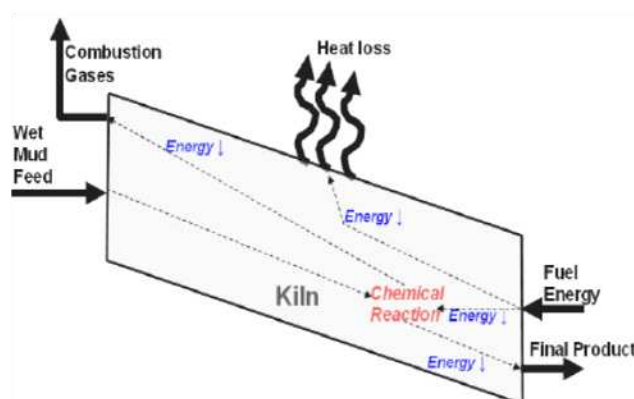
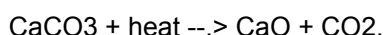


Figure 1. Lime kiln process [3]

The entire lime kiln can be divided into three temperature zones namely the drying section where the wet lime mud is dried at temperature 230 Fahrenheit, the heating section where mud powder is heated up to temperature 600 Fahrenheit and the calcination section where the lime mud is converted to lime. This reaction takes place at temperature 1500

Fahrenheit. The measure of the lime quality is the amount of residual carbon dioxide in the resulting CaO.

A speed controller for an induction motor based on quasi inverse neural model is presented in [4]. This controller contains two cascade feedforward neural network subsystems. The desired stator current components for the control algorithm and the corresponding voltage components for PWM converter are provided by first and second subsystem respectively.

Demetri Psaltis et al. introduced a modified backpropagation algorithm and proposed various learning architectures like general learning architecture, indirect learning architecture and specialized learning architecture [5].

A new approach for the weights estimation is implemented on a simulated wastewater treatment system having non stationary dynamics. This approach is based on simultaneous perturbation gradient approximation [6].

A neural network controller has been designed for steering a trailer truck while backing upto a loading dock which can guide the truck to the dock from any initial position [7]. The hybrid of neural network and fuzzy logic approaches has been reported to be very effective to design controllers. It shows an improved performance and robustness [8].

2. Plant Model and its Decoupling

In the present work two temperatures are controlled in the kiln, the front-end temperature (T_{fe}), and the backend temperature (T_{be}). The process has two manipulated variables: the fuel gas flowrate (F), and the percent opening of the induced draft damper (vp). Expression (1) shows the model of an industrial lime kiln (developed from mill tests) that will be used to design the controller.

$$\begin{bmatrix} T_{fe} \\ T_{be} \end{bmatrix} = \begin{bmatrix} \frac{0.6}{3s+1} & \frac{-2.1}{(6s+1)(5s+1)} \\ \frac{0.1}{(10s+1)(s+1)} & \frac{0.9}{(7s+1)(10s+1)} \end{bmatrix} \begin{bmatrix} F \\ vp \end{bmatrix} \quad (1)$$

The open loop step response of this plant model is shown in Figure 2.

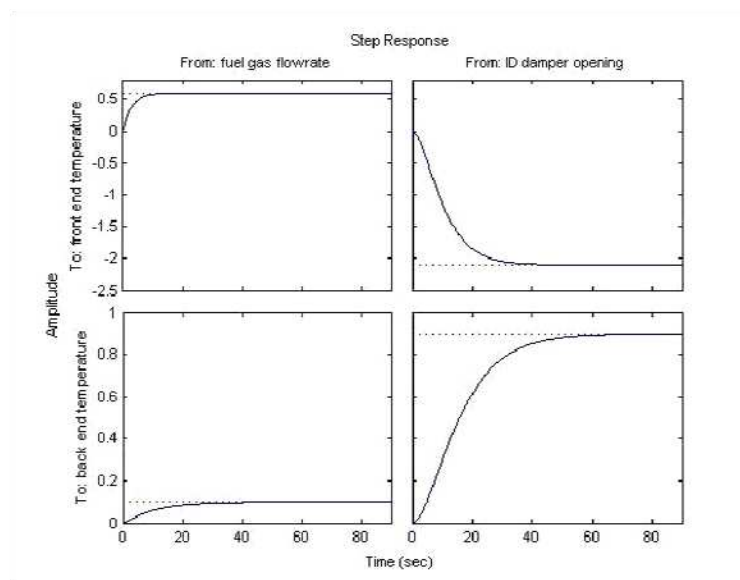


Figure 2. Open loop step response of plant

First of all, let's determine the suitable pairing between manipulated and controlled variables by investigating the relative gain array (RGA). The RGA for the considered plant is presented in expression (2)

$$RGA = \begin{bmatrix} 0.72 & 0.28 \\ 0.28 & 0.72 \end{bmatrix} \quad (2)$$

This RGA suggests that the suitable pairing is u_1 - y_1 and u_2 - y_2 .

The MIMO systems have severe loop interactions which degrades the set point tracking performance of the control system. In order to avoid loop interactions, decoupling of the system is done.

Now let $G(s)$ be the transfer matrix of a 2x2 MIMO system.

$$[G(s)] = \begin{bmatrix} g_{11}(s) & g_{12}(s) \\ g_{21}(s) & g_{22}(s) \end{bmatrix} \quad (3)$$

Then the transfer functions of the two decoupled SISO systems are expressed in expressions (4) and (5) [9]

$$G_{1(s)} = \left[g_{11}(s) - \frac{g_{12}(s)g_{21}(s)}{g_{22}(s)} \right] \quad (4)$$

$$G_{2(s)} = \left[g_{22}(s) - \frac{g_{12}(s)g_{21}(s)}{g_{11}(s)} \right] \quad (5)$$

$G_1(s)$ represents the fuel gas flow rate \rightarrow front end temperature system. Hence this system is of our interest as we require to control the front end temperature. Using (4) we obtain,

$$G_1(s) = \frac{162 s^4 + 281.7 s^3 + 112.3 s^2 + 16.08 s + 0.75}{810 s^5 + 1458 s^4 + 830.7 s^3 + 204.3 s^2 + 22.5 s + 0.9} \quad (6)$$

The conventional PI controller's setpoint tracking response for this SISO system with tuned values $K_p=0.8143$ and $K_i=0.6532$ is depicted in Figure 3 having settling time of 70 seconds and peak overshoot of 10.5%.

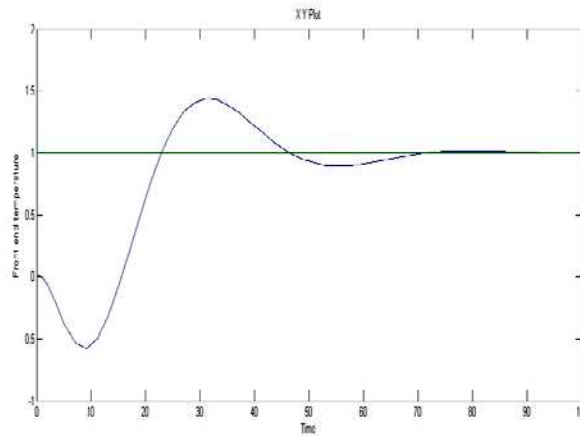


Figure 3. PI Controller response

3. Neural Network Controller

The conventional PID controllers are simple to design and implement but are not very effective in compensating plant parameter variations and changes in the environment. The development of ANN has resulted in more effective control performance. It does not require a priori mathematical model of the plant and has an outstanding capability to adapt to the changing environment and the plant dynamics unlike conventional methods. Mainly two steps

are involved in designing of a neuro controller, first is system identification and second is control design. In first step a neural network model of the plant to be controlled is developed. In second step the NN plant model is used to train the controller.

Now, two different approaches for neurocontroller design will be exploited for controller design namely,

- (i) NN predictive control
- (ii) NARMA-L2 control

Each has some advantages and shortcomings for a given application.

For training, 2184 training I/O samples will be used. The corresponding plots are depicted in Figure 4 and 5.

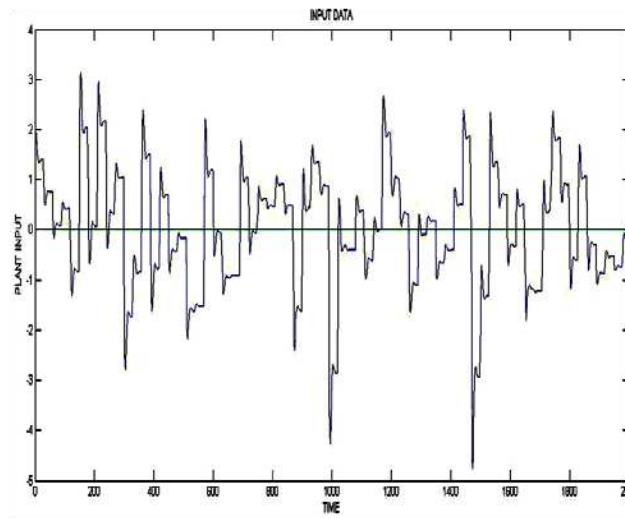


Figure 4. Input Data

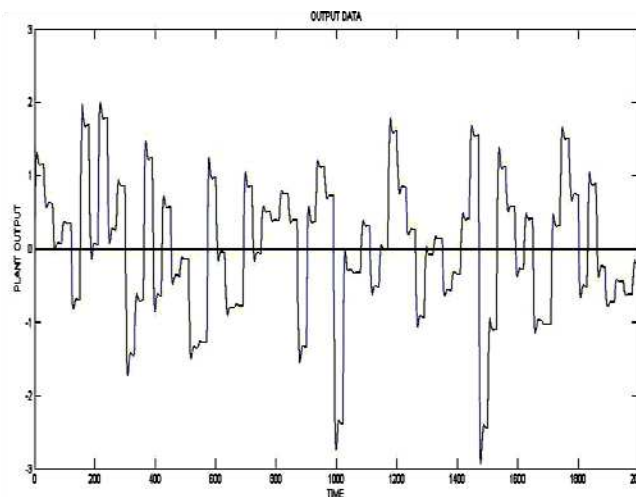


Figure 5. Output Data

3.1 NN Predictive Controller Design

The schematic of NN predictive controller is presented in Figure 6. The NN model of the plant predicts the plant response over a specified time horizon. Now an optimization function J

given by expression (7) is determined using these predictions and the optimum control signal is determined such that J is minimized.

$$J = \sum_{j=N_1}^{N_2} [(y_r(t+j) - y_m(t+j))]^2 + \rho \sum_{j=1}^{N_u} [(u'(t+j-1) - u'(t+j-2))]^2 \quad (7)$$

Where N_1 , N_2 and N_u define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, y_r is the desired response and y_m is the network model response. The ρ value represents the weight that the sum of squares of the control increments has, for the evaluation of J . The optimization block finds the values of u' that minimizes J , and then the optimal u is sent to the plant.

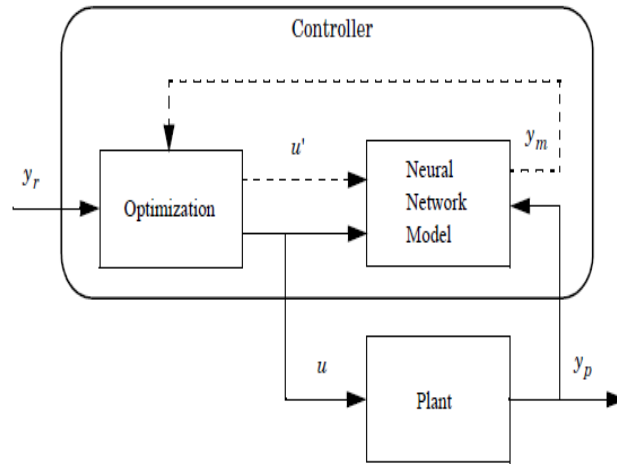


Figure 6. Schematic of NN Predictive Controller [10]

The simulink model of the NN predictive control system for the considered plant of lime kiln is depicted in Figure 7. The corresponding design parameters are specified in table 1 and the training error plot is shown in Figure 8.

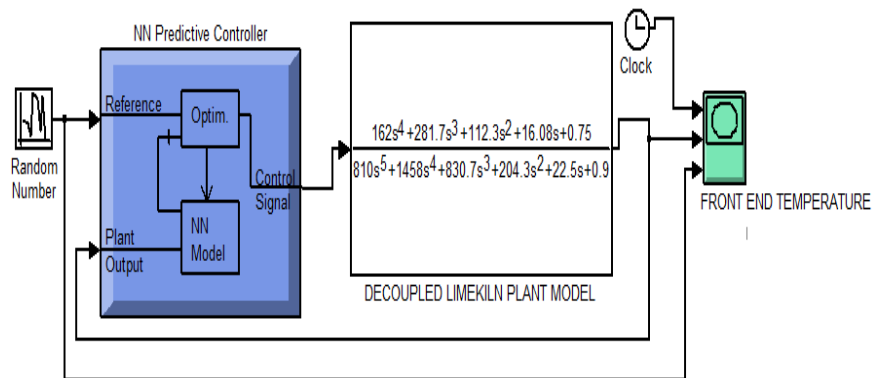


Figure 7. Simulink Model of NN Predictive Control System

Table 1. Design Parameters for NN Predictive Control System

Parameter	Value
Control horizon(N2)	7
Control horizon(Nu)	2
Weight(ρ)	0.05
Search parameter	0.001
Iterations per sample	2
Size of hidden layer	7
Sampling Interval	0.2
No. of delayed plant inputs	2
No. of delayed plant outputs	2
Training epochs	100
Training function	trainlm

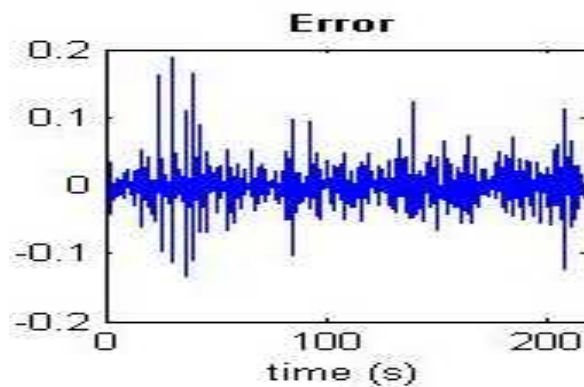


Figure 8. Training Error for NN Predictive Controller

The set point tracking response of this controller is shown in Figure 9 revealing that this controller has excellent setpoint tracking performance. The closed loop step responses of PI controller and NN predictive controller are shown in Figure 10 presenting performance comparison of PI and NN predictive controller which clearly indicates that the latter has much better performance with no overshoot and settling time much smaller than the former.

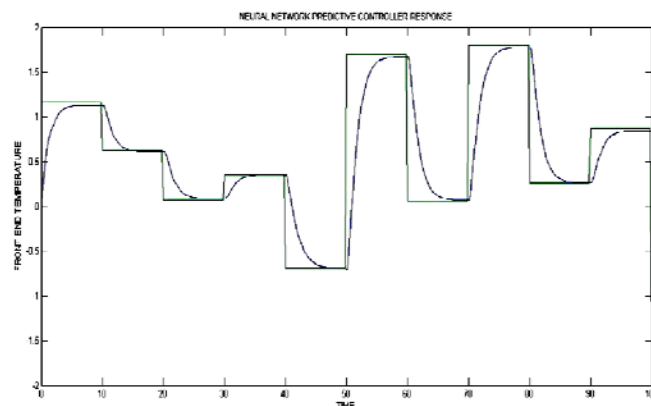


Figure 9. Setpoint Tracking Response of NN Predictive Controller

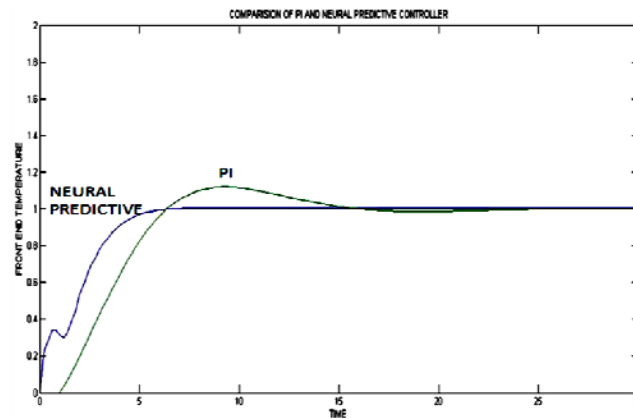


Figure 10. Performance Comparison of PI and NN Predictive Controller

3.2 NARMA-L2 Controller Design

The NARMA-L2 (non linear autoregressive moving average) approach employs the feedback linearization control technique. It cancels the non linearities and converts non linear dynamics into linear dynamics. The schematic of this technique is revealed in Figure 11. The generation process of the f and g functions of the controller is depicted in Figure 12 where y_r is reference signal, u is controller output, y is the plant output and e_c is the tracking error.

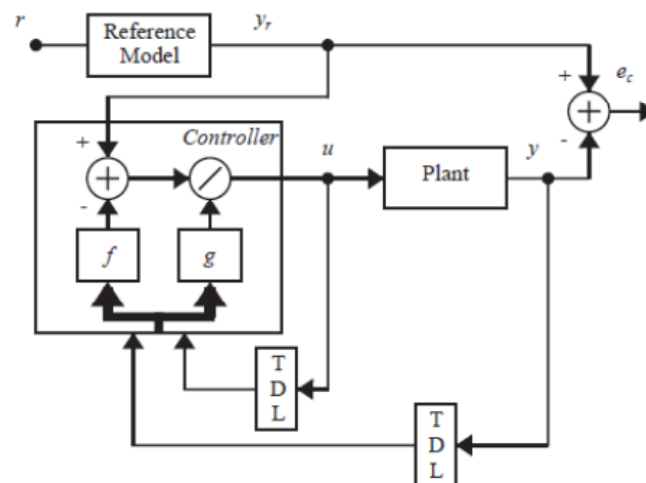
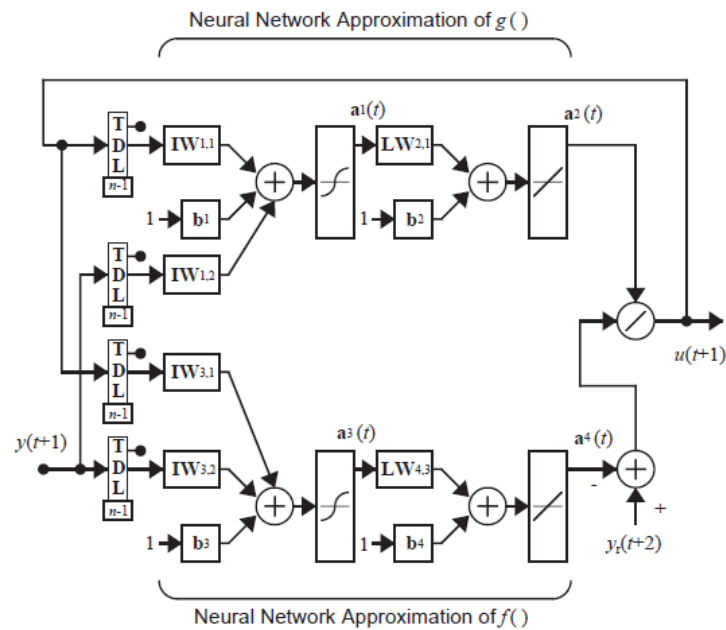


Figure 11. Schematic of NARMA-L2 Control system [10]

Figure 12. Neural Network Approximation of g and f functions [10]

The control signal generated by this controller is expressed in expression (8)

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)]}{g[y(k), \dots, y(k-n+1), u(k), \dots, u(k-n+1)]} \quad (8)$$

Which is realizable for $d \geq 2$.

The simulink model of the NN predictive control system for the considered plant of lime kiln is depicted in Figure 13. The corresponding design parameters are specified in table 2 and the training error plot is shown in Figure 14.

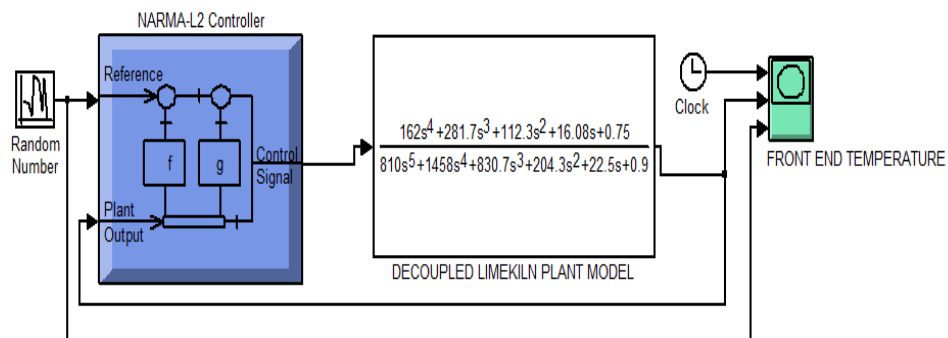


Figure 13. Simulink Model of NARMA-L2 Control System

Table 2. Design Parameters for NARMA-L2 Control System

Parameter	Value
Training samples	2184
Size of hidden layer	9
Sampling Interval	0.01
No. of delayed plant inputs	3
No. of delayed plant outputs	2
Training epochs	100
Training function	trainlm

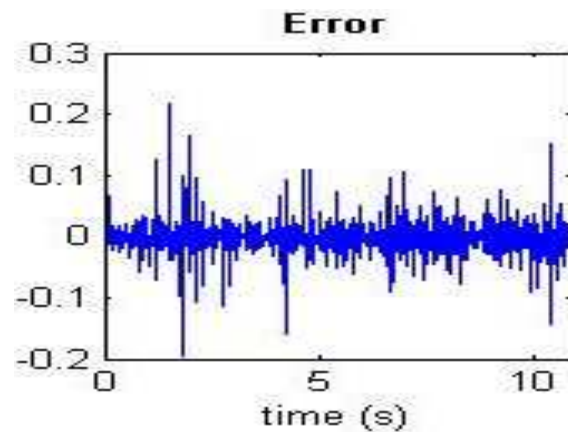


Figure 14. Training Error for NARMA-L2 Controller

The set point tracking response of NARMA-L2 controller is shown in Figure 15. The closed loop step responses of PI controller and NARMA-L2 controller are shown in Figure 16 which gives performance comparison of PI and NARMA-L2 controller. It clearly indicates that the latter has much better performance than the former.

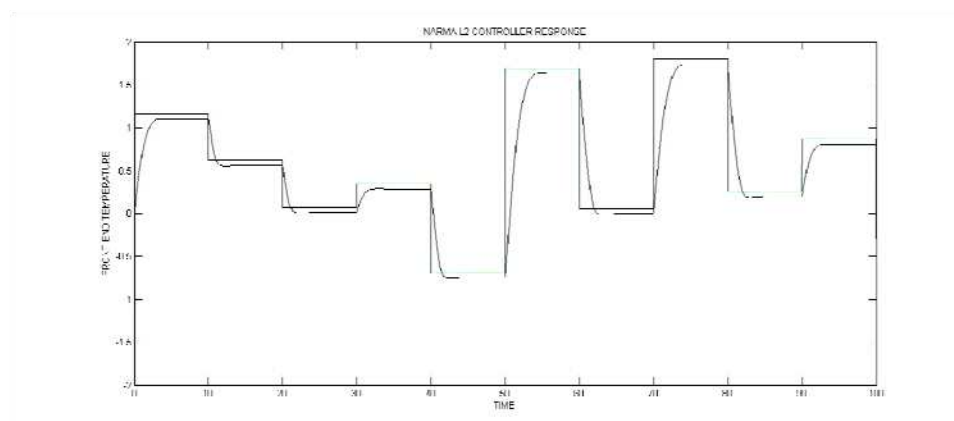


Figure 15. Setpoint Tracking Response of NRMA-L2 Controller

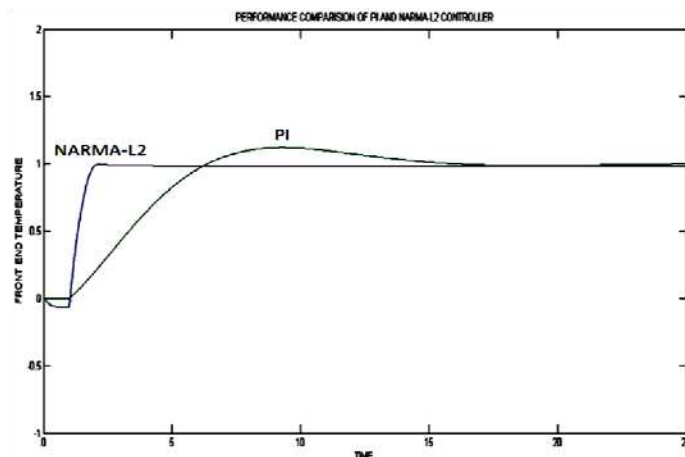


Figure 16. Performance Comparison of PI and NARMA-L2 Controller

4. Conclusion

In the present work the ANN controllers for a decoupled lime kiln process has been designed using two different strategies namely NN predictive control and NARMA-L2 control. It was observed that both have excellent set point tracking performance with no overshoot and much smaller settling time than the conventional PI controller.

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