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Research article

Designing LQG controller based on neural network estimator for boiler system

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Abstract

Due to demands for the economical operations of power plants, performance control of a boiler-turbine unit has great importance. Besides, the multi-input multi-output (MIMO) structure of boiler systems has some challenges that make their control some problems. In this research, the control of boiler systems is performed based on the neural network algorithm. In the boiler system, the liquid (usually water) reaches its desired temperature and its output steam is employed for making electricity, locomotive movement, environmental heating, health domain and etc. Since the water level in the tank has a great effect on the stability of the boiler, controlling dram water level significantly affects the system's performance. In this paper, controlling the water level of the boiler system is applied utilizing LQG and a neural network algorithm. For the system variables estimation, neural networks are employed instead of system conditions, due to their high ability in system identification in various conditions. The simulation results of the proposed method are compared with the Kalman-filter-based LQG controller.

Keywords: Boiler, LQG controller, Kalman filter, Neural network.

1- Introduction

Power plants are complex, nonlinear, time-varying systems whose control inherently involves multiple loops and interactions between different loops. The interaction between input and output variables greatly complicates the design of controllers suitable for MIMO systems. Several control techniques are available to handle systems with multiple variables [1-6]. Centralized proportional-integral-derivative (PID) controllers traditionally solve multivariable control problems to obtain the desired overall control function [7,8]. However, distributed PID control is widely used in MIMO industrial processes due to its simplicity of implementation and good loop fault tolerance of the control system. The MIMO system is partitioned and tuned into individual SISO PID loops in this configuration. Mainly on a single-loop basis. By designing a suitable decoupler in this way a distributed controller can be used to compensate for interactions between variables. A MIMO system is separated into multiple SISO systems and can be controlled via a simple feedback controller. However, using a decoupler imposes additional restrictions on the feedback characteristics of the system [9].

Boiler control refers to the various methods used to control the operation of a boiler system. The purpose of boiler control is to ensure that the boiler operates safely, efficiently, and reliably, while meeting the required heating demands of the building or process it is serving [10]. Boiler control systems typically include a variety of sensors, controllers, and actuators that work together to regulate the temperature, pressure, and flow of water or steam within the boiler. The main components of a boiler control system include [2]:

1. Thermostat: The thermostat is responsible for sensing the temperature of the water or steam in the boiler and sending signals to the control system to adjust the heating output accordingly.
2. Pressure sensor: The pressure sensor monitors the pressure inside the boiler and ensures that it stays within safe limits.
3. Water level sensor: The water level sensor monitors the level of water in the boiler and ensures that it stays within safe limits.
4. Control panel: The control panel is the central hub of the boiler control system, where all the signals from the various sensors and controllers are received, processed, and acted upon.
5. Actuators: Actuators are devices that are used to control the flow of water or steam within the boiler. Examples include valves and pumps.

Overall, the control of a boiler system is critical to ensuring its safe and efficient operation, as well as maximizing its lifespan. Effective boiler control can help to reduce energy costs, minimize maintenance requirements, and improve overall performance [11].

Boiler control is a complex process that involves many variables, such as temperature, pressure, and flow rate. To effectively control a boiler system, it is important to have a good understanding of the principles of thermodynamics and heat transfer, as well as knowledge of the specific requirements of the system being controlled [12].

One important aspect of boiler control is the use of feedback control loops. These loops continuously monitor the output of the boiler and adjust the control parameters to ensure that the desired output is achieved. For example, a temperature control loop may adjust the heating input to the boiler based on the temperature of the water or steam leaving the system [13].

Another important aspect of boiler control is the use of safety controls. These controls are designed to prevent dangerous situations from occurring, such as overpressure or low water levels in the boiler. Safety controls may include pressure relief valves, low water cut-offs, and flame sensors [14].

In addition to traditional control methods, advanced control techniques such as model predictive control (MPC) [15,16] and adaptive control [17,18] are also being used to optimize boiler performance. MPC involves using mathematical models of the boiler system to predict its behavior and adjust the control parameters accordingly. Adaptive control, on the other hand, uses real-time measurements of the system to adjust the control parameters and improve performance.

Finally, it is important to regularly maintain and inspect the boiler system to ensure that it is operating safely and efficiently. This may involve monitoring the system for leaks or other issues, cleaning the heat exchangers, and performing regular tune-ups to ensure that the system is operating at peak performance. By properly controlling and maintaining a boiler system, it is possible to achieve significant energy savings and reduce environmental impact.

In addition to the traditional methods of boiler control, there are also newer techniques that are being increasingly used to optimize boiler performance. Two such methods are neural network control and linear quadratic Gaussian (LQG) control [19].

Neural network control involves the use of artificial neural networks to model and control the behavior of the boiler system [20,21]. By training the neural network on historical data, it is possible to predict the behavior of the boiler and adjust the control parameters accordingly in real-time. This can lead to significant improvements in efficiency and performance, as the neural network can account for complex and non-linear relationships between different parameters that may be difficult to model using traditional control methods.

LQG control, on the other hand, is a mathematical control theory that uses a combination of linear control techniques and probabilistic models to optimize the performance of a system. In the case of a boiler system, LQG control can be used to predict the behavior of the system and adjust the control parameters accordingly to minimize energy consumption and maximize efficiency. This approach is particularly useful for large-scale boiler systems where traditional control methods may not be sufficient [22].

Overall, the use of advanced control techniques such as neural network and LQG control can help to optimize the performance of boiler systems and reduce energy costs, making them an increasingly important area of research and development in the field of boiler control.

The use of an LQG controller based on neural networks for boiler control offers several advantages over traditional control methods:

- Improved efficiency: By using a neural network to model the behavior of the boiler, the LQG controller can adjust the control parameters in real-time to optimize performance and minimize energy consumption. This can lead to significant improvements in efficiency, reducing operating costs and environmental impact.
- Better accuracy: The neural network can account for complex and non-linear relationships between different parameters, allowing for more accurate modeling and control of the boiler system. This can result in more precise control and better overall performance.
- Enhanced safety: The LQG controller can be designed to include safety controls that monitor the system for dangerous situations and take corrective action to prevent accidents. This can improve the safety of the boiler system and reduce the risk of equipment damage or downtime.
- Adaptability: The use of adaptive control techniques in the LQG controller allows it to adjust to changing conditions in real-time, such as changes in load demand or variations in the feedwater temperature. This makes it well-suited to dynamic operating

environments, such as those found in industrial processes.

- Reduced maintenance: By optimizing the performance of the boiler system, the LQG controller can reduce wear and tear on equipment and minimize the need for maintenance and repairs. This can lead to cost savings and improved system reliability.

Overall, the use of an LQG controller based on neural networks for boiler control can offer significant advantages over traditional control methods, improving efficiency, accuracy, safety, adaptability, and reducing maintenance requirements.

2- Modeling the studied system

Generally, finding an appropriate model for describing the relation between system components has great importance [23-25]. There are many effective parameters in controlling the water level of the drum, such as the incoming water flow, the steam flow, the steam pressure, the temperature of the drum, etc., among these, the changes in the steam flow and the incoming water flow are the main factors in the control and stability of the water level. According to [26], the dynamic equations of the drum's water level are as follows:

$$F(t) = Q_w(t) - Q_D(t) \tag{1}$$

In (1), Q_w and Q_D are the steam flow and the incoming water flow, and F is the change in the water level of the drum, which is measured through sensors and is expressed by the following mathematical relations:

$$C\rho \frac{dH(t)}{dt} = \alpha \sqrt{\Delta P_w} - \beta \sqrt{\Delta P_D} \tag{2}$$

In (2), C is the selected area of the steam boiler, ρ is the water coefficient of the boiler, H is the water level, and alpha and beta are the steam flow coefficients of water and inlet water. A and B are the pressure differences of steam flow and inlet water flow. The control inputs of the system are water flow and steam flow. Its output is also the water level of the drum. According to [19], the state space equations of the system are as follows:

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) \tag{3}$$

where

$$A = \begin{bmatrix} 0 & 1 \\ 0 & -1.5 \end{bmatrix},\ B = \begin{bmatrix} 0 & 0.203 \\ 0.0025 & -0.016 \end{bmatrix},$$
$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}.$$

3- LQR controller design

Linear quadratic regulator (LQR) is actually the summary of the term introducing the optimal linear regulator with quadratic performance index [27]. The linear-quadratic (LQ) method is perhaps the most important modern control result in the design of state feedback controllers. Many engineering problems have been solved by this method and various numerical methods have been invented to solve the problems. The optimal LQR mode feedback control design problem is defined as follows. Consider the following LTI linear system with initial conditions $X(0) = x_0$:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{4}$$

In this section, the goal is to design the state feedback control $u = -kx$ in such a way that it minimizes the following performance criterion:

$$J = \int_0^\infty (x^T Q\, x + u^T R\, u)dt \tag{5}$$

where the Q, R matrices are positive and symmetric and its performance criteria will be as follows:

$$\dot{x} = (A - Bk)x \tag{6}$$
$$J = \int_0^\infty [\, x^T(Q + k^T R\, k)x \,]dt \tag{7}$$

For solving this problem, the controller must first be able to make the system stable. Therefore, at least unstable generators must be stable or in a more comprehensive state, the system must be controllable [28].

3-1- LQR controller theorem

In order for the gain matrix of the stabilizing loop k to minimize the design criterion J for all initial conditions $X(0)$, it must apply to the following equation:

$$k = R^{-1}\, B^T\, P$$
$$u = -kx \tag{8}$$

where P applies to the Riccati matrix equation:

$$A^T\, P + P\, A - PBR^{-1}B^T P + Q = 0 \tag{9}$$

To solve the LQR problem, we have to solve the equation for P, then we calculate K and test A-KB for internal stability. Because Riccati's equation is a nonlinear equation, in general, it has countless solutions. Therefore, only stable solutions should be found and determine the comprehensive minimum point for them by comparing J. These steps are very difficult and time-consuming, but fortunately, there is no need to do all these steps in practice.

3-2- Optimal observer, Kalman filter

Suppose that (A, C) is detectable, in this case, for $(V = 0,\ V(0) > 0)$, the optimal observer benefit that minimizes the performance index of the error variance is obtained from the following equation:

$$G = PC^T V^{-1} \tag{10}$$

where P is the positive definite solution of the following matrix algebraic Riccati equation:

$$AP + PA^T - PC^T V^{-1} CP + W = 0 \tag{11}$$

where the following should be considered:
$V = Cov(v(t)), W = Cov(w(t))$

4- Results and simulations

At first, the design of the LQG controller based on the Kalman filter is examined, then it is used to estimate the state variable of the system using a neural network, and finally, we design the LQG controller based on the neural network observer.

4-1- Design of LQG controller based on Kalman filter

The first step in the design of the LQG controller is to check the observability and controllability of the system. For this purpose, we form the controllability and observability matrix of the boiler system. If the controllability and observability matrices are of complete order, the system will be controllable and observable, and the LQG controller can be designed for it based on Eq. (3).

Now controllability and observability will be checked:

- Controllability

$$\varphi_C = [B \quad AB] \tag{12}$$
$$= \begin{bmatrix} 0 & 0.203 & 0.0025 & -0.016 \\ 0.0025 & -0.016 & -0.0029 & 0.0184 \end{bmatrix}$$

-Observability:

$$\varphi_o = \begin{bmatrix} C \\ C\,A \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{13}$$

Since these two matrices are of complete order, it is possible to design an LQG controller for the system. The second step in the design of the LQG controller is to find the optimal mode feedback gain based on the quadratic performance index. We want to design the state feedback control in such a way that it minimizes the following performance criterion:

$$J = \int_0^\infty (x^T\, Q\, x + u^T\, R\, u)\, dt \tag{14}$$

where

$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $R = \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix}$.

The equation of the closed loop system and its performance criteria will be as follows:

$$\dot{x}(t) = (A - Bk)x \tag{15}$$

and

$$J = \int_0^\infty \left[x^T \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + [k_1 \quad k_2] * \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix} * \begin{bmatrix} k_1 \\ k_2 \end{bmatrix} \right) x \right] dt \tag{16}$$

In order for the gain matrix of the stabilizing loop K to minimize the design criterion J for all initial conditions, it must apply in the following equation:

$$k = R^{-1} B^T\, P \tag{17}$$

where P applies to the Riccati matrix equation (9).

After solving the Riccati equation by MATLAB, the matrix was obtained as follows:

$$k = \begin{bmatrix} 0.0048 & 0.0042 \\ 0.4472 & 0.36 \end{bmatrix} \tag{18}$$

In the third stage of designing the LQG controller, it is time to design the Kalman filter estimator. Assuming that the equation of the observer is as follows:

$$\hat{x}(t) = A\hat{x}(t) + Bu(t) + G\,(y - C\hat{x}) \tag{19}$$

The optimal observer gain matrix that minimizes the error variance performance index is obtained from the following equation, where the positive definite solution of the algebraic Riccati equation is based on (11).

After solving the Riccati equation in MATLAB, the gain matrix is calculated as follows:

$$G = \begin{bmatrix} 0.1218 \\ 0.0019 \end{bmatrix} \tag{20}$$

Using the input and output of system X, we estimate the state variable of the system, whose value we do not know, and in the last step, it is time to design the controller.

4-2- The use of neural networks in the estimation of system state variables

Multilayer Perceptron (MLP) neural network is one of the most practical and popular neural networks. This network is able to perform a non-linear mapping with desired accuracy by properly choosing the weight of the neural cells and the bias of the transfer functions [29]. This is what many It is known as an identifier or estimator from engineering technical issues. In this part, we will examine and describe the network used to identify and estimate the state variables of the considered boiler system. The MLP neural network used has 4 inputs and one output.

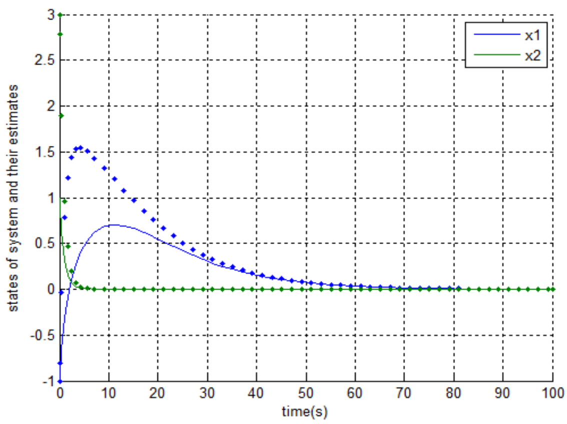

Fig. 1 Kalman Filter estimation from state variables of the boiler

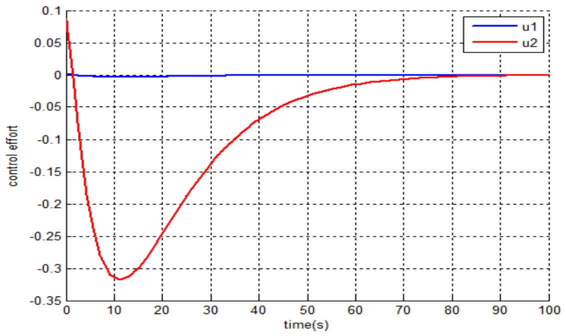

Fig. 2 Control signal (u) produced by LQG controller

It's important to have a clear and comprehensive description of the parameters used in the training of an ANN for designing an LQG controller based on a neural network estimator.
In this paper, the training parameters of ANN can be expressed as follows:

- **Neuron Activation Function:** The choice of the neuron activation function should be performed based on the application. Due to the ANN is being used to estimate the state variables of a boiler system, the activation function should be able to model the non-linear relationships between the input and output variables. In this study, Tanh (hyperbolic tangent) activation functions are employed.

- **Training Data:** The quantity and quality of the training data can significantly affect the accuracy of the ANN estimator. It is important to ensure that the data used for training covers a wide range of operating conditions and is representative of the problem domain. The data should be pre-processed and normalized to facilitate the training process. The optimal number of training samples depends on the complexity of the problem, but a general rule of thumb is to have a minimum of 10 times the number of network parameters.

- **ANN Parameters:** The ANN architecture and parameters should be selected to optimize the accuracy and speed of the estimator. This includes the number of layers, number of neurons in each layer, learning rate, momentum, and regularization. In this study, 3 hidden layers with 256 neurons in each layer is applied for the MLP estimator. Besides, learning rate is selected as 0.001.

- **Validation Data:** The validation data is used to evaluate the performance of the ANN estimator during training and overfitting prevention. The validation data should be representative of the problem domain and separated from the training data. Several performance metrics such as mean squared error or coefficient of determination can be used for estimator evaluation.

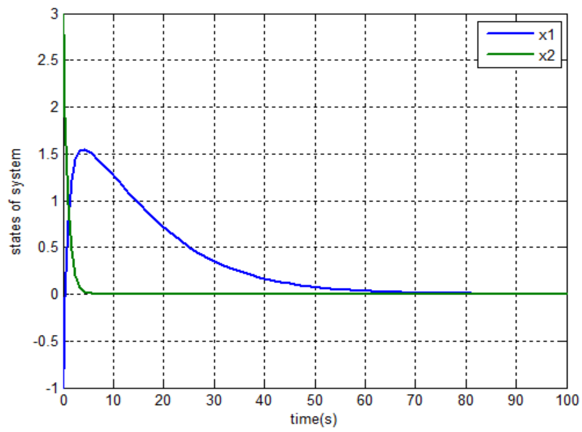

Fig. 3 The closed loop response of the system

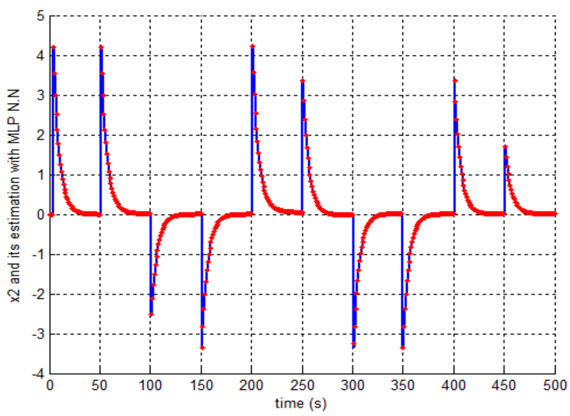

Fig. 4 The neural network's estimation of x_2

In the simulations, we have used an MLP neural network with four inputs and one output and eight nodes in the middle layer. To train this network, we have used 500 training data series. Fig. 4 shows the quality of neural network training in x_2 estimation on the training data:

4-3- LQG controller using neural network viewer

Since neural networks have the ability to approximate boiler system state variables, neural networks can be used in the LQG controller instead of using observers such as the Luenberger observer or the Kalman filter. The response of the LQG controller using neural networks. It is shown in the figs 5-7.

By using the neural network in the closed loop system of controller, as we can see, it has controlled the water level of the drum well with proper estimation.

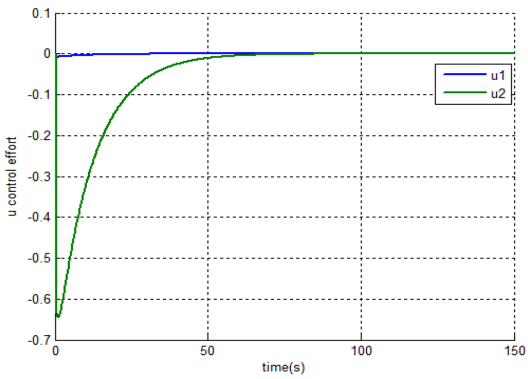

Fig. 5 Control signal produced by LQG controller based on neural network

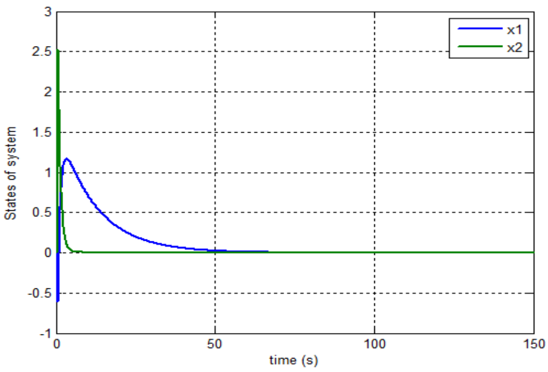

Fig. 6 Closed loop response of the boiler system

4-4- Performance comparison of two proposed methods

Since the neural network is not based on the model, therefore, a factor such as modeling error will have less effect on the estimation of the system state variable, on the other hand, the proper estimation of the system state variables requires proper training of the neural network. The results of the simulations in noise conditions (with the presence of noise in system) is as follows:

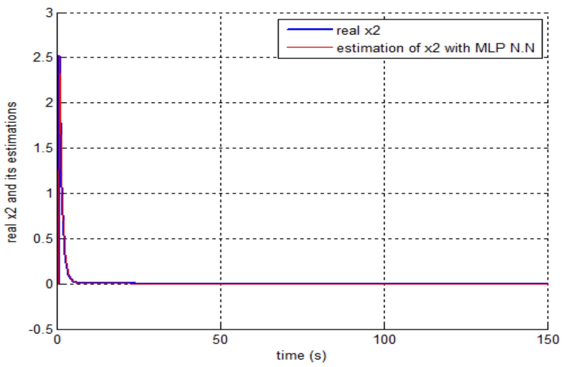

Fig. 7 Neural network estimation from x_2

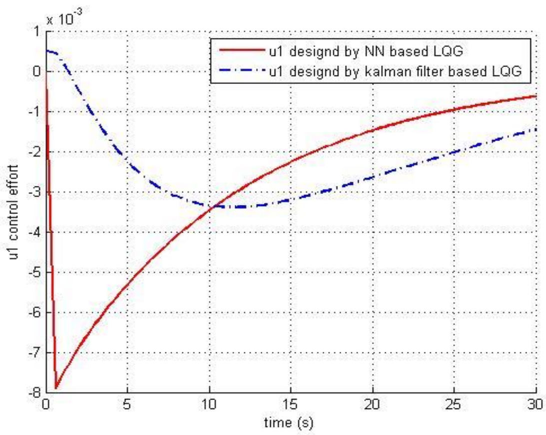

Fig. 8 Neural network estimation and Kalman filter from state variable x_2

As the results show, since the neural network is not based on the model, it has better identification in the presence of noise. As it is known, the convergence of the water level is faster in the case of LQG controller based on neural network.

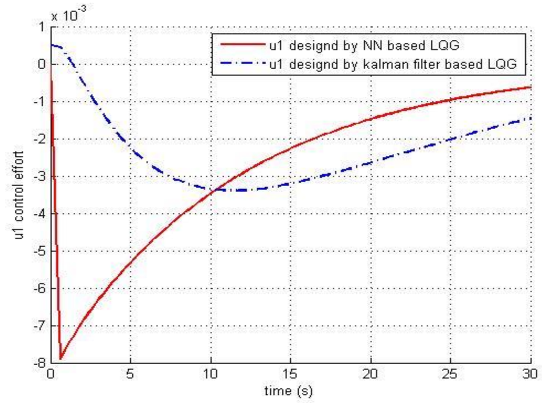

Fig. 9 First control signals produced by LQG controller based on neural network and Kalman filter

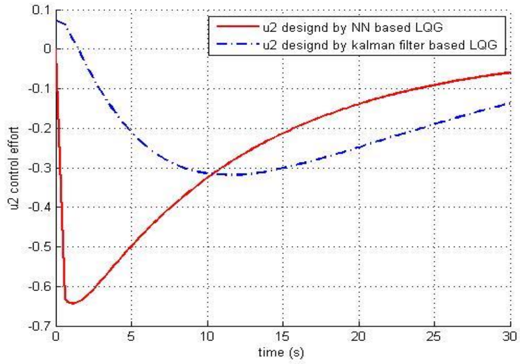

Fig. 10 Second control signals produced by LQG controller based on neural network and Kalman filter

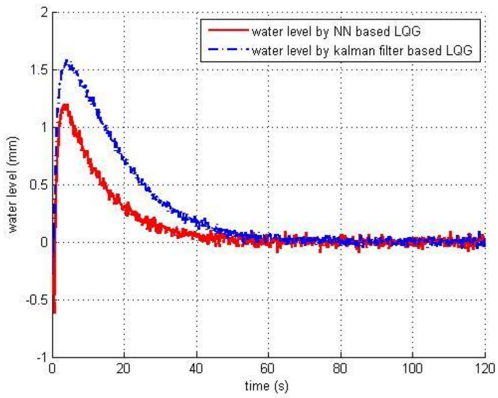

Fig. 11 Water level control of boiler drum by LQG controller based on neural network and Kalman filter

5- Conclusion

In this study, the optimal LQG controller for controlling boiler-turbine systems is discussed. A neural network is used as an observer to estimate the state of the system. For the classical LQR controllers, the desired trajectory tracking is performed in an optimal path. In this paper, LQG is applied for set point tracking to get the output as close to the desired trajectory. LQG controller results using the set point tracking method are superior to the Kalman method.

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