

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

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## 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. 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.

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### 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 in 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. Search 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  $\Delta u$  may need many parameters that cause 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].

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

$$L(k+1) = A_L L(k) \quad (2)$$

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

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).

$$J = \sum_{m=1}^{Np} x(k+m|k)^T Q x(k+m|k) + \eta^T R \eta \quad (4)$$

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

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

$$\Delta u = -K_{mpc} x \quad (7)$$

where,

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

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

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

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

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  $Q \in \mathbb{R}^{ns \times ns}$  and  $R \in \mathbb{R}^{ni \times ni}$  are weighting matrices,  $\eta \in \mathbb{R}^{ns \times N}$  is the parameter vector of  $N$  Laguerre function and  $\phi$  is a Hessian matrix.  $N_p$  is the number of prediction horizon and  $\Delta u$  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  $\dot{r}$  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].

$$y = PQr + (1-GQ)d_m \quad (8)$$

$$u = Qr - Qd_m \quad (9)$$

$$e = (1-PQ)r - (1-GQ)d_m \quad (10)$$

The difference between IMC and the classical control<sup>41</sup> 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.

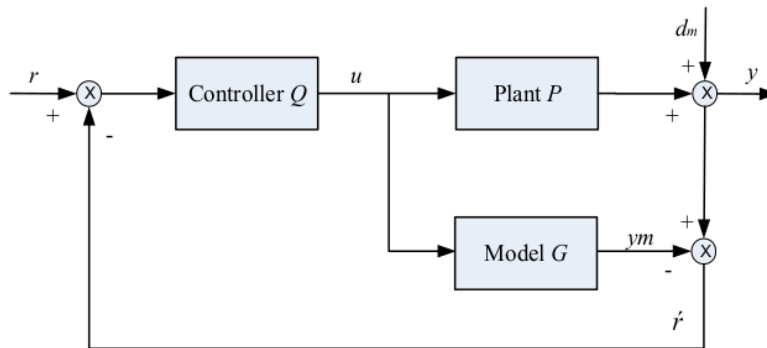


Figure 1.IMC principle

## 2.3. Extreme Learning Machine<sup>1</sup>

An ELM is basically a single hidden layer feed-forward neural network (SLFN) which has an excellent training algorithm. Input weight and hidden layer bias<sup>10</sup>s 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  $x_j = [x_{j1}, x_{j2}, \dots, x_{j\tilde{n}}]^T$  and  $t_j = [t_{j1}, t_{j2}, \dots, t_{j\tilde{n}}]^T$ , an SLFN with  $\tilde{N}$  hidden neurons and activation function  $g(x)$  is expressed as [26, 27]

$$\sum_{i=1}^{\tilde{N}} \beta'_i g(x_j) = \sum_{i=1}^{\tilde{N}} \beta'_i g(w_i x_j + b_i) = o_j, j = 1, 2, \dots, \tilde{n} \quad (11)$$

where  $w_i = [w_{i1}, w_{i2}, \dots, w_{i\tilde{n}}]^T$ ,  $\beta'_i = [\beta'_{i1}, \beta'_{i2}, \dots, \beta'_{i\tilde{n}}]^T$ ,  $b_i$  and  $o_j$  are the connecting weight of  $i^{th}$  hidden neuron to input neuron, the connecting weights of the  $i^{th}$  hidden neuron to the output neurons, the bias of the  $i^{th}$  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.

$$\sum_{i=1}^{\tilde{N}} \beta'_i g(w_i x_j + b_i) = t_j, j = 1, 2, \dots, \tilde{n} \quad (12)$$

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

$$\beta' = H^+ T \quad (13)$$

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

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

## 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  $\Delta u$  and frequency deviation  $\Delta f$  as input and output data respectively. After trained, the ELM model is used to predict frequency deviation  $\Delta f$  for a given controller signal  $\Delta u$ . 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.      $\vdots$
5.     for  $i=1$  to n-area
6.         calculate  $\Delta u$
7.         update state matrix  $\Delta \hat{x}_i$
8.         train ELM model
9.         predict ELM output  $\Delta y_{mi}$
10.        calculate  $\Delta \hat{y}_i = \Delta y_i - \Delta y_{mi}$
11.      $\vdots$
12.     end
13. end

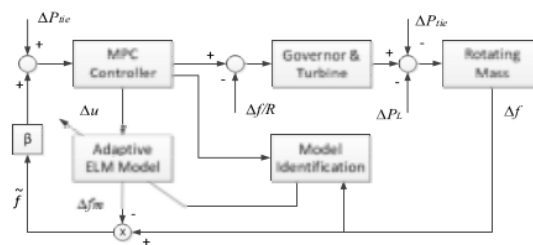


Figure 2. Proposed Adaptive IMC Scheme

## 2.5. Power system model

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

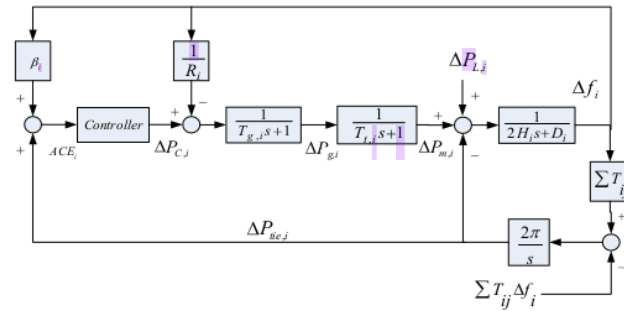


Figure 3. Power system dynamics

$$\Delta \dot{f}_i = \frac{1}{2H_i} (\Delta P_{m,i} - \Delta P_{L,i} - d_i \Delta f_i - \Delta P_{tie,i}) \quad (15)$$

The prime mover [38] 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].

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

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

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

$$ACE_i = \Delta P_{tie,i} + \beta_i \Delta f_i \quad (19)$$

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  $\beta_i$  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.



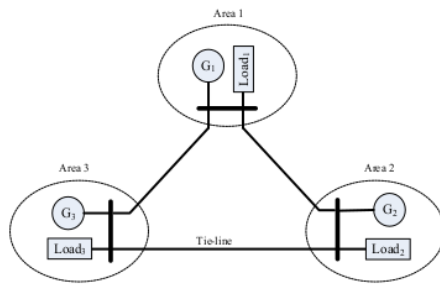


Figure 4. Three-area power system configuration

Table 1. Three Area Power System Parameters

Area	$d$ [pu/Hz]	$\frac{2H}{7}$ [pu s]	$R$ [Hz/pu]	$T_g$ [s]	$T_i$ [s]	$\frac{1}{\omega}$ [pu/Hz]	$\frac{T_d}{T_g}$ [pu/Hz]
1	0.015	0.166 7	3.00	0.08	0.40	0.3483	$T_{12}=0.20$ $T_{13}=0.25$
2	0.016	0.201 7	2.73	0.06	0.44	0.3827	$T_{21}=0.20$ $T_{23}=0.12$
3	0.015	0.124 7	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  $\alpha$  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

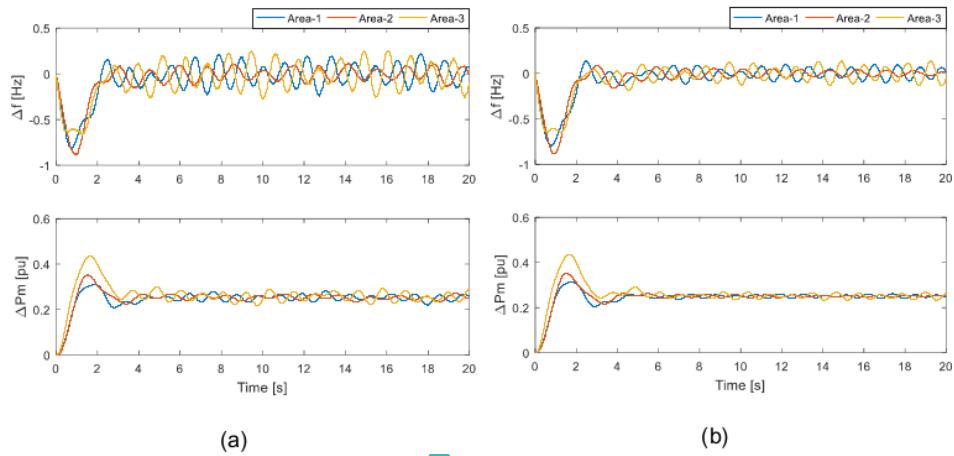


Figure 5. MPC controller <sup>4</sup> responses (a) case i and (b) case II

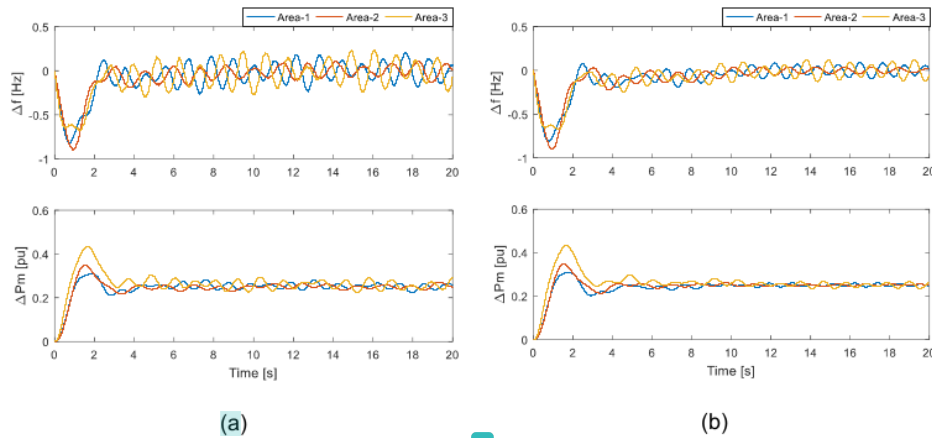


Figure 6. Adaptive IMC controller <sup>4</sup> responses (a) case i and (b) case ii

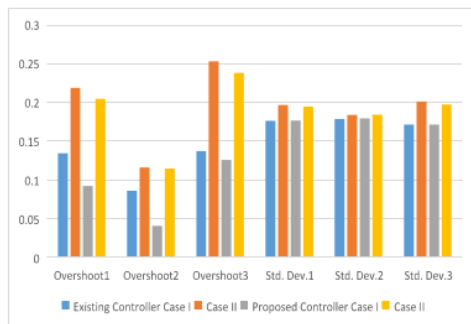


Figure 7. Frequency deviation

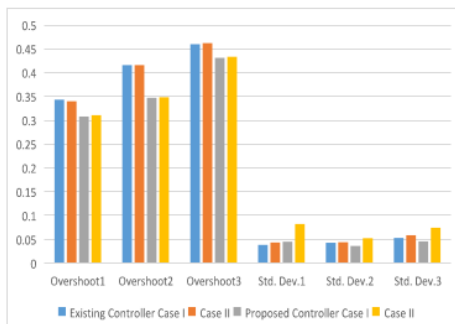


Figure 8. mechanical power deviation



The signal measured based evaluation of the proposed controller including Integral of the absolute value of the error (IAE), Integral of the square <sup>32</sup>ue 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. <sup>27</sup>

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 <sup>15</sup> has been introduced in this paper. A three area power system is chosen to vali<sup>37</sup> 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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#### References

- [1] Mohamed TH, Morel J, Bevrani H, Hiyama T. Model predictive based load frequency control-design concerning wind turbines. *Int J Electr Power Energy Syst* [Internet]. 2012;43(1):859–67. Available from: <http://dx.doi.org/10.1016/j.ijepes.2012.06.032>
- [2] Ersdal AM, Imsland L, Uhlen K. Model Predictive Load-Frequency Control. *IEEE Trans Power Syst*. 2016; 31(1) :777–785.
- [3] Jain SK, Bhargava A, Pal RK. Three area power system load frequency control using fuzzy logic controller. In: International Conference on Computer, Communication and Control. 2015: 1–6.
- [4] Cai L, He Z, Hu H. A New Load Frequency Control Method of Multi-Area Power System via the Viewpoints of Port-Hamiltonian System and Cascade System. *IEEE Trans Power Syst*. 2017; 32(3): 1689–1700.
- [5] Kumtepelı V, Wang Y, Tripathi A. Multi-area model predictive load frequency control: A decentralized approach. In: 2016 Asian Conference on Energy, Power and Transportation Electrification, ACEPT 2016. 2017: 25–7.
- [6] Rehiara AB, Sasaki Y, Yorino N, Zoka Y. A Performance Evaluation of Load Frequency Controller using Discrete Model Predictive Controller. In: 2016 International Seminar on Intelligent Technology and Its Applications. 2016: 659–64.

- [7] Rehiara AB, Chongkai H, Sasaki Y, Yorino N, Zoka Y. An adaptive IMC-MPC controller for improving LFC performance. In: *2017 IEEE Innovative Smart Grid Technologies - Asia*. Auckland, New Zealand; 2018: 1–6.
- [8] He C, Rehiara AB, Sasaki Y, Yorino N, Zoka Y. *The Application of Laguerre functions based Model Predictive Control on Load Frequency Control*. 24<sup>th</sup> International Conference on Electrical Engineering. 2018: 1190-1195.
- [9] Abdillah M, Setiadi H, Rehiara AB, Mahmoud K, Farid IW, Soeprijanto A. Optimal selection of LQR parameter using AIS for LFC in a multi-area power system. *J Mechatronics, Electr Power, Veh Technol* [Internet]. 2016; 7(2): 93. Available from: <http://www.mevjournal.com/index.php/mev/article/view/301>
- [10] Qiu Z, Santillo M, Sun J, Jankovic M. *Enhanced composite adaptive IMC for boost pressure control of a turbocharged gasoline engine*. Proc Am Control Conf. 2016; 2016–July(August): 3286–3291.
- [11] Liping F, Xiyang W. *Internal model based iterative learning control for linear motor motion systems*. Proc - ISDA 2006 Sixth Int Conf Intell Syst Des Appl. 2006; 3: 62–6.
- [12] Watanabe, Keiji; Muramatsu E. *Adaptive Internal Model Control of SISO Systems*. In: SICE Annual Conference. Fukui, Japan; 2003: 3084–3089.
- [13] Gu J-J, Shen L, Zhang L-Y. *Application of internal model and self-adaptive PSD controller in the main steam temperature system*. 2005 Int Conf Mach Learn Cybern Icmlc 2005. 2005;(August): 570–573.
- [14] Xie WF, Rad AB. Fuzzy adaptive internal model control. *IEEE Trans Ind Electron*. 2000; 47(1): 193–202.
- [15] Miliars-Argeitis A, Khammash M. *Adaptive Model Predictive Control of an optogenetic system*. In: 54th IEEE Conference on Decision and Control (CDC). Osaka; 2015: 1265–1270.
- [16] Valencia-Palomo G, Rossiter JA. *Using Laguerre functions to improve efficiency of multi-parametric predictive control*. In: 2010 American Control Conference. USA; 2010: 4731–4736.
- [17] Liuping Wang. *Model Predictive Control System Design and Implementation Using MATLAB*. Springer-Verlag. London; 2009: 103-403.
- [18] Seki H. *Adaptive IMC-PI controllers for process applications*. 12th IEEE Int Conf Control Autom. 2016: 455–460.
- [19] Ho WK, Lee TH, Han HP, Hong Y. Self-tuning IMC-PID control with interval gain and phase margins assignment. *IEEE Trans Control Syst Technol*. 2001; 9(3): 535–541.
- [20] Baba Y, Shigemasa T, Yukitomo M, Kojima F, Takahashi M, Sasamura E. *Model-driven PID control system in single-loop controller*. Proc SICE 2003 Annu Conf. 2003; 1:187–190.
- [21] Shamsuzzoha M, Lee M. *IMC Based Control System Design of PID Cascaded Filter*. SICE-ICASE Int Jt Conf 2006. 2006;Oct. 18(2): 2485–2490.
- [22] Shigemasa T, Yukitomo M, Kuwata R. *A model-driven PID control system and its case studies*. Proc Int Conf Control Appl [Internet]. 2002;1:571–6. Available from: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1040248>
- [23] Jin Q, Feng C, Liu M. *Fuzzy IMC for Unstable Systems with Time Delay*. 2008 IEEE Pacific-Asia Work Comput Intell Ind Appl. 2008; 2: 772–778.
- [24] Yan L, Rad AB, Wong YK, Chan HS. *Model based control using artificial neural networks*. In: the 1996 IEEE International Symposium on Intelligent Control. 1996: 283–288.
- [25] Psichogios DC, Ungar LH. *Nonlinear internal model control and model predictive control using neural networks*. In: 5th IEEE International Symposium on Intelligent Control. 1990: 158–163.
- [26] Cao J, Zhang K, Luo M, Yin C, Lai X. Extreme Learning Machine and Adaptive Sparse Representation for Image Classification. *Neural Networks*. 2016; 81(C):91–102.
- [27] Huang G, Song S, Gupta JND, Wu C. Semi-Supervised and Unsupervised Extreme Learning Machines. *IEEE Trans Cybern*. 2014; 44: 2405–2417.

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Tarek Hassan Mohamed, Jorge Morel, Hassan Bevrani, Ahmed Abd-Elawwab Hassan, Yehia Sayed Mohamed, Takashi Hiyama. "Decentralized model predictive-based load-frequency control in an interconnected power

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system concerning wind turbines", IEEJ Transactions on Electrical and Electronic Engineering, 2012

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Marko Č. Bošković, Tomislav B. Šekara, Milan R. Rapačić. "Novel tuning rules for PIDC and PID load frequency controllers considering robustness and sensitivity to measurement noise", International Journal of Electrical Power & Energy Systems, 2020

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42

Wang, L.. "Discrete model predictive controller design using Laguerre functions", Journal of

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