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Drum Type Fossil Fueled Power Plant Control Based on Fuzzy Inverse MIMO Model

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Abstract: - In this paper, a new fuzzy controller is proposed based on inverse model of boiler-turbine system. Gain scheduling scheme is used to keep feedback rule as close as possible to optimal condition while generating plant Input/Output data. Interaction between state variables of the system is studied and as a result, a MIMO structure controller is developed. Considering possible operating zone, number of rules in Sugeno-type FIS is reduced. It is shown that the proposed controller has better performance such as smaller rise time than the optimal controller. It is also shown that the controller has robust performance in the presence of uncertainty and parameters variation.

Key-Words: - Inverse model control - Drum type fossil fueled power plant (FFPP) - ANFIS - Nonlinear model – Interaction - Robustness

1 Introduction

Everyday large amount of fossil fuel is burnt for power generation purposes. Drum type power plant is one of the most frequent types of plant which is built all over the world for this purpose. Nonlinear nature, interaction between state variables and process complexities of this type of plant challenged control engineers for many years. In order to minimize risk of new control strategy implementation, it is first evaluated on developed models. Gain scheduling is one of the most frequent efforts which have been done by power plant control engineers to improve controller performance. Dieck-Assad and Masada used lookup table to determine controller parameters in some specified points [1]. Generally, this method’s drawback is interpolation problem for large systems. Hogg and Ei-Rabaie applied self tuning generalized predictive control (GPC) to a boiler system [2]. Prasad et al presented model predictive control based on NNs [3]. Bolis et al developed controller with self tuning characteristics, but the controller does not perform well in the presence of big nonlinearities [4]. Diemo and Lee used genetic algorithm to find the optimal value of PI and LQR controller parameters. They showed that the developed controller has desirable performance in wide range of operation [5]. Ben Abdennour and Lee used robust control methods to control boiler and turbine subsystems [6]. However; robust control methods has some limitation in the presence of severe nonlinearity in large systems. Alturki and Abdennour trained a neuro-fuzzy controller by the data generated from 5 linear quadratic regulators linearized in 5 operating points [7]. The main drawbacks of this method is that the trained controller dose not work in optimal condition, since the training data is not generated in the optimal condition. In this paper, utilizing gain scheduling technique, this drawback is eliminated. Moon and Lee proposed a self-organizing fuzzy controller [8]. In that study, despite the existence of interaction between state variables, SISO controller is designed which is not a realistic approach. Tan et al proposed a new definition to measure nonlinearity in a system and showed that the nonlinearity can be avoided by careful choice of operating ranges [9]. Therefore; conventional linear controllers could be used in the predefined ranges.

In this paper, new controller is proposed based on inverse model characteristics. Considering the nonlinearities discussed and measured in [9], NN is used to train a fuzzy controller which emulates the behavior of the inverse model. Due to interaction between state variables, MIMO structure is devised for the controller. Large number of rules problem is resolved by considering possible operating points and eliminating extra impossible operating ranges.

2 Drum Type FFPP Model

The mathematical equations which describe the behavior of power plant derived in [10] are

$$\dot{x}_1 = -0.0018 \cdot u_2 x_1^{9/8} + 0.9 \cdot u_1 - 0.15 \cdot u_3 \quad (1)$$

$$\dot{x}_2 = (0.073 \cdot u_2 - 0.016) \cdot x_1^{9/8} - 0.1 \cdot x_2 \quad (2)$$

$$\dot{x}_3 = (141 \cdot u_3 - (1.1 \cdot u_2 - 0.19) x_1) / 85 \quad (3)$$

where x_1 , x_2 and x_3 are drum pressure(kg/cm^2), generated electric power(MW) ,and fluid density, respectively. The input values are u_1, u_2 and u_3 which denote the actuator valve normalized position. Actuators are fuel valve and turbine valve and water supply valve respectively.

$$y_1 = x_1 \tag{4}$$

$$y_2 = x_2 \tag{5}$$

$$y_3 = \Delta l = 0.05(0.13073x_3 + 100\alpha + q/9 - 67.975) \tag{6}$$

As indicated by (4) and (5), the first two outputs are the same as the first two state variables and the third output is determined in terms of α and q which are steam quality and evaporation rate, respectively.

$$\alpha = \frac{(1-0.001538x_3)(0.8x_1 - 25.6)}{x_3(1.0394 - 0.0012304x_1)} \tag{7}$$

$$q = (0.854u_2 - 0.147)x_1 + 45.59u_1 - 2.514u_3 - 2.096 \tag{8}$$

Equations (1) to (8) are determined by mass and energy conversion equations. The parameters are tuned based on the data garnered from Synvendska Kraft AB plant in Malmo, Sweden. Actuator valves limitations are represented by inequalities (9) through (12).

$$0 \le u_i \le 1 \qquad (i = 1,2,3) \tag{9}$$

$$-0.007 \le \dot{u}_1 \le 0.007 \tag{10}$$

$$-2 \le \dot{u}_2 \le 0.02 \tag{11}$$

$$-0.05 \le \dot{u}_3 \le 0.05 \tag{12}$$

3 Inverse Model Controller

The proposed Model in [10] for boiler-turbine unit is a nonlinear MIMO model. Thus, its general discrete description is

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)) \tag{13}$$

where $\mathbf{x}(k+1)$ is the state vector at time $k+1$, $\mathbf{x}(k)$ is the state vector at time k, and $\mathbf{u}(k)$ is the controlling vector at time k. Computing system state vector at time $k+n$, equation (14) is reached.

$$\mathbf{x}(k+n) = \mathbf{F}(\mathbf{x}(k), \mathbf{U}) \tag{14}$$

where n is the order of the plant, $\mathbf{F}$ is a multiple composite function of $\mathbf{f}$, and $\mathbf{U}$ is the control action defined by (15).

$$\mathbf{U} = [\mathbf{u}(k), \mathbf{u}(k+1), \ldots, \mathbf{u}(k+n-1)]^T \tag{15}$$

Equation (14) reveals that, if the control input $\mathbf{U}$ from k to $k+n-1$ is equal to the right side of (15), the state of the plant will move from $\mathbf{x}(k)$ to $\mathbf{x}(k+n)$ in n time steps [11]. If we were able to find $\mathbf{U}$ as a function of $\mathbf{x}(k+n)$ and $\mathbf{x}(k)$ explicitly, then we could bring the system to any desirable state in n time increments.

$$\mathbf{U} = \mathbf{G}(\mathbf{x}(k+n), \mathbf{x}(k)) \tag{16}$$

Accordingly, the problem is to find the function $\mathbf{G}$ which is the inverse model of the system. In case of linear systems, if the controllability matrix is full-rank, finding $\mathbf{G}$ in an analytical form is an easy task to do. However; for nonlinear systems, there may not exist an analytical form. Therefore, instead of seeking solution explicitly, adaptive network fuzzy inference system (ANFIS) is used to approximate the inverse mapping $\mathbf{G}$. The first step is to generate a set of input/output data points to train the fuzzy system with. After the fuzzy controller has been trained, it generates an estimated $\hat{\mathbf{U}}$ as (17) that brings $\mathbf{x}(k)$ to the desired state after n time steps.

$$\hat{\mathbf{U}} = \hat{\mathbf{G}}(\mathbf{x}(k), \mathbf{x}_d(k+n)) \tag{17}$$

3.1 Training Data

In order to train the adaptive network to reach the prescribed $\hat{\mathbf{G}}$ a set of data points must be prepared. It is worth noting that actuator constraints must be considered in data generation procedure. The first alternative in mind is to use pure random inputs and check that whether the pressure and power navigate through all possible points in the power-pressure plane.

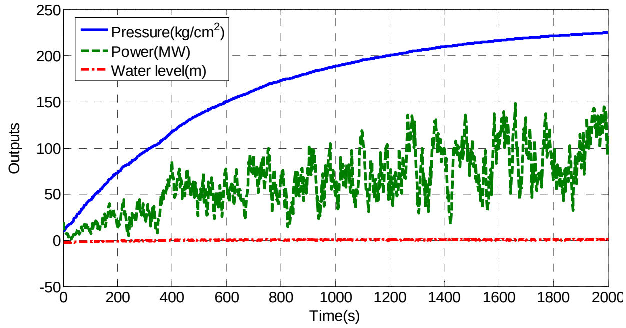

Fig.1 Plant outputs for pure random inputs

Figure 1 shows that the plant outputs do not cover the whole operating area in the power-pressure plane for pure random inputs. Consequently; a pure random input is not a suitable identification signal for this system. Several other types of inputs have been tested, but all of them have the aforementioned problem. Therefore; instead of open loop identification, closed loop identification will be used to prepare training data. For this purpose 7 nominal operating points as those in [9] are considered. These values along with their steady-state inputs are shown in Table 1.

Table 1 Diagonal line in power-pressure plane

	P.1	**P.2**	**P.3**	**P.4**	**P.5**	**P.6**	**P.7**
Pressure	75.6	86.4	97.2	108	118.8	129.6	140.4
Power	15.27	36.65	50.5	66.65	85.06	105.8	128.9
Input 1	0.119	0.209	0.27	0.340	0.418	0.505	0.590
Input 2	0.380	0.551	0.62	0.690	0.759	0.828	0.961
Input 3	0.122	0.255	0.34	0.433	0.543	0.663	0.797

The 7 operating points form the diagonal line of the operating region. Consequently, in order that the controller has good performance in the whole operating range of the plant, every node in the pressure-power plane corresponding to the power and pressure mentioned in Table 1 shall be used to generate the training data.

Remark 1- Note that impossible nodes must be excluded from the region. In other words, some demand powers can not be generated in some specified drum pressures. Therefore; the dark (red) area shown in Figure 2 is excluded from the data generation zone.

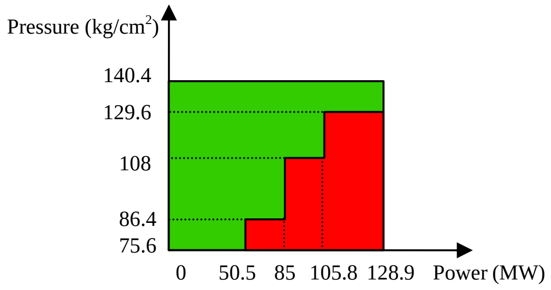

Fig.2 Data generation Zone (Bright area)

In order to navigate through the pressure-power plane in Figure 2, linear quadratic regulators are used. Careful choice of weighting function (Q and R) is necessary to develop desirable characteristics in the trained fuzzy controller. Moreover, if R is assumed small in comparison with Q, outputs of controller will be much more grater than 1 (upper threshold of the actuators) which is unrealistic and causes aggressive oscillations in the generated power.

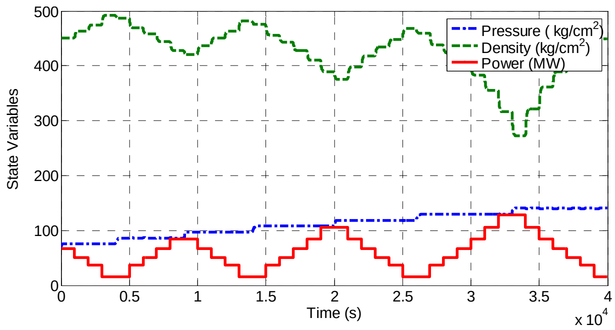

Fig.3 Plant state variables under LQR control

Figure 3 shows that pressure and power moving in the bright (green) area shown in Figure 2 desirably, under LQR control. Therefore; the generated data are suitable to train the inverse model fuzzy controller.

Remark 2- If linear quadratic regulators are designed for these operating points, then the performance of the plant in the surrounding area will go away from the optimal condition. If a fuzzy logic controller is designed based only on these operating points, then the response of the closed loop system will deteriorate from its desired value for other points. This is the case which can be seen in the simulation results of [7]. However, in our paper, to overcome this problem a fuzzy system has been used for the purpose of gain scheduling. In this case at each node optimal control is guaranteed and in the area between nodes, an interpolation of feed back gain matrix is applied.

3.2 Fuzzy Controller Structure

Before tuning controller parameters by means of generated data, controller structure must be determined. Firstly interaction between each channel in the model is scrutinized. In some studies such as [8], SISO controller is designed to control the plant. In these studies dominant input/output pairs are chosen with the following argument. “From (2), x_2 is controlled by u_2 “. But, it must be noted that x_2 is affected by x_1 which itself is affected by u_1. Further, in (3), since x_1 is in the order of 100 in nominal operating conditions, the coefficients of u_2 and u_3 are of the same order. So, the effect of u_2 on x_3 can not be neglected. Considering interaction in time domain, it can be also studies in frequency domain. Deriving, the linearized system transfer function in operating point 4, it can be seen that off-diagonal terms can not be neglected. One of the most common ways to asses the interaction between state variables of a MIMO plant is drawing Gershgorin bands. Diagonal dominance Idea is first presented by Rosenbrock. As Diagonal dominance increases, System variable interaction decreases and vice versa, and both of these characteristic could be evaluated by the following definition.

Definition 1- An m×m system matrix transfer function G, is row diagonal dominant, if for all values of ω

$$\left|G_{ii}(j\omega)\right| > \sum_{\substack{j=1 \\ j\neq i}}^{m} \left|G_{ij}(j\omega)\right| \qquad i = 1,\Lambda\ ,m \tag{18}$$

Similarly, G is column diagonal dominant, if for all values of ω

$$\left|G_{jj}(j\omega)\right| > \sum_{\substack{i=1 \\ i\neq j}}^{m} \left|G_{ji}(j\omega)\right| \qquad j = 1,\Lambda\ ,m \tag{19}$$

The Gershgorian band is defined as the locus of all circles drawn in the imaginary plane as ω changes from zero to infinity. For each row or the column of the matrix transfer function G, the origin of the circle is located at G_{ii} and the radii is equal to the summation of all off-diagonal elements’ magnitudes of that row or column, respectively. The encirclement of the origin by Gershgorian band shows the interaction of state variables.

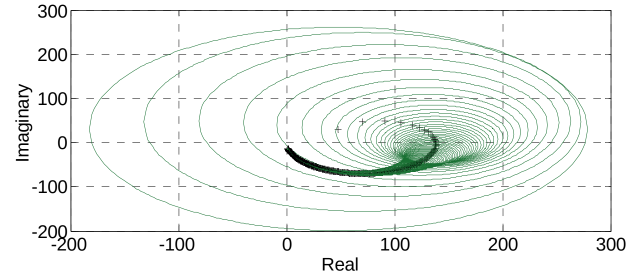

Fig.4 Gershgorian Band for the second row

As Figure 4 shows for lower frequencies, origin is encircled by the band, which shows that the dominance criterion is not satisfied.

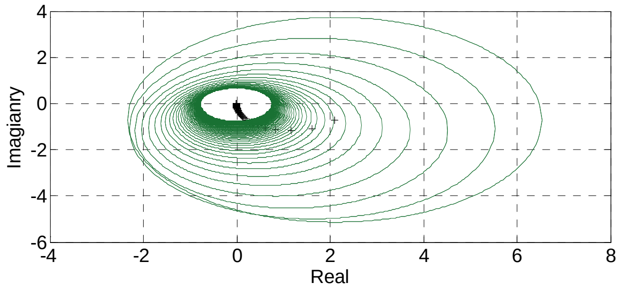

Fig.5 Gershgorian Band for the third row

Considering Gershgorian band for the third row of *G*, Figure 5 shows that for all frequencies origin is encircled. Therefore; it is not possible to neglect interaction between state variables.

In the first trial, minimum number of inputs is designated for the basic structure of fuzzy controller. So, the general form of the *j*-th rule is

If $y1_{desired}$ is $A1_j$ and $y2_{desired}$ is $A2_j$ and $y3_{desired}$ is $A3_j$ and $y1(k)$ is $B1_j$ and $y2(k)$ is $B2_j$ and $y3(k)$ is $B3_j$ and $u1(k-1)$ is $C1_j$ and $u2(k-1)$ is $C2_j$ and $u3(k-1)$ is $C3_j$ Then $u1(k)$ is $D1_j$ and $u2(k)$ is $D2_j$ and $u3(k)$ is $D3_j$
j=1,…, n (20)

where *yi* and *ui* denote plant *i*-th output and *i*-th input respectively. Ai, Bi, Ci and Di are their corresponding membership functions. Furthermore, *k* denotes sampling time.

If each linguistic variable is partitioned by only 2 membership functions, there must be 2^9 =512 rules which is great number of rules. However; due to existence of impossible operating points, as shown in Figure 2, not that much number of rules is needed. After many times of iteration, it is found out that 150 are enough for the purpose. In the other words, performance of the model did not increased any more by increasing the number of rules.

Performance of the system is not desirable with this type of controller. It indicates that controller information from previous sampling time is not complete. Consequently; the number of sampling times is increased for both *y* and *u* in the antecedent of the fuzzy rules. The general form of the *j*-th fuzzy rules is as indicated in (21).

If $y1_{desired}$ is $A1_j$ and $y2_{desired}$ is $A2_j$ and $y3_{desired}$ is $A3_j$ and $y1(k)$ is $B1_j$ and $y2(k)$ is $B2_j$ and $y3(k)$ is $B3_j$ and $y1(k-1)$ is $C1_j$ and $y2(k-1)$ is $C2_j$ and $y3(k-1)$ is $C3_j$ and $u1(k-1)$ is $D1_j$ and $u2(k-1)$ is $D2_j$ and $u3(k-1)$ is $D3_j$ and $u1(k-2)$ is $E1_j$ and $u2(k-2)$ is $E2_j$ and $u3(k-2)$ is $E3_j$ Then $u1(k)$ is $F1_j$ and $u2(k)$ is $F2_j$ and $u3(k)$ is $F3_j$
j=1,…, n (21)

Based on the same argument and after several times of iteration it turns out that the total number of 200 rules is an optimum number for the proposed controller. The performance of the proposed controller is discussed in the next section.

4 Simulation Results

To evaluate the performance of power plant under control of new control strategy, different cases (different working conditions) are studied. System initial condition is considered to be as the vectors (22) to (24) in all cases.

X0= [90 45 460.24] (22)
Y0= [90 45 0] (23)
U0= [0.2436 0.6094 0.3066] (24)

The steady-state initial condition is determined to be different from the controller design points. Since there is a mapping between desired power and the drum pressure, the set points for both must be determined with regard to each other. At first, response of the system with regard to operating point variations is studied. Then, in order to evaluate the robustness of the controller, the effect of parameters variation is studied.

4.1 Operating point variation

Case A:

In this case, drum pressure and generated power are increased to 110 kg/cm^2 and 70 MW respectively, while keeping drum water level deviation constant at zero.

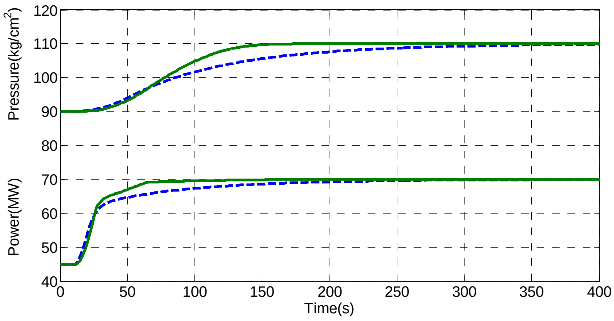

Fig.6 System response for case A, Inverse model controller (solid), LQR (dashed)

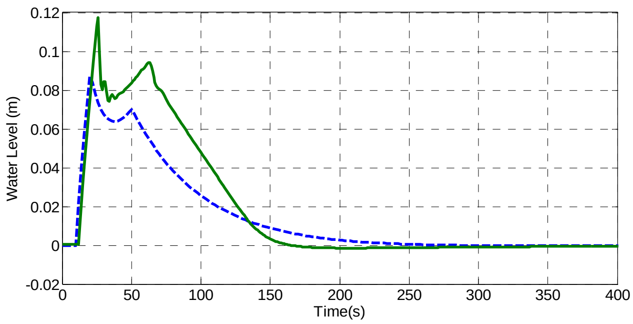

Fig.7 Water level deviation for case A, Inverse model controller (solid), LQR (dashed)

Figures 6 and 7 compare system response under LQR and Inverse model control. It is clear that system response under inverse model controller is much faster than the LQR controller. The settling time with regard to 5% criteria is 96s smaller for inverse model controller. Besides, in both cases drum pressure dose not have oscillations which is acceptable. Furthermore, drum water level deviation reaches zero much faster in case of proposed controller. Controlling inputs variations for inverse model controller are shown in Figure 8.

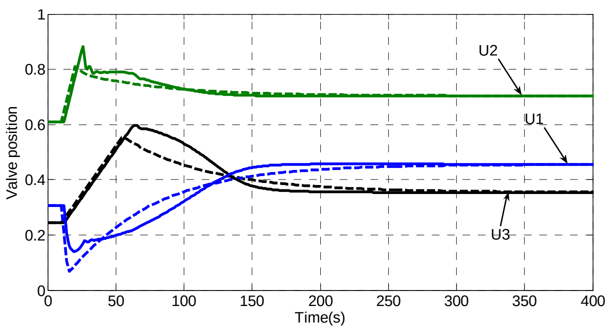

Fig.8 Controlling inputs for case A, Inverse model controller (solid), LQR (dashed)

Figure 8 shows that turbine valve opens more in case of inverse model control which with the combination of other valves positions, guarantees faster response of system in generating desired power.

Case B:

In case A, 25 MW power is added to unit load demand which is an ordinary change in a power generation plant. In this case a more severe change will be applied to the set points. Consequently; drum pressure and generated power are increased to 125 kg/cm^2 and 100 MW respectively, while keeping drum water level deviation constant at zero. So a 55 MW increase in generated power is demanded.

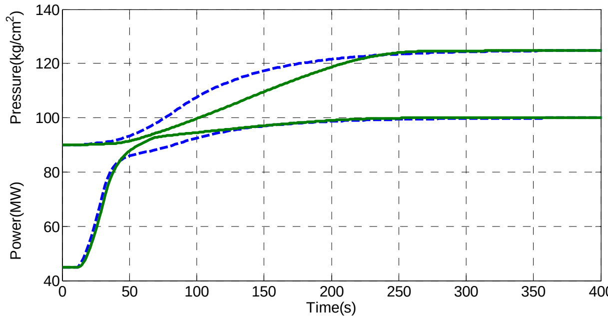

Fig.9 System response for case B, Inverse model controller (solid), LQR (dashed)

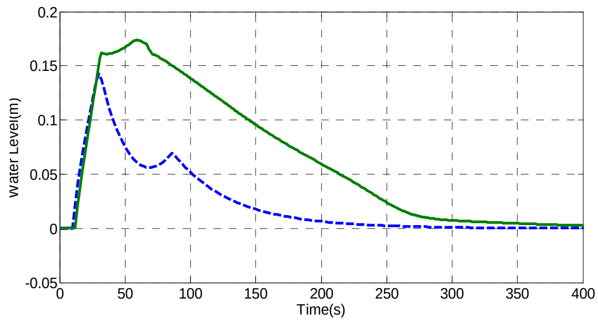

Fig.10 Water level deviation for case B, Inverse model controller (solid), LQR (dashed)

System response depicted in Figure 9 does not show considerable improvement and this is due to actuator saturation.

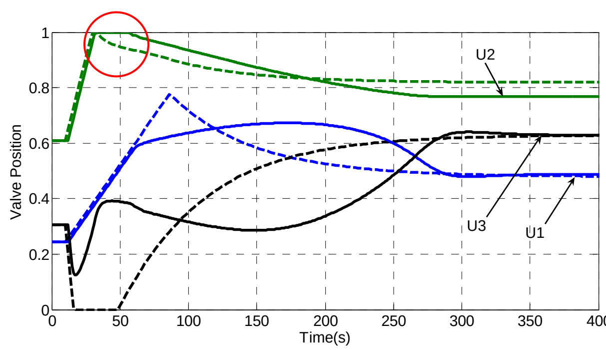

Fig.11 Controlling inputs for case B, Inverse model controller (solid), LQR (dashed)

Figure 11 shows that second controlling input which is turbine valve is saturated for about 20 seconds. An anti-windup will be helpful in reducing the effect of saturation and improves controller performance. However; for the sake of brevity it is not brought in this paper. The saturation area is encircled in Figure 11.

Case C:

In the last two cases a single change is applied to the set points. In the real situations; however, consecutive changes in unit load demand happens. Besides, due to nonlinearities, power plant characteristics vary to a great extent in response to decrease and increase in unit load demand (Figure 12).

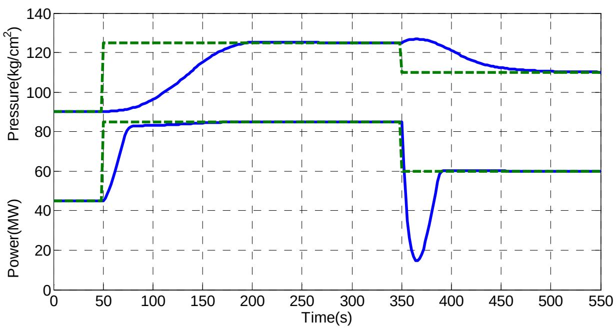

Fig.12 System response under LQR control, to an increasing and decreasing load profile

Figure 12 shows that controller performance must be evaluated in response to decreasing and increasing load demand in wide range of operation.

Consequently; in this case drum pressure and generated power are first increased to 110 kg/cm^2 and 70 MW, and then decreased to 100 kg/cm^2 and 60 MW respectively, while keeping drum water level deviation constant at zero during the whole process.

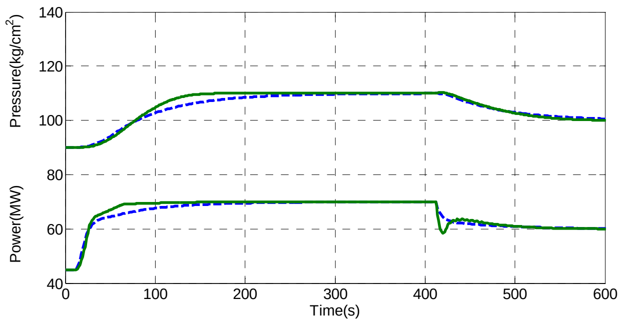

Fig.13 System response for case C, Inverse model controller (solid), LQR (dashed)

Figure 13 shows that the newly proposed controller, in addition to keeping extremely fast response in the rising set point part, has smaller settling time for the falling set point part (11 s smaller). Water level deviation and controlling inputs for this scenario are shown in Figures 14 and 15 respectively.

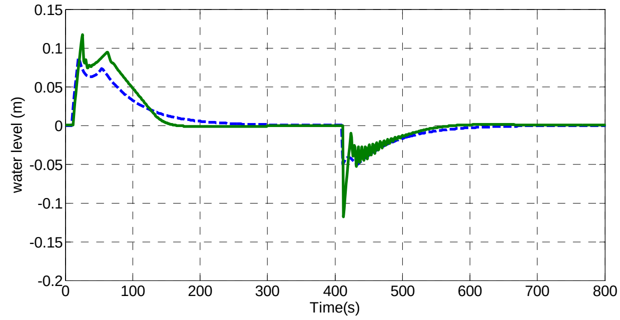

Fig.14 Water level deviation for case C, Inverse model controller (solid), LQR (dashed)

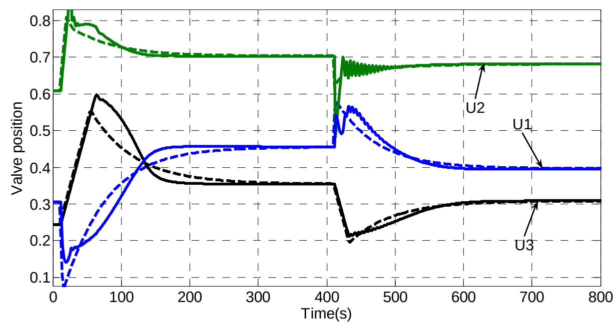

Fig.15 Controlling inputs for case C, Inverse model controller (solid), LQR (dashed)

4.2 Model parameter variation

Robustness is an extremely important characteristic for industrial process controllers. Normally; accurate mathematical description of industrial plants is not at hand. Power plant is a good example of such plants. There are lots of parameters which affect power plant transfer function and can not be determined accurately and are considered as uncertainties. These parameters are also changing over time due to corrosion, variation of climatic situation and etc. Consequently; in this section performance of newly proposed controller will be evaluated in the presence of model uncertainty and parameters variation. In this regard coefficients of equations (1) to (8) are decreased by 25% which is an extremely severe condition.

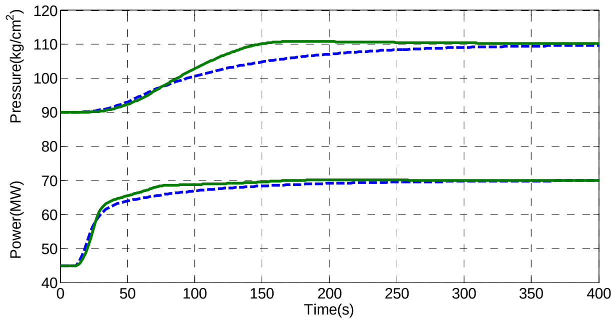

Fig.16 Response of the system with changed coefficients, Inverse model controller (solid), LQR (dashed)

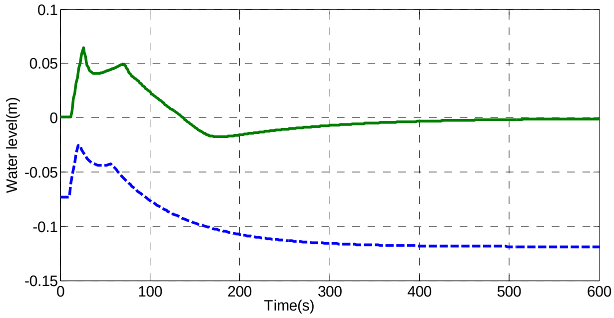

Fig.17 Water level deviation for the system with changed coefficients, Inverse model controller (solid), LQR (dashed)

Figure 17 shows that model parameter variation has direct effect in performance of quadratic regulators. This is due to the fact that optimal control calculates the feedback value based on the state variables. On the contrary, proposed controller has an input/output point of view to determine feedback value. It is shown that proposed controller has robust characteristic and brings drum water level deviation to zero regardless of parameters variation which is not the case for LQR. In the steady state, water level deviation is -0.12 m for the plant under LQR control. It is worth noting that water level deviation more than ±25 cm in drum, could cause power plant to trip which is an extremely costly event.

5 Conclusion

Since governing dynamics of an industrial plant like fossil fueled power plant can not be identified completely accurate, and there are various sorts of uncertainties, robustness becomes an important aspect of a newly designed controller. Simulation results show robust performance of newly designed controller in comparison with optimal controller is outstanding. In addition to robustness other characteristics of the controller such as rise time have improved a lot. Since there are lots of newly established power plants in Iran like Shazand power plant which have a drum type structure and are controlled utilizing a central software, the proposed control strategy could be implemented easily and with little costs.

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