An Adaptive Internal Model for Load Frequency Control using Extreme Learning Machine

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Abstract
As an important part of a power system, a load frequency control has to be prepared with a better controller to ensure internal frequency stability. In this paper, an Internal Model Control (IMC) scheme for a Load Frequency Control (LFC) with an adaptive internal model is proposed. The effectiveness of the IMC control has been tested in a three area power system. Results of the simulation show that the proposed IMC with Extreme Learning Machine (ELM) based adaptive model can accurately cover the power system dynamics. Furthermore, the proposed controller can effectively reduce the frequency and mechanical power deviation under disturbances of the power system.

Keywords: IMC, MPC, ELM, LFC, power system.

1. Introduction

In the power system operation, deviation of frequency would be a critical issues since the deviation could cause many troubles to devices connected to the power system. It is reported that the frequency change will affect operation and speed control of both synchronous and asynchronous motors, increase reactive power consumption and furthermore degrade load performance,overload transmission lines, and finally interfere system protection. An LFC is a main part of a power system to minimize frequency variation by maintaining power exchange between power system areas. Some works have been done in the area of LFC [1-9], including [1] designed a model predictive control (MPC) based LFC for a multi-area power system considering wind turbines operation, [2] compare MPC and PI performance against a conventional AGC system, [3] presented fuzzy controller for LFC of three area power system and recently [4] discussed a new LFC method for multi-area power system.

Internal Model Control (IMC) is a well-established control structure and it is widely applied in process control applications. An IMC incorporates a plant model into its structure as an internal model so that the controller output will be based on the difference between internal model and plant output. Morari in [10] has proved that the controller has dual stability, zero offset, and perfect control properties. Since plant models are mostly linearized models, it is almost impossible for an IMC to be a perfect control. An adaptive model will be a solution to be close to the "perfect control" since it can be updated in a certain time to do corrections for the existing model. Many previous researches have succeeded to apply the adaptive model into a controller i.e. PI/PID [10-13], Fuzzy controller [14], or MPC [15].

Since introduced a decade before, extreme learning machine (ELM) has been used in many cases and applications. It has accurate predictions in short time training compared to its ancestor which is a feed-forward neural network. An adaptive internal model has been introduced in [7] using prediction error minimization (PEM) algorithm. Due to time-consuming, this method is not appropriated to be used in an online application. Therefore, an ELM with its features is a good candidate to replace the PEM method. In this paper, an ELM based adaptive IMC controller is built by employing an internal model in an adaptive scheme and an MPC as the main controller to control a load frequency of a power system.

2. Research Method
2.1. Model Predictive Control

MPC is an advanced control method that used a plant model to predict the optimal movement of the plant. A Laguerre based MPC would be a solution for online computation compare to classical MPC [16, 17]. In addition, a Laguerre based MPC can increase the feasible region of the optimization problem [16]. Accurate approximation of control signal Δu may need many parameters that cause poor numerical solutions and heavy computational load when classical MPC is implemented in rapid sampling, complicated process dynamics and/or high demand on closed-loop performance [16, 17].

The discrete Laguerre function is transformed from its original using invert z-transformation as shown in (1). The Laguerre function vector and initial condition shown in (2) and (3) respectively [6, 8, 17].

$$\Gamma_N(z) = \frac{\sqrt{1-a^2}}{1-az^{-1}}\left(\frac{z^{-1}-a}{1-az^{-1}}\right)^{N-1} \tag{1}$$

$$L(k+1) = A_l \, L(k) \tag{2}$$

$$L(0)^T = \sqrt{\alpha}\left[1 - a \quad a^2 - a^3 \dots (-1)^{N-1}a^{N-1}\right]^T \tag{3}$$

Minimization of output errors for m sampling instant is done by taking a minimal solution of an objective function J as in (4). Closed loop feedback control with optimal gain K_{mpc} (6) is formulated in (5) and receding horizon control law is realized in (7).

$$J = \sum_{m=1}^{Np} x(k+m\mid k)^T Qx(k+m\mid k) + \eta^T R\eta \tag{4}$$

$$x(k+1) = (A - BK_{mpc})x(k) \tag{5}$$

$$K_{mpc} = L(0)^T \Omega^{-1}\Psi \tag{6}$$

$$\Delta u = -K_{mpc}x \tag{7}$$

where,

$$A_l = \begin{bmatrix} a & 0 & 0 & 0 & \cdots & 0 \\ \alpha & a & 0 & 0 & \cdots & 0 \\ -a\alpha & \alpha & a & 0 & \cdots & 0 \\ a^2\alpha & -a\alpha & \alpha & a & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ -a^{N-2}\alpha & -a^{N-3}\alpha & -a^{N-4}\alpha & \cdots & -a^{N-N}\alpha & a \end{bmatrix}$$

$$\eta = \Omega^{-1}\Psi$$

$$\Omega = \sum_{m=1}^{Np} \phi(m)Q\phi(m)^T + R_L$$

$$\Psi = \sum_{m=1}^{Np} \phi(m)QA^m$$

The parameters of N, a, A_l and L are the length of Laguerre network, time scaling factor, a Toeplitz matrix with $\alpha = (1-a^2)$, and Laguerre function's state vector respectively. The matrices of $Q \in \Re^{ns \times ns}$ and $R \in \Re^{ni \times ni}$ are weighting matrices, $\eta \in \Re^{ns \times N}$ is the parameter vector of N Laguerre function and ϕ is a Hessian matrix. Np is the number of prediction horizon and Δu is a vector of the control parameter.

2.2. Internal Model Control

An internal model that placed into a normal closed-loop control system, including controller, plant and/or sensor, may perform Internal Model Control systems as shown in Figure1. The difference between signal correction $\acute{r}$ and set-point r is the command to the controller to signal u to the plant. Control law applied for the IMC control can be written as follows [18].

$$y = PQr + (1-GQ)d_m \tag{8}$$

$$u = Qr - Qd_m \tag{9}$$

$$e = (1-PQ)r - (1-GQ)d_m \tag{10}$$

The difference between IMC and the classical controller is that an IMC will correct the actual output before it is fed back. An IMC can use the internal model to predict the future output of the plant and also to make correction of the output. It can also work with another controller to control a plant [10], to tune other controller [19], or to combine with the other controller such as PI/PID[13, 18-22], Fuzzy controller [14, 23], Neural Network [24] or MPC [15, 24, 25].

An adaptive IMC controller refers to a model and/or controller that can be updated in a certain time. By tuning a proper gain to the model and/or controller following the disturbance, the controller can be adaptive to the disturbance. In order to perform adaptive scheme of an IMC, another block for system identification should be presented inside the IMC structure as appeared in the dotted block of Figure1.
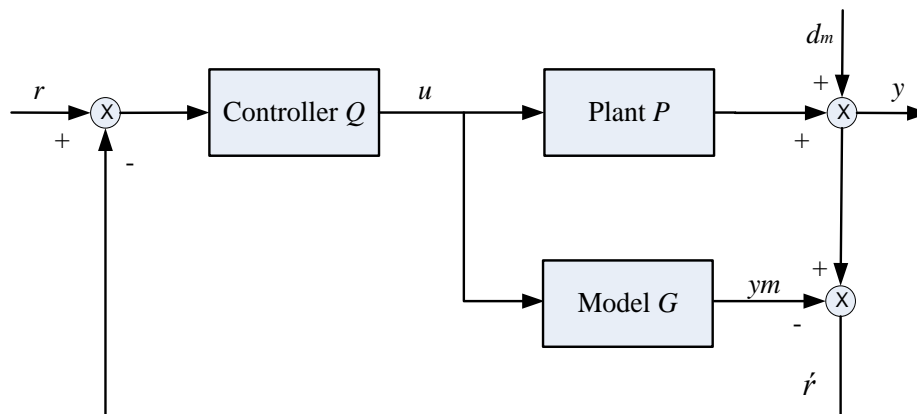

Figure 1.IMC principle

2.3. Extreme Learning Machine

An ELM is basically a single hidden layer feed-forward neural network (SLFN) which has an excellent training algorithm. Input weight and hidden layer biases are not necessarily adjusted and those can be chosen arbitrarily in this algorithm. Then the output weight of the SLFNs can be determined by a generalized inverse operation of the hidden layer output matrices. In fact, this procedure has been fastening this algorithm.

For a given $\tilde{n}$ training set samples (x_j, t_j) where $x_j=[x_{j1}, x_{j2},…, x_{j\tilde{n}}]^T$ and $t_j=[t_{j1}, t_{j2},…, t_{j\tilde{n}}]^T$, an SLFN with $\tilde{N}$ hidden neurons and activation function $g(x)$ is expressed as [26, 27]

$$\sum_{i=1}^{\tilde{N}} \beta_i' g(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i' g(w_i x_j + b_i) = o_j, j = 1, 2,...,\tilde{n} \tag{11}$$

where $w_i=[w_{i1}, w_{i2},…, w_{i\tilde{n}}]^T$, $\beta'=[\beta'_{i1}, \beta'_{i2},…, \beta'_{i\tilde{n}}]^T$, b_i, and o_j are the connecting weight of ith hidden neuron to input neuron, the connecting weights of the ith hidden neuron to the output neurons, the bias of the ith hidden node, and the actual network output with respect to input x_j respectively. Because the standard SLFN can minimize the error between t_j and o_j, (11) can be rewritten as follows.

$$\sum_{i=1}^{\tilde{N}} \beta_i' g(w_i x_j + b_i) = t_j, j = 1, 2,...,\tilde{n} \tag{12}$$

In simple (12) can be $H\beta'=T$ so that the output weight matrix β' can be solved by least square solution as in (13).

$$\beta'=H^\dagger T \tag{13}$$

The hidden layer output matrix H and the network output T are formulated as follows.

$$H(w_i, b_i) = \begin{bmatrix} g(w_1 x_1 + b_1) & \cdots & g(w_{\tilde{N}} x_1 + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(w_1 x_{\tilde{n}} + b_1) & \cdots & g(w_{\tilde{N}} x_{\tilde{n}} + b_{\tilde{N}}) \end{bmatrix}, \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{n}}^T \end{bmatrix} \tag{14}$$

2.4. Proposed Controller

As proposed in this research, an adaptive model will be used to provide an updated model of the plant. The adaptive model is generated by using a classification based extreme learning machine (ELM) algorithm by utilizing input and output data. The proposed controller uses MPC controller as its main controller combining with an adaptive ELM model as the internal model. The complete block diagram of the proposed controller is shown in Figure 2. The ELM model was trained using controller output Δu and frequency deviation Δf as input and output data respectively. After trained, the ELM model is used to predict frequency deviation Δf for a given controller signal Δu. The algorithm for simulation is written in Algorithm 1.

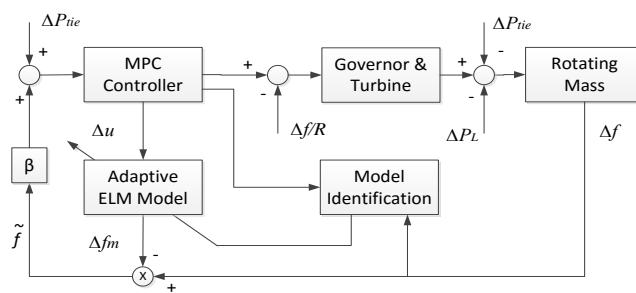| Algorithm 1 : Adaptive IMC |
|---|
| 1. set disturbances and noises |
| 2. configure ELM model |
| 3. for j=1 to simulation time |
| 4. ⋮ |
| 5.   for i=1 to n-area |
| 6.   calculate Δu |
| 7.   update state matrix $\Delta\dot{x}_i$ |
| 8.   train ELM model |
| 9.   predict ELM output Δym_i |
| 10.   calculate $\Delta\dot{y}_i=\Delta y_i-\Delta ym_i$ |
| 11. ⋮ |
| 12.   end |
| 13. end |

Figure 2. Proposed Adaptive IMC Scheme

2.5. Power system model

A model of power system dynamics can be redrawn in Figure 3. The frequency deviation of the power system, including tie-line power interchange, is expressed as follows.
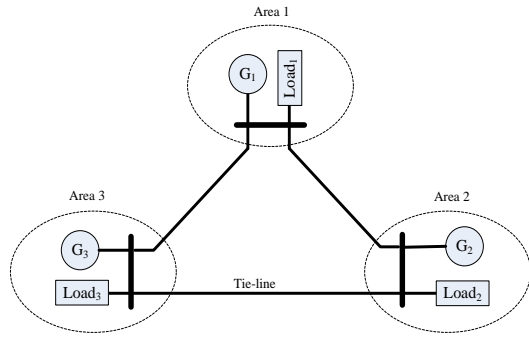
Figure 3. Power system dynamics

$$\dot{\Delta f_i} = \frac{1}{2H_i}\left(\Delta P_{m,i} - \Delta P_{L,i} - d_i\,\Delta f_i - \Delta P_{tie,i} \right) \tag{15}$$

The prime mover P_m, governor output P_g, tie-line power interchange P_{tie} are for n areas are formulated in (16-18). Area Control Error (*ACE*) is chosen as the controller input which is the result of frequency f and tie-line power changes within a control area of the power system defined in (19) [1].

$$\dot{\Delta P}_{m,i} = \left(\frac{1}{T_{g,i}}\right)\Delta P_{g,i} - \left(\frac{1}{T_{t,i}}\right)\Delta P_{m,i} \tag{16}$$

$$\dot{\Delta P}_{g,i} = \frac{1}{T_{g,i}}\left(\Delta P_{C,i} - \frac{\Delta f_i}{R_i} - \Delta P_{g,i} \right) \tag{17}$$

$$\dot{\Delta P}_{tie,i} = 2\pi\left[\sum_{\substack{j=1 \\ j\neq i}}^{n} T_{ij}\,\Delta f_i - \sum_{\substack{j=1 \\ j\neq i}}^{n} T_{ij}\,\Delta f_j \right] \tag{18}$$

$$ACE_i = \Delta P_{tie,i} + \beta_i \Delta f_i \tag{19}$$

where $P_{L,i}$ is the load/disturbance, $P_{C,i}$ is the controller output, H_i is the equivalent inertia constant, d_i is the damping coefficient, R_i is the speed droop characteristic and β_i is the bias of frequency. T_{ij} is the tie-line synchronizing coefficient between area i and j, $T_{g,i}$ is the governor time constants and $T_{t,i}$ is the turbine time constants of area i.

3. Results and Analysis
3.1. Simulation

The power system configuration for testing the proposed controller is based on [6, 8] with the parameters as shown in Table 1 while the system dynamics are figured in Figure 4. Simulations were done in two cases and the simulation setup is configured in Table 2, where step and random disturbance are imposed on the load in all area. The random disturbance implies load changes of white noise with a maximum 0.1 pu while step disturbance is assumed as load change in constant for a certain time.

Figure 4. Three-area power system configuration

Table 1. Three Area Power System Parameters

Area	d [pu/Hz]	$2H$ [pu s]	R [Hz/pu]	T_g [s]	T_i [s]	$\square$ [pu/Hz]	T_{ij} [pu/Hz]
1	0.015	0.1667	3.00	0.08	0.40	0.3483	T_{12}=0.20 T_{13}=0.25
2	0.016	0.2017	2.73	0.06	0.44	0.3827	T_{21}=0.20 T_{23}=0.12
3	0.015	0.1247	2.82	0.07	0.30	0.3692	T_{31}=0.25 T_{32}=0.12

Table 2. Simulation Setup

Case	Step Disturbance [pu]	Random Disturbance [pu]
I	0.2	0.1
II	0.2	-

A Laguerre function based MPC controller is built to control a three area power system frequency. To ensure the MPC stability, the scaling factor a is tuned to 0.1 while network lengths N is set to 4 for each area controller. The model will be updated each second with the input-output data using ELM method. Overall simulation responses of frequency and mechanical power deviation for both existing and proposed controller are plotted in Figures 5 and 6.

3.2. Discussion

The controller performance is evaluated based on system responses and signal measures. Standard deviation is also provided to indicate how sensitive the controller to response the errors.

For the system responses based evaluation, overshoot and standard deviation are analyzed and the results are provided in Table 3 as well as its visual in Figure 7 and 8 based on system responses in Figure 5 and 6. According to the figures and table, it can be simply known that the proposed controller has very good response overshoot of frequency and mechanical power compared to the existing MPC controller in all areas of both cases. On the other hand, the proposed controller slightly aggressive to the disturbances as shown in high standard deviations in some areas and cases. These are the evidence that the proposed controller can accurately cover the power system dynamics and also it shows the ability to increase controller performance by sending proper feedback to the controller by utilizing the adaptive model.

By the treatment as same as in the case I, the other adaptive internal model for LFC application introduced in [7] has overshoot responses 0.1465, 0.1729, and 0.1652 and standard deviation 0.0294, 0.0443, and 0.0278 for area 1-3 respectively. Compared to the proposed controller, it is proved that the proposed controller has smaller overshoot and higher standard deviation compared. These are the indications that the proposed controller is more active to maintain the frequency change during the simulation and so it only has a small overshoot on the simulation.

Table 3. Frequency and Mechanical Power Deviation Analysis

| | Area | Frequency Deviation | | | | Mechanical Power Deviation | | | |
| | | MPC Cases | | Adaptive IMC Cases | | MPC Cases | | Adaptive IMC Cases | |
		I	II	I	II	I	II	I	II
Overshoot	1	0.1346	0.2190	0.0923	0.2047	0.3437	0.3401	0.3080	0.3109
	2	0.0860	0.1162	0.0407	0.1147	0.4164	0.4165	0.3473	0.3484
	3	0.1374	0.2530	0.1259	0.2384	0.4605	0.4625	0.4318	0.4340
Standard Deviation	1	0.1762	0.1967	0.1767	0.1946	0.0372	0.0428	0.0442	0.0814
	2	0.1786	0.1838	0.1795	0.1842	0.0418	0.0432	0.0354	0.0514
	3	0.1714	0.2012	0.1714	0.1976	0.0522	0.0580	0.0450	0.0738

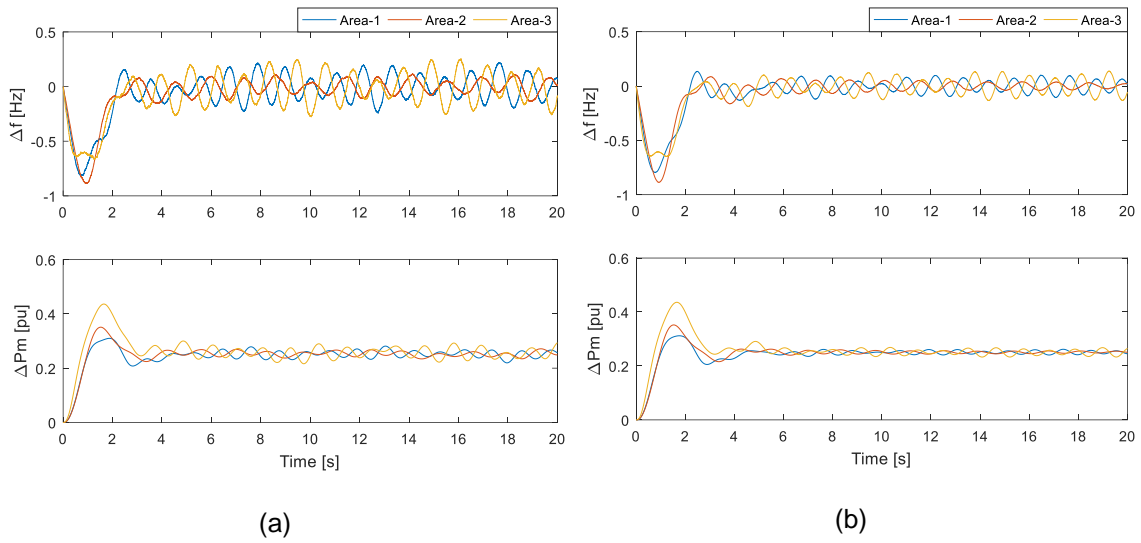(a)   (b)

Figure 5. MPC controller responses (a) case i and (b) case II
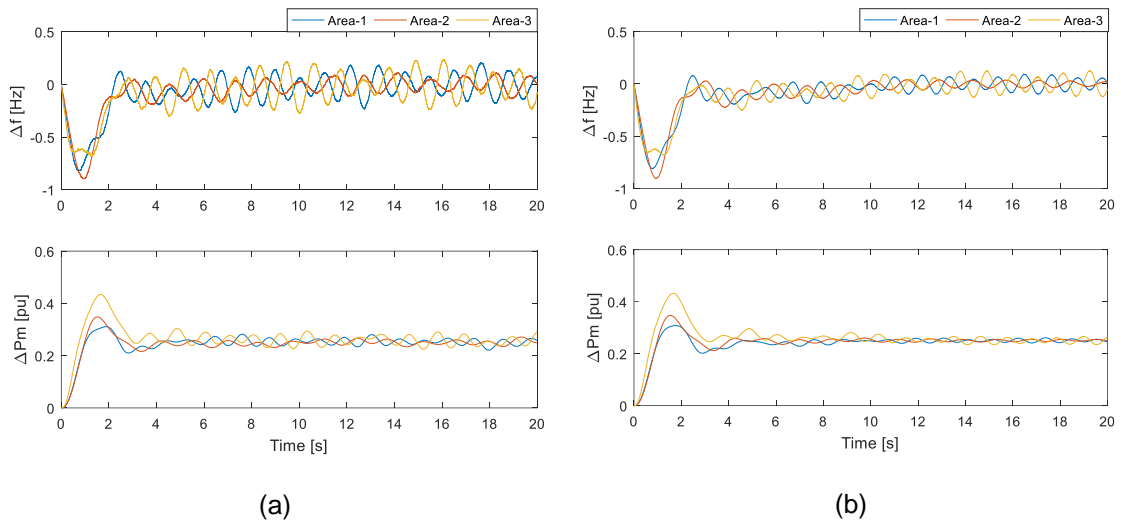

(a)   (b)

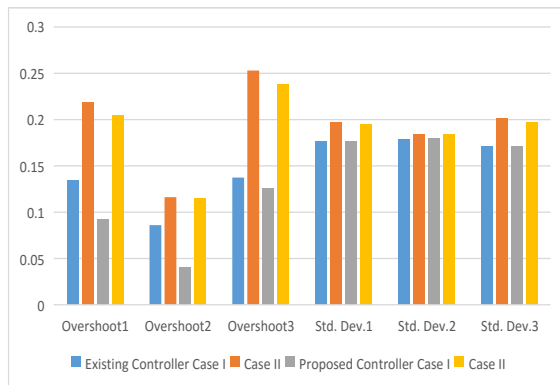Figure 6. Adaptive IMC controller responses (a) case i and (b) case ii
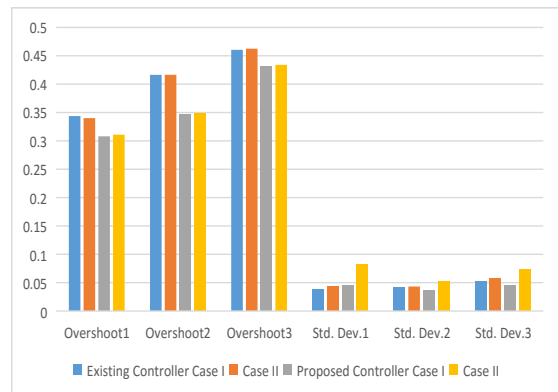

Figure 7. Frequency deviation

Figure 8. mechanical power deviation

The signal measured based evaluation of the proposed controller including Integral of the absolute value of the error (IAE), Integral of the square value of the error (ISE) and Integral of the time-weighted absolute value of the error (ITAE) are provided in Table 4. It is shown that the proposed controller has small errors in IAE and ITAE index while it has high deviation in the ISE index in both cases. These are the validation that the proposed controller has no persisting high errors and it adaptively follows the load changes in the simulation.

The specifications of the machine to run the simulation runs are Intel Core i7 2.9 GHz CPU and 16 GB RAM using MatLab 2016a under Windows 10 environment. CPU time for both cases of MPC, and case I and II of adaptive IMC are 1.5509, 1.5446, 6.6927 and 6.4599 seconds respectively. It seems like the proposed controller will need time 4 times longer than the existing controller since it needs to build its own model in a certain period which is in this cases every second. This may not degrade the performance in real operation since the CPU time is still littler than simulation setting time.

Table 4. Controller Index Analysis

Area		MPC			Adaptive IMC		
		IAE	ISE	ITAE	IAE	ISE	ITAE
Case I	1	1.9340	0.6858	10.6362	1.9039	0.6900	10.1068
	2	1.6508	0.7028	6.9319	1.6532	0.7118	6.8517
	3	2.1407	0.6593	14.1713	2.0966	0.6589	13.4449
	avg	1.9085	0.6827	10.5798	1.8846	0.6869	10.1345
Case II	1	2.2608	0.7425	15.0622	2.2289	0.7444	14.4818
	2	1.6748	0.7204	6.8818	1.6792	0.7297	6.8696
	3	2.6418	0.7685	20.5055	2.5884	0.7626	19.6189
	avg	2.1924	0.7438	14.1498	2.1655	0.7456	13.6567

4. Conclusion

A novel adaptive IMC controller based on ELM method has been introduced in this paper. A three area power system is chosen to validate the controller in handling load frequency control including step and random disturbance. Simulation results show that the proposed controller presents superior responses in all areas of both cases compared to the existing MPC controller.

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