Control Performance Standard based Load Frequency Control of a two area Reheat Interconnected Power System considering Governor Dead Band nonlinearity using Fuzzy Neural Network

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ABSTRACT: The frequency control of reheat interconnected two area power systems are mainly characterized by non-linearity and uncertainty. A hybrid neural network and fuzzy control is proposed for load frequency control in the power systems considering governor dead band (GDB) non-linearity. Fuzzy with neural network is employed to forecast the control input requirement and system's future output, based on the current Area Control Error (ACE) and the predicted change-of-ACE. The Control Performance Standard (CPS) criterion is adopted to the fuzzy controller design, thus improves the dynamic quality of system. The system was simulated and the output responses of frequency deviations in area 1 and area 2 and tie-line power deviations for 1% step-load disturbance in area 1 were obtained. The comparison of frequency deviations and tie-line power deviations for the two area interconnected thermal power system considering GDB nonlinearity with Redox Flow Batteries (RFB) reveals that the system with hybrid fuzzy neural controller enhances a better stability than that of system with integral controller.

Keywords: Automatic Generation Control, Governor Dead Band, Control Performance Standards, Redox Flow Batteries.

1. INTRODUCTON

Load frequency control is one of the major requirements in providing reliable and quality operation in multi-area power systems [1]. In interconnected large power systems, variations in frequency can lead to serious large scale stability problems. Load characteristics, unexpected changes in power demand and faults also affect the stability. For satisfactory operation, constant frequency and active power balance must be provided. As frequency is a common factor, any change in active power demand/generation of power systems is reflected throughout the system by a change in frequency. It is necessary to design a LFC system that controls the power generation and active power at the tie-lines. In conventional LFC applications, proportional integral (PI) controllers [2] are most commonly used, but it is not easy to obtain the proper gain parameters of the PI controller as the frequency within a certain scope is realized through maintaining the total power input of the tie-line bias control of power system. The inherent non-linearity in system components has led researchers to consider Neural Network (NN) and fuzzy logic techniques [3-9] to build a non-linear controller with high efficiency. A feed forward neural network has been trained by back propagation-through-time algorithm to control the steam turbine admission valve. The NN based controller for a two area interconnected system which consists of reheat turbines and generation constraints have been studied. The inputs to the proposed NN controller are system state variables and disturbance vector. Back propagation-through-time algorithm has been used to cope with the continuous time dynamics as the learning rule. In using neural networks for dynamic power system control, since it contains large number of parallel input vector, the total system may be too complicated. This is initially designed for a fuzzy logic controller in the load frequency control of the power system. A specified control scheme has been designed for a two area interconnected power system with control dead zone [2]. A combined fuzzy logic and NN based controller for LFC have also been designed using conventional Area Control Error (ACE) Criterion. A new type of control scheme called Control Performance Criteria (CPC) has been used to evaluate LFC performance, which is of great importance as high quality control in required in the present day power transfer applications. The Control Performance Standard (CPS) is specifically designed to comply with the performance standards imposed by the North American Electric Reliability Council (NERC) for equitable operation of an interconnected system. Fuzzy logic system is usually designed to assure that the control performance is in compliance with NERC's control performance standards [8,9]. Considering the power system load frequency control, this paper establishes a recurrent neural network model to predict the future frequency of the target object, thus forecasting the ACE and the CPS standard index. Based on this prediction, the optimized controller is designed, which follows the CPS performance standards through the fuzzy logic control. Simulation results show the effectiveness of the proposed method.

2.1 Modeling of two area interconnected power system with RFB

The linearized mathematical model of the two area (thermal–reheat) power system, is given by the following set of the state variable differential equations as

$$\Delta F_1(s) = \frac{Kps_1}{1+sTps_1}\left[\Delta Pg_1(s) + Kc_1.\Delta Pc_1(s) - \Delta Pd_1(s) - \Delta Ptie(s)\right] \tag{2.1}$$

$$\Delta Pg_1(s) = \frac{1+sKr_1Tr_1}{1+sTr_1}\Delta Pt_1'(s) \tag{2.2}$$

$$\Delta Pt_1'(s) = \frac{1}{1+sTt_1}\Delta Xe_1(s) \tag{2.3}$$

$$\Delta Xe_1(s) = \frac{1}{1+sTg_1}\left[\Delta Pc_1(s) - \frac{1}{R_1}\Delta F_1(s)\right] \quad (2.4)$$

$$\Delta Ptie(s) = \frac{2\pi.T_{12}}{s}\left[\Delta F_1(s) - \Delta F_2(s)\right] \quad (2.5)$$

$$\Delta F_2(s) = \frac{Kps_2}{1+sTps_2}\left[\Delta Pg_2(s) + Kc_2.\Delta Pc_2(s) - \Delta Pd_2(s) - a_{12}.\Delta Ptie(s)\right] \quad (2.6)$$

$$\Delta Pg_2(s) = \frac{1+sKr_2Tr_2}{1+sTr_2}\Delta Pt_2'(s) \quad (2.7)$$

$$\Delta Pt_2'(s) = \frac{1}{1+sTt_2}\Delta Xe_2(s) \quad (2.8)$$

$$\Delta Xe_2(s) = \frac{1}{1+sTg_2}\left[\Delta Pc_2(s) - \frac{1}{R_2}\Delta F_2(s)\right] \quad (2.9)$$

The system state space equations are developed as

$$\dot{X} = \bar{A}x + \bar{B}u + \bar{\Gamma}d$$

$$Y = \bar{C}X \quad (2.10)$$

where, x, u and d are the state, control and disturbance vectors. The control and disturbance vectors are given by

System Control input vector $u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} \Delta P_{c1} \\ \Delta P_{c2} \end{bmatrix}$

Disturbance vector $d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} \Delta P_{D1} \\ \Delta P_{D2} \end{bmatrix}$

Where ,

Augmented system matrix $\bar{A} = \begin{bmatrix} 0 & C \\ 0 & A \end{bmatrix}$

Augmented control input matrix $\bar{B} = [0 \quad B]$

Augmented disturbance matrix $\bar{\Gamma} = [0 \quad \Gamma]$

Augmented output matrix $\bar{C} = [0 \quad C]$

Two state vectors $\int ACE_1$ and $\int ACE_2$ are included in the augmented state matrix

$$\int ACE_i = \int \beta_i \Delta f_i + \Delta P_{tie} \qquad i=1, 2 \quad (2.11)$$

Substituting the value we get,

$$\begin{bmatrix} \bar{Y} \\ \dot{\bar{X}} \end{bmatrix} = \begin{bmatrix} 0 & C \\ 0 & A \end{bmatrix} \begin{bmatrix} \int ACE.dt \\ \bar{X} \end{bmatrix} + \begin{bmatrix} 0 \\ B \end{bmatrix} U \quad (2.12)$$

2.2 The Governor Dead Band (GDB)

GDB is defined as the total magnitude of a sustained speed change within which there is no change in valve position. The limiting value of dead band is specified as 0.06%. The speed-governor dead band has a significant effect on the performance of the governors and it has a destabilizing effect on the transient performance of the system. A describing function approach is used to express the GDB nonlinearity. For an element with a backlash characteristic of hysteresis type in nature, the describing function giving the output-to-input relationship for the component of the fundamental frequency shows that the output lags the input by an angle which is independent of frequency but is a function of the ratio of the amplitude of the input oscillation to the width of the backlash loop. An adequate description of GDB nonlinearity is expressed as

$$y = F(x, \dot{x}) \quad (2.13)$$

If the variable 'x' in the nonlinear function $F(x, \dot{x})$ has the sinusoidal form, then the variable $F(x, \dot{x})$ is generally complex, but is also a periodic function of time. As such, it can be developed in a Fourier series as follows:

$$F(x, \dot{x}) = F^0 + N_1 x + (N_2/W_0)\dot{x} + \quad (2.14)$$

As the backlash nonlinearity is symmetrical about the origin, Fo =0. Further, it has been found that the backlash nonlinearity tends to produce a continuous sinusoidal oscillation with a natural period of about 2 seconds. Then A typical value of backlash is 0.06%. However, by referring to the discussion of A/D = 4 will imply a backlash of approximately 0.05%.

This value of A/D is chosen for simulation results and the following Fourier Coefficients are obtained.

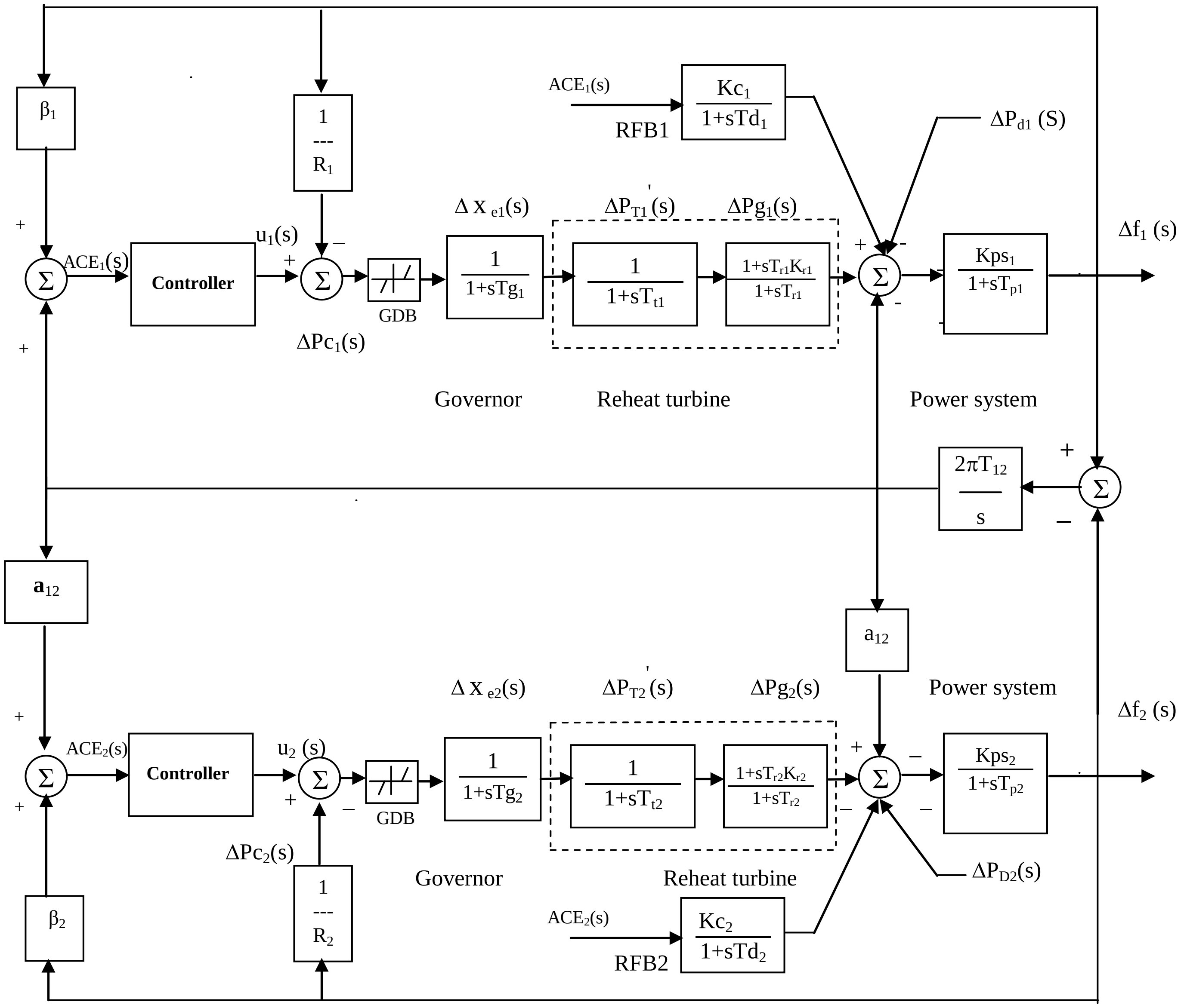

Fig.1 Block diagram of a two-area interconnected thermal reheat power system with RFB and considering Governor Dead Band nonlinearities

$$\frac{N_1}{k} = 0.8 \text{ and } \frac{N_2}{k} = -0.2 \qquad (2.17)$$

$\omega o = 2\pi fo = \pi$ with fo = 0.5Hz. (2.15)

The governor transfer function with linearized dead band is given as [2]

$$G(s) = (N_1+N_2 s)/(1+T_{Gi}s) \qquad (2.16)$$

where N1 and N2 are Fourier coefficients whose values are obtained as N1 = 0.8 and N2 = -0.2/π

2.3 Modeling of RFB Units

Redox flow battery, in addition to load leveling, a function commonly assigned to them, have range of allocations such as Load Frequency Control (LFC) and power quality maintenance for decentralized power supplies [10].

$$\Delta P_{rfbi} = \frac{Kc_i}{1+sTd_i}\Delta Pc_i$$

$$\Delta P_{rfbi} = Kci.\Delta Pc_i \qquad (2.18)$$

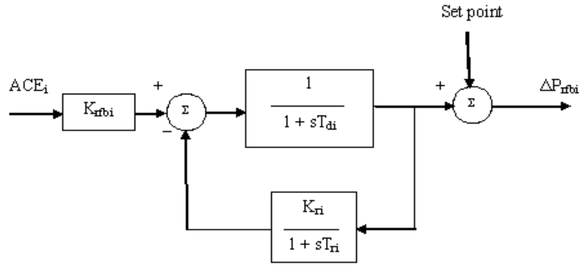

Fig 2 REDOX FLOW BATTERY MODEL

2.4.1 Control Performance Standard criterion

In 1997 NERC developed more sophisticated criteria called Control Performance Standard (CPS_1, CPS_2) which ensures better quality control with more measurements and data collection. The CPS_1 assesses the impact of ACE on frequency over a certain period window or horizon and it is defined as follows: over a sliding period, the average of the "clock-minute averages" of a control area's ACE divided by "10 times its area frequency bias" times the corresponding "clock-minute averages of the interconnection of frequency error" shall be less than the square of a given constant, E_1, representing a target frequency bound. These strategies lead to the conclusion that ACE should satisfy a decreasing function of T.

$$RMS\ \{AVG_T\ \{ACE\}\} = \varphi\ (T) \qquad (2.19)$$

where φ(T) is the root-mean-square (RMS) of all the T minute average ACE values over the past 12 months. It is shown in [8] that if ACE were a random signal, φ (T) would be proportional to 1/T. Of course ACE itself cannot be made to meet this condition because its next data cycle value is far more likely to be close to the present value than to be random. However, a good control algorithm can make AVG_T {ACE} nearly random for T. Moreover, this can be accomplished with far less generation maneuvering than that of many present AGC schemes.

2.4.2 CPS_2

Since CPS allows areas to benefit from a large |ACE| when ACE x ΔF is negative, a second Control performance standard, CPS_2 is applied to ten minute average ACE. This standard is derived from an interconnection objective:

$$RMS\ \{\Delta F_{10}\} \leq E_{10} \qquad (2.20)$$

Where ΔF_{10} is the ten minute average of F, and 10 is a target bound for the 12 month RMS often minute average interconnection frequency error. This standard is is a rolling 12 month condition to

be met 90% of the time. The CPS_2 standard is based on the dimensionless compliance factor:

$$CF2=1/L_{10*}|ACE_{10}| \qquad (2.21)$$

Where L_{10} is the 10 minute average

$$L_{10} = 1.65\ E_{10} \qquad (2.22)$$

The number L_{10} is the area's average B over the ten minute interval reassessment! The multiplier 1.65 is the statistical conversion factor from a 68.3% confidence limit (1 standard deviation) to a 90% confidence limit. The parameter v relates the size of the area to that of the interconnection.

A derivation of Bi based on fair considerations for electric interconnection is given in (2.22). Thus, if all B values are constant, it is simplifies to:

$$L_{10}=1.65E_{10}\sqrt{}\ (-10Bi)*(-10Bi) \qquad (2.23)$$

For most areas, L_{10} values given by (2.23), using NERC's recommended 10 target for each of the NERC Interconnections, are larger than that of the criterion used earlier(i.e before 1997).

To measure compliance with CPS_2, one first compute the ratio of ten minute interval counts:

$$CPS2=100(1-R) \qquad (2.24)$$

The interval counts in 6 per hour are over one month for reporting purposes, and over rolling twelve month durations for compliance measure. An area fails compliance if CPS_2 is less than 90%.

It should be noted that CPS_2 is insensitive to ACE non-randomness or its coincidence with other ACEs. Hence, the chosen L_{10} values are appropriate only if the coincidence among ACEs does not significantly increase.

3.1 FUZZY CONTROLLER BASED ON CPS

Fuzzy logic rules are designed to manipulate by sugeno type inference system. The proposed control structure is shown in Fig.3. The controller uses information that reflects based with CPS1 and CPS_2 as the inputs to the fuzzy logic rules. Sugeno–style inference is preferred and the typical fuzzy rule is:

If x is A and y is B then z=f(x, y)

where A and B are fuzzy sets in the antecedent and $z = f(x, y)$ is a crisp function in the consequent. Usually, function z is a first-order or a zero-order. According to the optimized rules from the Table 1, the membership functions of CPS_1, CPS_2 could be defined as Fig. 3 Fuzzy rules are summarized.

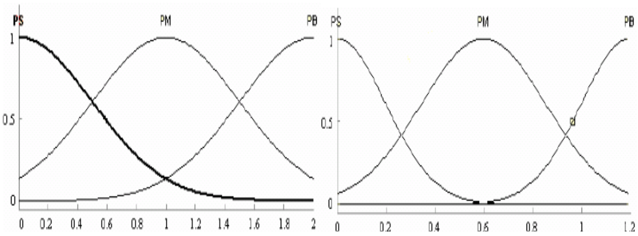

Fig.3. membership functions of input variables CPS_1 and CPS_2

3.2 NEURAL NETWORK FUZZY CONTROL

In the control scheme, neural network is chosen to create the real-time dynamic model of the power system. In accordance with the current controller output u(r), the tie-line power deviation dPtie(r) and the frequency deviation df(r), the neural network is used to predict the next moment's frequency deviation df(r+1), thus calculate the ACE, the ACEN as well as CPS. The predicted CPS_1 and CPS_2 are used as input variables to the fuzzy controller that offers optimal controller parameters.

Elman network is a typical dynamic recurrent neural network whose feedback consists of a group of connected modules and is used to record the implicit memory. Meanwhile, the feedback, along with the network input, acts as the import to hidden units in the next moment. This nature renders recurrent neural network with dynamic memory and thus the capacity to predict future output, which is quite fitful to power system load frequency control.Fig.4 represents the Elman neural network structure in the Load Frequency Control.

The network structure, α (0≤α≤1) is the feedback link gain. The external inputs to the network are the fuzzy controller output u(r) € **R**, the tie-line power deviation dPtie(r) € **R** and frequency deviation df(r) € **R**. The network output is the predicted frequency deviation for the next moment df(r+1) € **R**, in which r is the sampling instant. Let the hidden layer output be x (r+1) € $\mathbf{R}_5$, then:

$$X\,(r+1) = f\,(W_1 \alpha x_c(r) + W_2 u(r) + W_3 dPtie(r) + W_4 df(r)) \quad ...... \quad (2.31)$$

$$Output = df\,(r+1) = g\,(W_5\, x(r+1)) \qquad (2.32)$$

WhereW1, W2, W3, W4 are the weight matrix of connected units to the hidden units and W5 is the weight matrix of hidden units to output unit respectively.
f (•) and g (•) are the nonlinear vector function of the activation function of the hidden layer neural cell and output layer neural cell; xc (r+1) represents
the state at r+1 moment. Here, x(r+1) is the total state of the power system dynamic.

Table: 1 Fuzzy controller for CPS_1 and CPS_2

Cps1 / Cps2	PS	PM	PB
PS	Kp=PB Ki=ZE	Kp=ZE Ki=ZE	Kp=NS Ki=PS
PM	Kp=PB Ki=PS	Kp=ZE Ki=PM	Kp=NS Ki=PM
PB	Kp=PS Ki=PB	Kp=ZE Ki=PB	Kp=NB Ki=PB

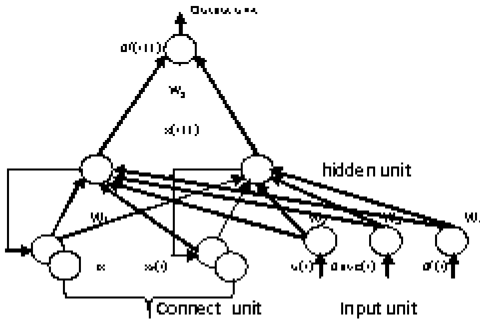

Fig.4. The Elman Neural Network Structure used in The Load Frequency Control.

3c. CONTROL ALGORITHM

The proposed algorithm based on fuzzy neural network method can be summarized as follows:

(1) Set the initial values of the desired frequency deviation df(r) desired ACE(r) and desired ACEN(r) to 0;
(2) Forecast the frequency deviation df(r+1) at the (r+1) moment using recurrent neural network as shown in Fig. 1, resulting the forecasting of ACE(r+1);
(3) Forecast CPS1(r+1) and CPS2(r+1) at the (r+1) moment based on ACE(r+1) and the CPS.

4. SIMULATION RESULTS

Simulation studies were made under the condition that a step load disturbance of 0.01p.u.MW is applied to the area 1. From Fig.5 and Fig 6, the proposed method offers a much better frequency response than that the frequency response of the system with the traditional Integral control. Due to the impact of a random source, the frequency output based on the traditional fuzzy neuro control oscillates constantly with the maximum overshoots being -0.004 and 0.00066.

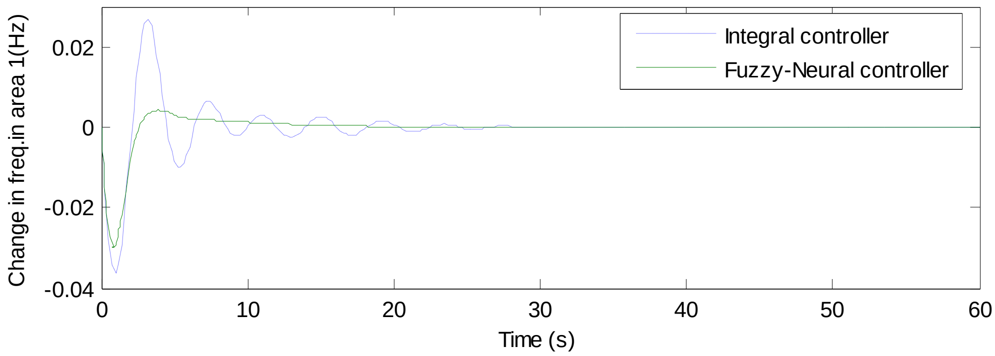

Fig5: Frequency deviations (Hz) of area 1 in a two area interconnected thermal reheat power system-GDB including RFB with integral and neural-fuzzy controller for 1% step load disturbance in area 1

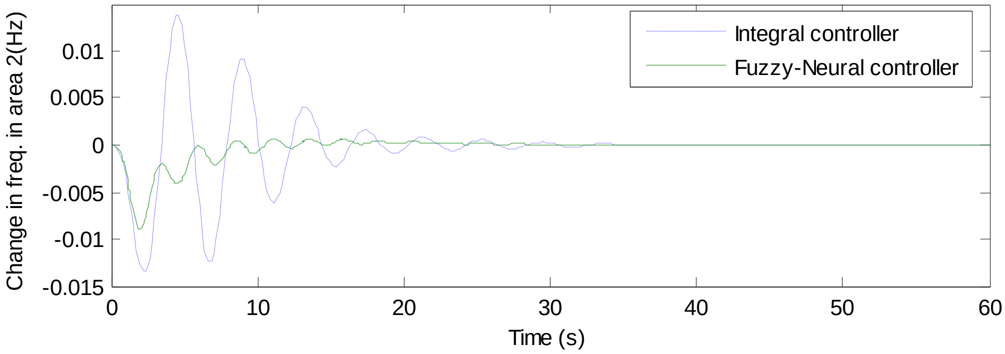

Fig6: Frequency deviations (Hz) of area 2 in a two area interconnected thermal reheat power system-GDB including RFB with integral and neural-fuzzy controller for 1% step load disturbance in area 1

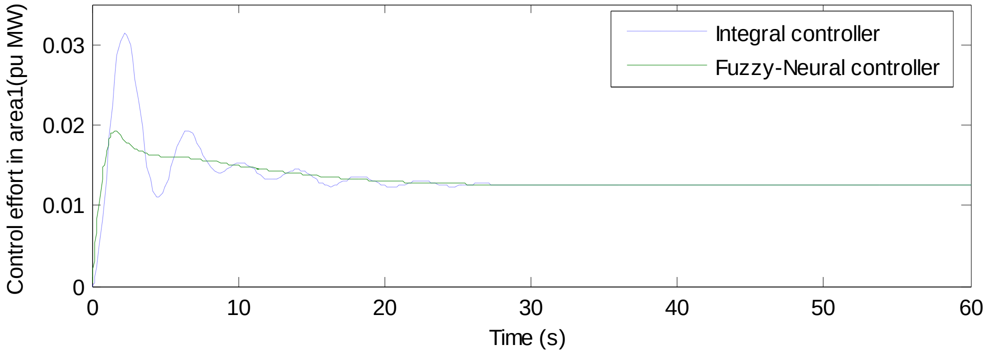

Fig 7: Control effort (p.u mw) of area 1 in a two area interconnected thermal reheat power system GDB Including RFB with integral and neural-fuzzy controller for 1% step load disturbance in area 1

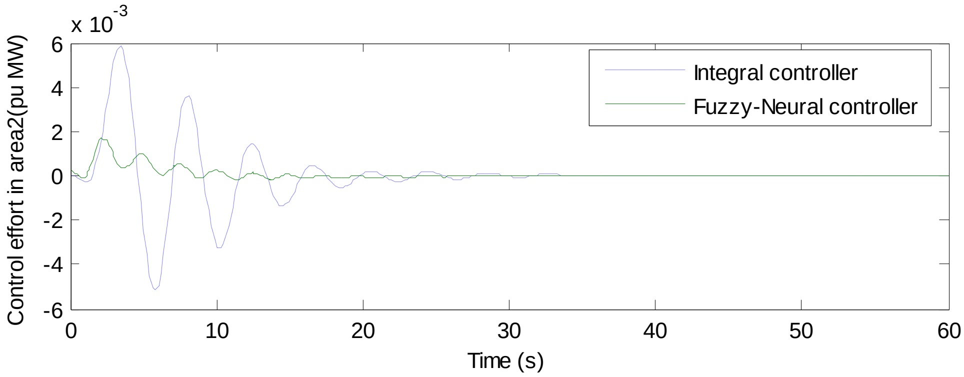

Fig 8: Control effort (p.u mw) of area 2 in a two area interconnected thermal reheat power system GDB Including RFB with integral and neural-fuzzy controller for 1% step load disturbance in area 1

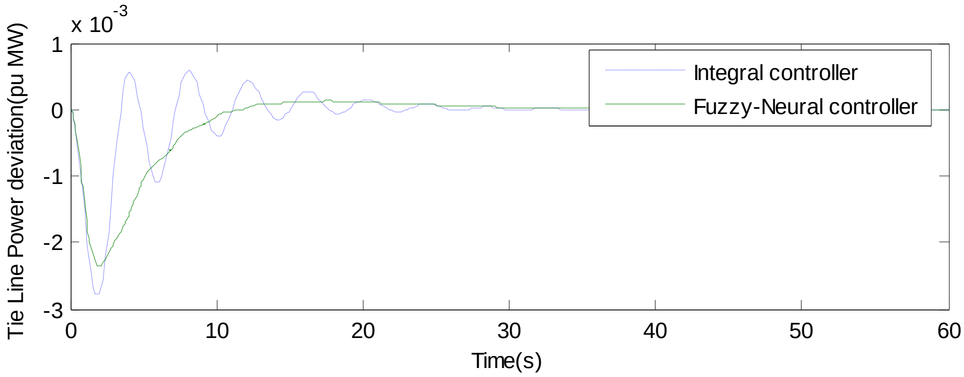

Fig 9: Tie-line power deviation (p.u mw) from area 2 and area 1 in a two area interconnected thermal reheat power system-GDB including RFB with integral and neural-fuzzy controller for 1% step load disturbance in area 1

Table 2.Comparison between Integral and Fuzzy neural controllers for the PowerSystem considering GDB nonlinearity with RFB units

Two area Reheat Interconnected Power system considering GDB non linearity with RFB units	Settling time in seconds				
	ΔF_1	ΔF_2	$\Delta Ptie_{1,2}$	ΔPc_1	ΔPc_2
With Integral controller	34.0	84.72	38.5	40.74	73.4
With fuzzy neural controller	20.3	28.6	33.6	27.48	34.6

From Fig.7 and Fig.8, the control effort under the
NN predictive fuzzy control is much less than that of traditional control, which means wear and tear of generating unit's equipments, is quite reduced. From Fig9, the tie line power is quickly driven to zero and have smaller overshoots using the proposed method. From Fig.5-Fig.9, the neural network prediction fuzzy control can better meet the CPS performance standards in a better way.

5. CONCLUSIONS

In this paper, hybrid fuzzy neural network is proposed to enhance the load frequency control of a two-area power system considering GDB with RFB Units. Fuzzy control strategy was chosen to comply with the NERC's control performance standards, CPS2.

To demonstrate the effectiveness of the proposed method, the control strategy is tested under load perturbation. The simulation results show that the proposed Fuzzy neural controller has better control performance compared to the conventional integral controllers with RFB. In addition, it is effective and can ensure the stability of the overall system for all admissible uncertainties and load changes. The simulation results obtained also show that the performance of fuzzy neural controller is better than that of conventional integral controller against the load perturbation.

6. ACKNOWLEDGEMENT

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List of symbols:

f Frequency
K_p Power system gain
K_r Reheat thermal power system gains
T_r Reheat time constants
T_t Time constant of turbine
X_e Governor valve position
T_g Time constant of governor
P_g Turbine output power
R Regulation parameter
T_{ij} Tie-line synchronizing coefficient
a_{ij} Operator
T_p Power system time constant
P_{ref} The output of ACE
X State vector
A, B State matrices
Δf_i Frequency deviation of area i (i = 1, 2)
NN Neural network
ACE Area control error
RFB Redox flow battery

Appendix

Data for the interconnected two area thermal power system [2, 10].

Rating of each area=2000 MW
Base power=2000 MVA
f = 60 Hz
R_1=R_2= 2.4 Hz/pu MW
T_{g1} = T_{g2}=0.08 sec
Tr_1 = Tr_2=10 sec.
T_{t1} = T_{t2}=0.3 sec.
T_{p1} =T_{p2}= 20 sec
K_{p1} = $K_{p\ 2}$=120 Hz/pu MW
B_1 =B_2= 0.425 pu MW/Hz
T_{12} = 0.545 MW/Hz
ΔP_{d1}=0.01pu MW/HZ
a_{12} = -1.
Krfb=1.8.
Kr_1=kr_2=0.5
N_1=0.8
N_2=-0.2
T=2sec

8. AUTHORS PROFILE

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