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GREY FUZZY CONTROLLER VS PID CONTROLLER: A CASE STUDY

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ABSTRACT
The fuzzy controlled applications are rapidly increasing in industry today due to the easily interpretable form of the controller rule base which makes the tuning procedure more effortless. Two important performance measures i.e., surface roughness (Ra) as a parameter for job quality and material removal rate (MRR) for economic production of the components were optimized. The fuzzy based controller has the properties such as, controlling the overshoot and rise time of the response whereas the conventional controller reduces the steady state error quickly. The grey output is fuzzified into eight membership functions and 27 rules were developed. The highest grey fuzzy reasoning grade (GFRG) obtained. The proposed grey fuzzy logic approach found more effective to evaluate the multiple performance characteristics and simplifies the optimization procedure in optimizing complicated process responses. In this paper, the use of grey relational analysis and the fuzzy-based Taguchi method is used for optimizing the turning process in machining Al-SiCp composites using polycrystalline diamond tool (PCD). In this work a fuzzy hybrid technique is designed to generate the controller action.

Keywords: Fuzzy logic, Grey fuzzy logic, polycrystalline diamond tool (PCD).

1. INTRODUCTION
The grey relational analysis developed based on the grey system theory by Deng (1898) is used for solving the complicated interrelationships among the multiple responses. The fuzzy-based Taguchi method is used to optimize the multi-response process through the settings of process parameters. In fuzzy logic the 'max–min' fuzzy inference and centroid defuzzification methods have been applied for dealing multiple responses. In power systems, natural energy is converted to electrical energy, and thus optimization of electrical equipment is necessary for superior output. It is also required to maintain both the voltage and frequency at a fixed desired value regardless of the change in loads, however, without any control, it is quite impossible to maintain the active and reactive power from varying [Nguyen N., Huang Q., and Dao T.M.P.]. To solve this issue, a control is needed in the system. Researchers have attempted to optimize different machining parameters *viz.*, spindle speed (*N*), feed (*f*) and depth of cut (*d*)on the surface roughness (*Ra*) and material removal rate, tool wear (*VB*), tool life etc. using different optimization techniques such as Taguchi grey relational analysis, fuzzy logic, genetic algorithm, particle swarm optimization etc. In this paper, the use of grey relational analysis and the fuzzy-based Taguchi method is used for optimizing the turning process in machining Al-SiCp composites using polycrystalline diamond tool (PCD). In GRA, the optimization of multiple response characteristics is converted into single grey relational grade.

2. GREY RELATIONAL ANALYSIS
In GRA, the optimization of multiple response characteristics is converted into single grey relational grade. The procedure involves: (i) conversion of experimental data into normalized values, (iii) evaluation of grey relational coefficients and (iv) generating grey relational grading. In this work it is decided to optimize simultaneously *R*a and *MRR*. Experimental data sets based on full factorial design 3^3 =27 data sets are used.

The response values are normalized to Zij (i.e.,0<Zij<1) by using Eq. (1) for smaller the better type and Eq. (2) is used for larger the better type.

…….(1)

Where n = number of replications and y_{ij} = observed response value with i=1, 2, ...,n and j =1, 2,...,k.

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, i=1,2,..n)}{\max(y_{ij}, i=1,2,..n) - \min(y_{ij}, i=1,2,..n)} \quad \text{.........(2)}$$

The grey relational coefficient (Z_{ij}) is expressed as the relation between the ideal best and actual normalized experimental values. It is given by Eq. (3)

$$\xi(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \quad \text{.........(3)}$$

Where i=1,2,….n; k=1,2,…n; Δ_{min} =min$i$ min$j$||x_0(k)-x_i(k)||; Δ_{max}= max$i$ max$j$||x_0(k)-x_i(k)|. The grey relational grade is determined by averaging the grey relational coefficients corresponds to each performance characteristics and it is given by Eq. (4).

$$\alpha_i = \frac{1}{n}\sum_{k=1}^{n} \xi(k) \quad \text{.........(4)}$$

The values of grey relational coefficients and grey relational grade for different experimental runs are presented in Table 1. The optimal factor and its level of combination evaluated as the mean of the grey relational grade for the spindle speed (*N*) at levels 1, 2 and 3 is obtained by averaging the grey relational grade for the experiments 1 to 9, 10 to 18, and 19 to 27 respectively. Similarly, the mean of grey relational grade for *f* and *d* are also evaluated. Table 2 summarizes the result.

The optimum combination is *N*3-*f*2-*d*3, which corresponds to highest GRG value of 0.59, 0.63 and 0.54 respectively for *N*, *f* and *d*. The experimental result of the optimum parameter combination is compared with predicted value. The rank gives important of the parameter among each other. The parameter having highest delta (Max-Min) has top priority and so on. GRG obtained on the basis of grey relational analysis possess some degree of uncertainty in the obtained optimal result and is improved using fuzzy logic. In this work triangular membership function is used to fuzzify the input and output values (Fig.1). The fuzzy grey relational coefficient of *R*a and *MRR* is fuzzified into three sets viz., Low, Medium and High. The output grey fuzzy reasoning grade is fuzzified into eight sets viz., very low, very low, Low, Medium1, Medium 2, High, very high and very high.

Table 1: Response table for grey relational grade

Level	N	f	d
1	0.51	0.54	0.53
2	0.54	0.63	0.54
3	0.59	0.46	0.57
Delta (Max-Min)	0.08	0.17	0.04
Rank	2	1	3
Optimum parameter combination: N3-f2-d3			

3.2 Grey Fuzzy Analysis

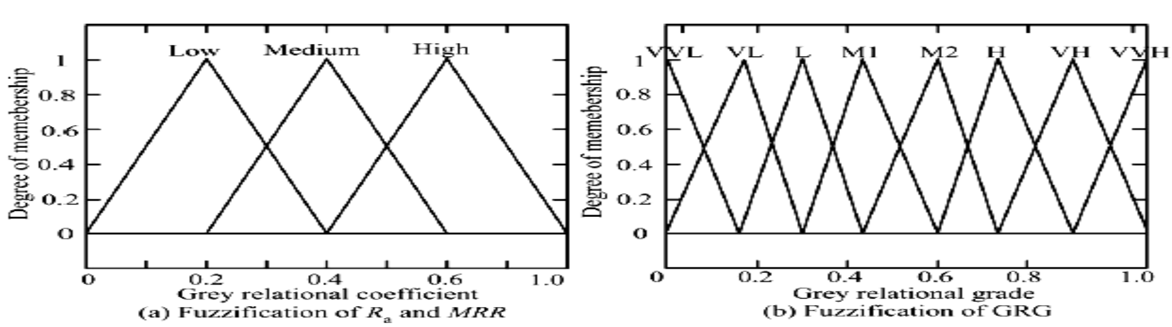

Fig.1 Fuzzification of inputs and output

The set of rules are framed based on 'IF-THEN' statement. The two grey relational coefficients with one multi response output, provide as

$$Rule\ 1: If\ \xi_1\ is\ A_{11} and\ \xi_2\ is\ A_{12}\ \ldots\ldots and\ \xi_n\ is\ A_{1n}\ then\ \eta\ is\ D_1 else$$

$$Rule\ 2: If\ \xi_1\ is\ A_{21} and\ \xi_2\ is\ A_{22}\ \ldots\ldots and\ \xi_n\ is\ A_{2n}\ then\ \eta\ is\ D_2 else$$

$$Rule\ 3: If\ \xi_1\ is\ A_{31} and\ \xi_2\ is\ A_{32}\ \ldots\ldots and\ \xi_n\ is\ A_{3n}\ then\ \eta\ is\ D_3 else$$

:

$$Rule\ n: If\ \xi_1\ is\ A_{n1} and\ \xi_2\ is\ A_{n2}\ \ldots\ldots and\ \xi_n\ is\ A_{nn}\ then\ \eta\ is\ D_n else$$

Here $A_{i1}, A_{i2} \ldots . A_{in}$ and D_i are fuzzy subsets defined by corresponding membership function, i.e., $\mu_A i1$, $\mu_A i2$,……. $\mu_A in$ and $\mu_D i$. The fuzzy multi-response output η is obtained from those above rules by employing the max-min interface operation. Inference results in a fuzzy set with membership function for the multi response output η can be expressed as

$$\mu_{D0}(\eta) = \{\mu_{Ai1}(\xi_1) \wedge \mu_{Ai2}(\xi_2) \wedge \mu_{Ai3}(\xi_3) \wedge \ldots\ldots \mu_{Ain}(\xi_n) \wedge \mu_{Di}(\eta) \ldots \vee \mu_{An1}(\xi_1) \wedge \mu_{An2}(\xi_2) \wedge \mu_{An3}(\xi_3) \wedge \ldots \mu_{Ann}(\xi_n) \wedge \mu_{Di}(\eta)\} \qquad \ldots\ldots\ldots(5)$$

Finally, the fuzzy multi-response output $\mu_{D0}(\eta)$ must be transferred to a non- fuzzy value, η_0 by the calculation of centroid defuzzification method using Eq. (6).

$$\eta_0 = \frac{\sum \eta \mu_{Di}(\eta)}{\sum \eta \mu_0(\eta)} \qquad \ldots\ldots\ldots(6)$$

This non-fuzzy value (D_0) is called the grey fuzzy reasoning grade (GFRG). MATLAB toolbox is used for obtaining the grey fuzzy output. The grey fuzzy reasoning D_0 can handle the optimization of complicate multiple machining responses. Using the value of grey fuzzy reasoning grade μ_{D0}, the relational degree between main factor and other factors is calculated for each response characteristics. The obtained result is verified through confirmation test. Table 2 shows the obtained grey fuzzy reasoning grade from the predicted values of fuzzy inference system (FIS) and its order.

3. FUZZY PD+I HYBRID CONTROLLER FOR LOAD FREQUENCY CONTROL

This makes the hybrid control actions quite suitable for the LFC. Initially, the hybrid approach is tested on a single area LFC for two turbine types i.e., non-reheated and reheated and then it is extended to multi-area cases. It is observed that the proposed controller displays better robustness toward ±50% parametric uncertainty and disturbance rejection capability as compared to the existing techniques.

Monitoring and controlling the real power generated within specified limits in response to changes in system frequency and tie-line power interchange is known as load frequency control (LFC). The key role of LFC is to retain the frequency at a desired constant value against the fluctuating active power loads. Several units make up an interconnected power system in a large-scale power system and therefore both constant frequency and constant tie-line power exchange should be provided for the stable operation of power systems. Moreover, numerous control techniques have been proposed to address the LFC over the past decade (Yakine Kouba N.E.L., Menaa M., Hasni M., and Boudour M.). These include using genetic algorithm, differential evolution, fuzzy controller, hybrid evolutionary fuzzy PI controller, bacteria foraging optimization algorithm. Recently, unified IMC PID tuning (Ali E.S. and Abd-Elazim S.M., 2011) and new control scheme using Laurent series (Panda S., Mohanty B., and Hota P.K., 2013) have presented to improve the load disturbance rejection performance. Certainly, PI/PID controllers for LFC were studied due to their simplicity in execution. References (Sahu R.K., Panda S. et.al.), suggested adaptive fuzzy or neural base controllers for load frequency control of power systems. It has been proved in literature to reveal the fact that fuzzy logic may at times be a better approach in designing controllers for various systems over the classical linear PID controllers as it has been verified for its robustness and being less sensitive to parametric variations. A new Fuzzy PD plus I (FPD+I) hybrid controller is presented, the mixture of a fuzzy logic controller and a conventional controller. In this way, the fuzzy based PD action plays a significant role in controlling the rise time and overshoot of the response whereas the conventional integral action reduces the steady state error quickly.

4. SINGLE AREA POWER SYSTEM MODEL

The main aim of power systems is to generate and supply power to its customers. In the case of the LFC, the power system considered is taken to have little variations in the load. Thus, this could appropriately be demonstrated by the linear model and so linearizing around the operating point. Moving on, a single area power system contains a turbine, load and machines, a governor and also droop characteristics (a kind of feedback gain included in the power system that improves the damping properties). Fig. 2 shows a single area power system as a linear model (Ali E.S. and Abd-Elazim S.M., 2011), where a single generator is used to supply power to a single area. Table 2 shows the nomenclature of the various parameters being used in the system. The transfer function model with droop characteristics of the overall system can be represented as (Ali E.S. and Abd-Elazim S.M., 2011):

$$G(s) = \frac{G_g(s)G_t(s)G_p(s)}{1 + G_g(s)G_t(s)G_p(s)/R}$$

Where $\frac{1}{R} = droop\ characteristics,$

$G_g(s) = Governor\ dynamics = \frac{1}{T_G s+1}.$

Case- 1: Non-reheated turbine: $G_t(s) = \frac{1}{T_t s+1}.$

Case -2: Reheated turbine: $G_t(s) = \frac{cT_t s+1}{(T_t s+1)(T_l s+1)}.$

$G_p(s) = Load\ and\ machine\ dynamics := \frac{K_p}{(T_p s+1)}.$

After substituting (2–5) in the system model (7), one can obtain the model as:

$$G(s) = \frac{K_p}{(T_p s+1)(T_T s+1)(T_G s+1)+K_p/R} \qquad \text{…………(7)}$$

Hydro turbine or a steam turbine might have been used as the type of turbine in the system. Two types of steam turbine are considered in this current work, Reheat Turbine (RT) and Non-Reheat Turbine (NRT). LetâŁ™s take into consideration a power system with a NRT and a RT proposed in (Ali E.S. and Abd-Elazim S.M., 2011). The model parameters are:

1. $Non-Reheated\ Turbine$: $K_p = 120, T_p = 20, T_T = 0.3, T_G = 0.08, R = 2.4.$

1. $Reheated\ Turbine$: $K_p = 120, T_p = 20, T_T = 0.3, T_G = 0.08, R = 2.4, T_r = 4.2, c = 0.35.$

5. FUZZY PD + I HYBRID DESIGN

In this section, the new Fuzzy PD plus I (FPD+I) controller technique is illustrated. Let's take first the linear conventional PID in parallel form and its transfer function written as:

$$C(s) = \frac{U(s)}{E(s)} = K_c + \frac{K_i}{s} + K_d s$$

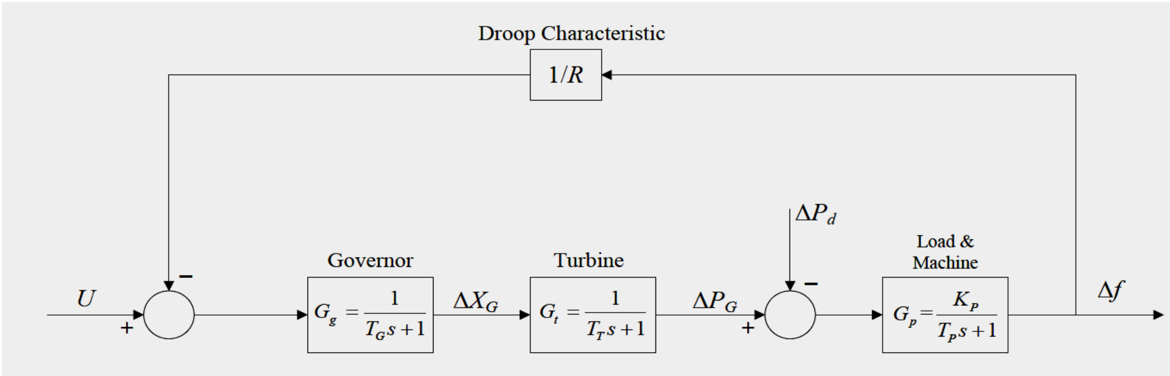

Fig. 2 A single area power system

Where K_c, K_i and K_d are the proportional, integral and derivative gains respectively.

This can be written in a continuous time domain is:

$$U(t) = K_c + K_i \int_0^t E(t)dt + K_d \frac{dE(t)}{dt}$$

The proposed technique of hybrid controller maintains the same linear structure of the PID parts; however, it contains constant coefficient yet self-tuned control gains. The scheme consists of fuzzy logic but is included only for the design as the fuzzy rule base does nâŁ™t need to be executed, and thus, it is in fact a conventional PID controller with analytic formulas.

6. OPTIMAL PID GAINS BASED ON CONSTRAINT

Many different approaches exist to find the optimal PID gains. The simplest way deals with the use of open-loop transfer function for guaranteed robust performance. Wang and Shao have proposed a robustness index λ such that the Nyquist curve of the loop transfer function is tangent to a line parallel to the imaginary axis in the left-half of the complex plane and it is defined as:

$$\frac{1}{\lambda} = \max_{0\le\omega\le\infty} |Re[C(j\omega)G(j\omega)|$$

Where: the quantity λ is simply the inverse of maximum of absolute real part of loop transfer function. Based on the constraint imposed on the integrated error criterion, the optimal controller tuning formulae are suggested as

$$K_c = \frac{1}{\lambda\alpha'(\omega_{90})}\left(\frac{\beta'(\omega_{90})}{\beta(\omega_{90})} - \frac{1}{\omega_{90}}\right)$$

$$K_i = -\frac{\omega_{90}}{\lambda\beta(\omega_{90})}$$

If these tuning rules are extended using standard relation of integral and derivative gain constants, one can derive relation for derivative gain as:

$$K_d = \frac{K_c^2}{4K_i}$$

Here, $\alpha_{(\omega 90)}$ and $\beta_{(\omega 90)}$ are the real and imaginary parts of the process transfer $G(j\omega)$. The frequency $\omega 90$ is the point when the Nyquist curve touches the imaginary axis.

7. TRANSFERRING GAINS FROM PID TO FUZZY

The aim is to transfer optimal values of the linear PID gains to the nonlinear fuzzy controller. In this control technique, a fuzzy logic controller for proportional-derivative actions and a conventional controller for integral action are combined in the FPD+I controller. Input of FPD has the error *(E)* and the change in error *(DE)*, as shown in Fig.3. In crisp PD terms, it is also called derivative of the error.

Now, the nonlinear fuzzy function gives the controller output from inputs, *error* and *change in error* as:

$$U_n = [f(GP * e_n, GD * de_n)] * GU$$

By adding an integral action as shown in Fig.3, the overall controller output can be written as:

$$U = [f(GP * e_n, GD * de_n)] * GU + GI * ie_n$$

Using linear approximation as suggested in given equation, the controller output is obtained as:

$$U = [(GP * e_n + GD * de_n)] * GU + GI * ie_n$$

$$= [(GP * GU * e_n + GD * GU * de_n)] + GI * ie_n$$

It is assumed to be non-zero GU and after comparing (8) and (13), the controller gains are related in the following way:

$$GP = \frac{K_c}{GU}, GD = \frac{K_d}{GU}, GI = K_i$$

In order to obtain a kind of nonlinear fuzzy advantage, the internal structure of fuzzy controller is designed as described below.

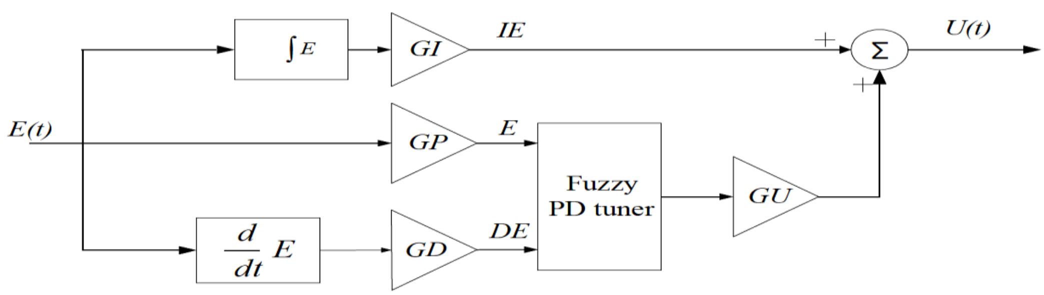

Fig.3 Controller structure Fuzzy PD plus I

8. DESIGNING NONLINEAR FUZZY PD ACTION

The FPD controller used in this paper has a standard structure, consisting of a Fuzzy Rule Base (FRB), Parameter Base (PB) and a Computational Unit (CU) that performs the following three basic operations: Fuzzyfication, Fuzzy Inference and Defuzification. The Parameter Base contains the parameters of all predefined Membership Functions for both inputs of the FPD, namely: the Error and Change-of-Error. Here, equal number of 7 membership functions is assumed to represent the respective Linguistic Variables for both inputs, as follows: Negative Large (NL), Negative Medium (NM), Negative Small (NS), Positive Small (PS), Zero (ZR), Positive Medium (PM) and Positive Large (PL). As for the centers of the membership functions they have been predefined to be located at equal distances within the normalized range [−1, +1] for the Error and Change of the Error, as follows:

NL at −1.0; *NM* at −0.66; *NS* at −0.33; *ZR* at 0.0; *PS*at +0.33; *PM* at +0.66 and *PL* at +1.0.

All pairs of neighboring membership functions, for example: *NL* and *NM*, *ZR* and *PS*, *PS* and *PL* etc. have maximal overlapping value of 0.5 at their cross point and they do not overlap with any other (not neighboring) membership functions.

In general, the fuzzy rules of the Mamdani-type fuzzy controller (Deng, J.L. *etal.* 1989 & Huang, Y.P. *etal.* 1996)have the following entirely linguistic structure:

IF (*Error* is {*LV*} and *Change-of-Error* is {*LV*}) THEN Change-of-Output is {*LV*}

Here {*LV*} represents a linguistic variable taken from the predefined list of linguistic variables for the *Error, Change-of-Error and Change-of-Output*.

In this paper, the Takagi-Sugeno-type (TS) fuzzy controller (Giménez, A.J. *etal.* 2014) is used, which differs from Mamdani-type controller in the *consequent* part of the rules, namely that they are now represented not linguistically, but by crisp numerical values,

Table 2: The Fuzzy Rule Base of the proposed FPD+I controller

Change of Error	PL	ZR	PS	PS	PM	PL	PL	PL
	PM	NS	ZR	PS	PM	PM	PM	PL
	PS	NM	NS	ZR	PS	PS	PM	PL
	ZR	NL	NM	NS	ZR	PS	PM	PL
	NS	NL	NM	NS	NS	ZR	PS	PM
	NM	NL	NM	NM	NM	NS	ZR	PS
	NL	NL	NL	NL	NM	NS	NS	ZR
Error		NL	NM	NS	ZR	PS	PM	PL

known as *singletons* (Giménez, A.J. *etal.* 2014). The following values for all 7 singletons in the proposed FPD+I controller have been assumed: *NL* is −1.0; *NM* is −0.66; *NS* is −0.33; *ZR* is 0.0; *PS* is +0.33; *PM* is 0.66 and *PL* is +1.0. Under the above design assumptions, the fuzzy rule base of the FPD+I controller consists of 7 × 7 = 49 fuzzy rules. They have been created in the form of linguistic decisions about the amount of the *change-of-output* of the controller for each combination of *Error* and *Change-of-Error*. These are common-sense decisions that a control engineer would make for each situation, based on his previous control experience. The FRB for the proposed FPD+I controller is given in Table 3. The number of all internal parameters of FPD+I controller that should be tuned for its optimal performance is usually large and grows rapidly with increasing the number of the membership functions that are used in generating the fuzzy rules in the FRM.

In order to optimize all these 21 parameters, a reliable optimization method and algorithm is needed that is able to find the global optimum, without being stalled at some of the numerous local optimums. The solution of this task goes beyond the scope of this paper.

9. SIMULATION RESULTS FOR SINGLE AREA SYSTEM

The simulation results obtained for both nominal and uncertain cases are presented for the proposed FPD+I hybrid controller. Table 4 shows the FPD+I controller parameters settings for all types of turbines models. It is seen that the hybrid technique, in both the types of turbines, provide an improved response for the nominal and for the uncertain case.

Table 3: Controller settings for single area system

Power system models	**FPD+I settings with GU=10**
NRTWD	GP=0.20, GD=0.14, GI=1.67
NRTD	GP=0.20, GD=0.06, GI=1.67
RTWD	GP=0.76, GD=0.49, GI=5.85
RTD	GP=0.60, GD=0.24, GI=2.14

NRTWD: Non-Reheat Turbine Without Droop, NRTD: Non-Reheat Turbine with Droop,

RTWD: Reheat Turbine Without Droop, RTD: Reheat Turbine with Droop.

Hence it is evident that the new FPD+I controller at present achieves much greater compared to the other methods. To examine the robustness of the FPD+I controller, the parameter variations of the system are taken as ±50% of their nominal values. In this case also, parametric uncertainty is included in the system, together with a 0.1 disturbance at time 1 s. It is observed from Figs. 4 and 5 that the suggested hybrid controller has a better performance in disturbance rejection as compared to the existing techniques under uncertain environment. Likewise, similar results were achieved for the Reheated Turbine power system. Figs. 6 and 7 shows the responses attained for the Reheated Turbine with and without droop for nominal along with uncertain cases. It is evident from the results obtained through simulation that the characteristics of the FPD+I controller enables it to be reliable and appropriate for the LFC.

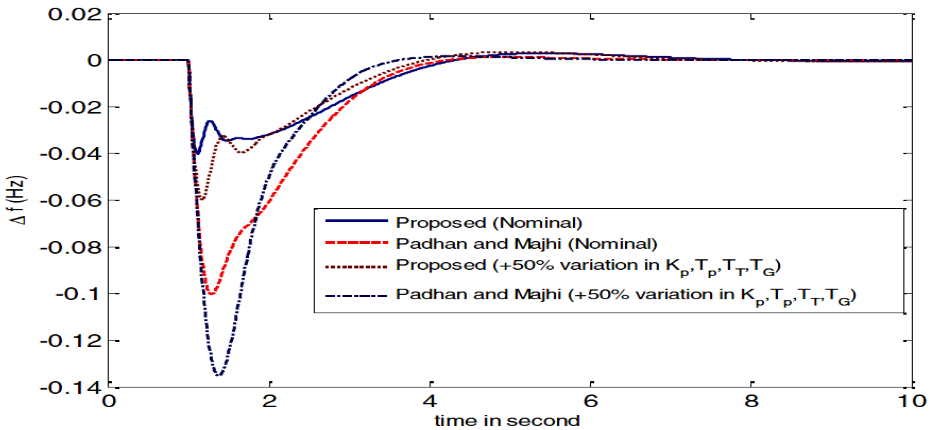

Fig.4 Frequency deviation for NRTWD

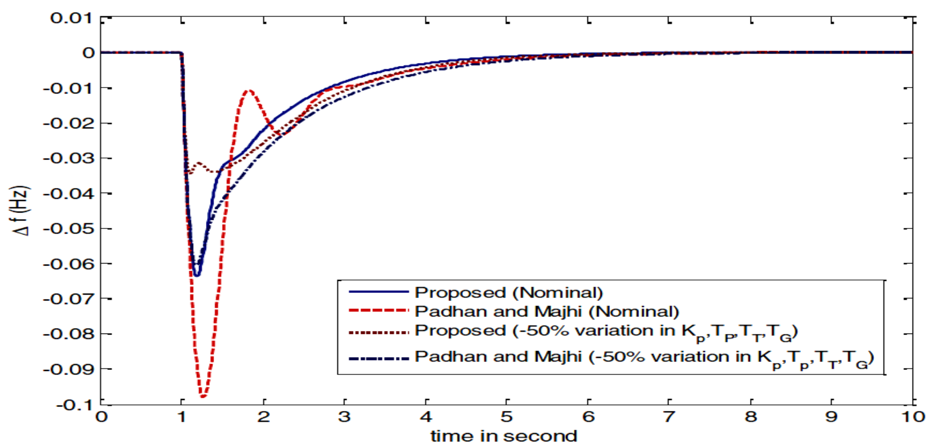

Fig.5 Frequency deviation for NRTD

10. CONTROL OF MULTI-AREA POWER SYSTEM

Areas interconnected by means of high voltage transmission lines or tie-lines are referred to as a multi-area power systemThe main goal of a decentralized LFC is to reduce the transient deviations of such variables and to make certain that their steady state errors become zero. Unpredicted external disturbances along with parameter and model uncertainties pose a huge challenge in designing the controller when operating with the LFC problem of power systems. For *N* control areas (Fig. 8), the total tie-line power change between area1 and other areas is given as:

$$\Delta P_{tiei} = \sum_{j=1,j\neq i}^{N} \Delta P_{tieij} = \frac{1}{s}\left[\sum_{j=1,j\neq i}^{N} T_{ij}\Delta f_i - \sum_{j=1,j\neq i}^{N} T_{ij}\Delta f_j\right]$$

By means of identifying the frequency and tie-line power deviations to generate the ACE signal, the steadiness amongst

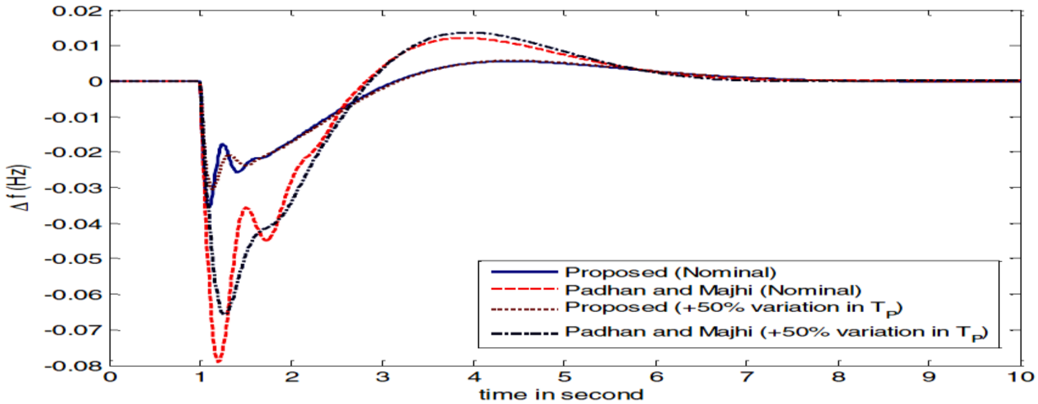

Fig.6 Frequency deviation for RTWD

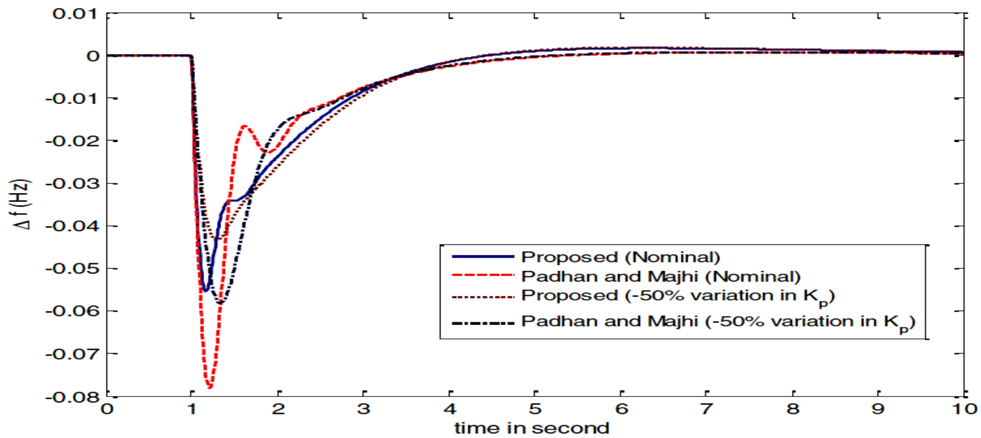

Fig.7 Frequency deviation for RTD

Adding on, linear combination of tie-line

$$ACE_i = B_i \Delta f_i + \Delta P_{tiei}$$

The Load Frequency Control system in each control area of an interconnected (multi-area) power system should control the interchange power with the other control areas along with its local frequency. The generalized system transfer function for multi-area power system is given by:

$$G_i(s) = B_i \frac{G_{gi}(s)G_{ti}(s)G_{pi}(s)}{1 + G_{gi}(s)G_{ti}(s)G_{pi}(s)/R_i}$$

Now, the FPD+I hybrid controller can be designed based on the individual area's transfer function in (Chang C. *etal.* 1997).

11. SIMULATION RESULTS FOR 4 AREA POWER SYSTEM

Fig. 9 shows a simplified 4 area interconnected power system that was taken for this study. LetâŁ™s consider the interconnected four area power system with one NRT and three RT studied in (Padhan, D.G. *etal.* 2012).

The model parameters are:

1. Area 1,2 and 3 reheated turbines: $K_{p1} = K_{p2} = K_{p3} = 120, T_{p1} = T_{p2} = T_{p3} = 20, T_{T1} = T_{T2} = T_{T3} = 0.3, T_{G1} = T_{G2} = T_{G3} = 0.2, R_1 = R_2 = R_3 = 2.4, T_{r1} = T_{r2} = T_{r3} = 20, c_1 = c_2 = c_3 = 0.333.$

2. Area 4 non − reheated turbine: $K_{p4} = 120, T_{p4} = 20, T_{T4} = 0.3, T_{G43} = 0.2, R_4 = 2.4$

3. Synchronizing constants: $T_{ij} = 0.0707$

4. Frequency bias constant: $B_i = 0.425$

The above parameter shows the proposed hybrid FPD+I controller settings for individual control area. For the same power system example Padhan and Majhi gave the PID controller settings for area 1, area 2 and area 3 as $K_c = 1.1895$, $T_i = 1.9090$ and $T_d = 0.5454$ and for area 4 as $K_c = 1.9822$, $T_i = 0.5242$ and $T_d = 0.1756$.

To prove the effectiveness of the hybrid control scheme, a step load _*Pd*1 = 0.03 is applied to area 1 at *t* = 20 s, followed by a step load _*Pd*2 = 0.05 is applied to area 2 at *t* = 100 s, followed by a step load _*Pd*4 = 0.01 is applied to area 4 at *t* = 200 s. The simulations have been conducted for two types of controllers following small step changes in areas 1, 2 and 4 and the results for frequency changes are shown in Figs. 10 to 13.

The results clearly show the advantage of using the new hybrid FPD+I controller. Upon simulation of the results, it can be observed that the frequency errors and tie-line power

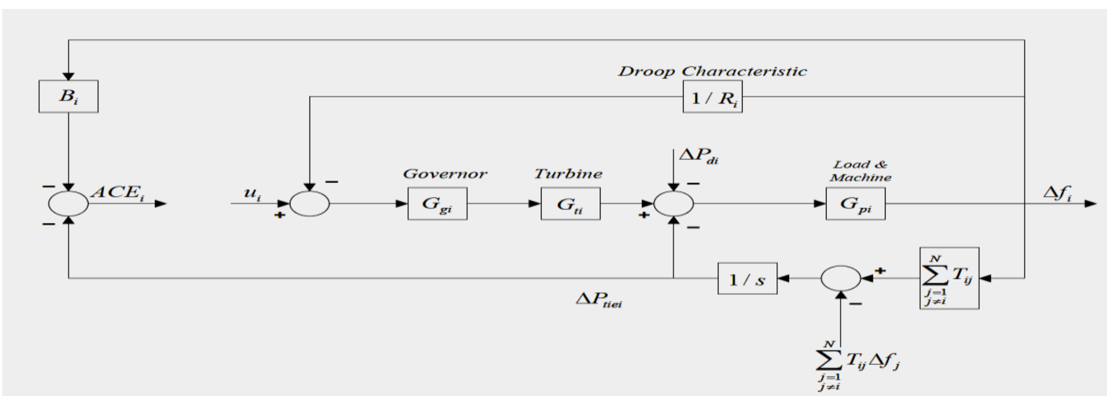

Fig.8 Block diagram representation of control area *i*

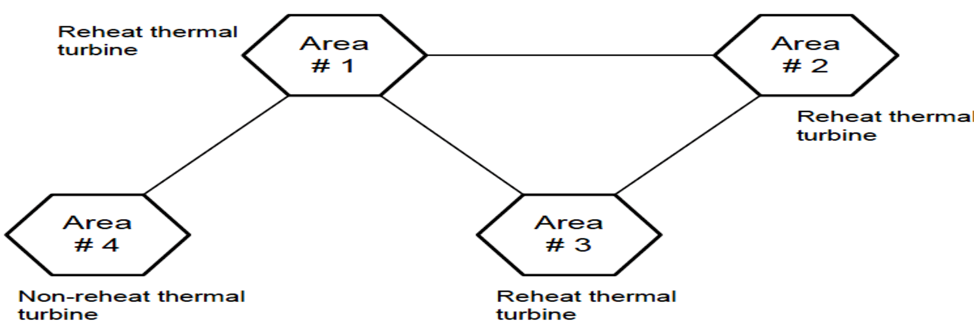

Fig.9 Simplified interconnected power system diagram

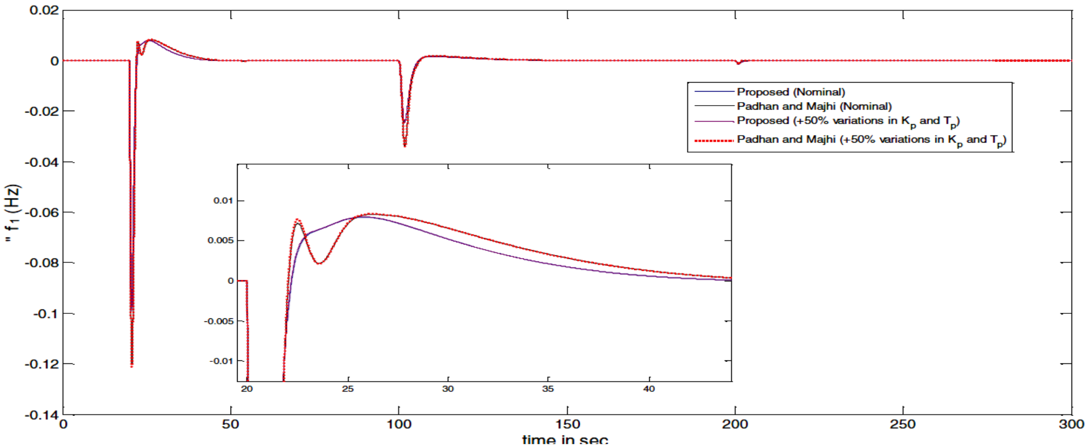

Fig.10 Frequency deviation in area 1 following a small change in loads *ΔPdi*

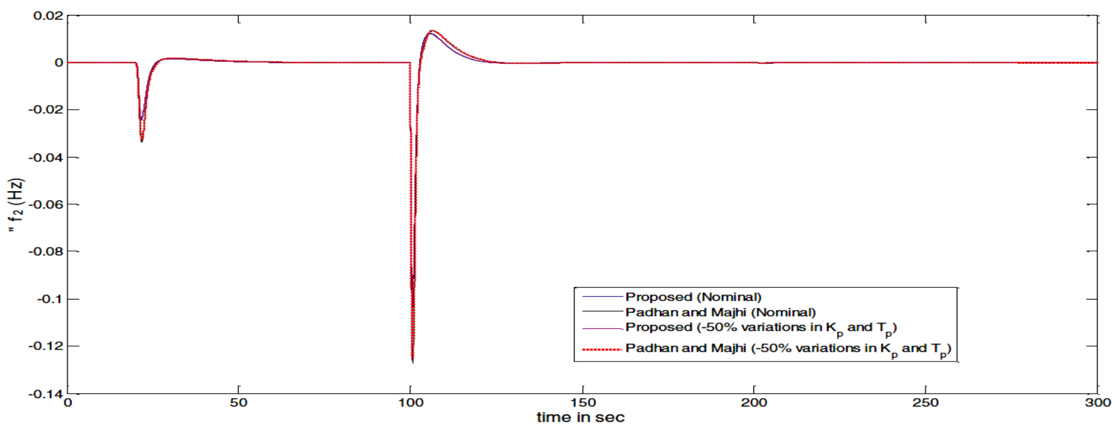

Fig.11 Frequency deviation in area 2 following a small change in loads *ΔPdi*

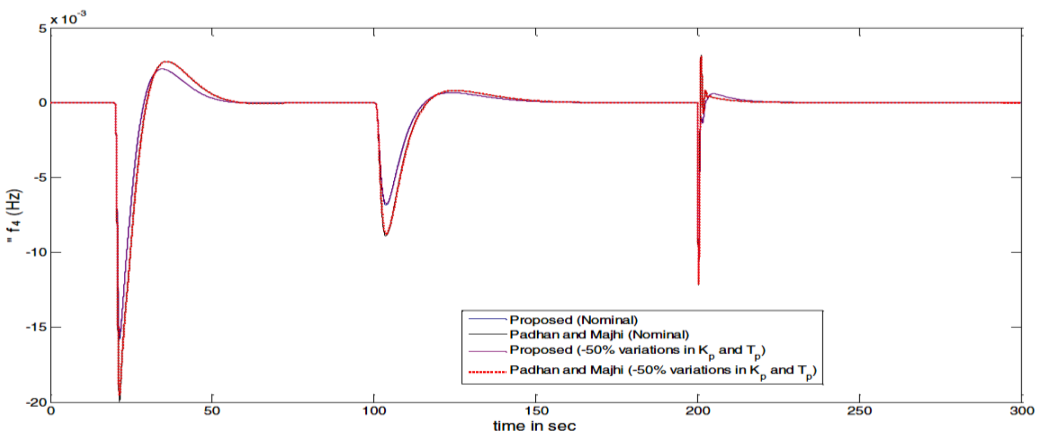

Fig.12 Frequency deviation in area 3 following a small change in loads *ΔPdi*

Table 4 Controller settings for four area system

Power system	**FPD+I settings with GU=10**
Area 1,2 and 3	GP=0.17, GD=0.10, GI=0.85
Area 4	GP=0.20, GD=0.04, GI=2.00

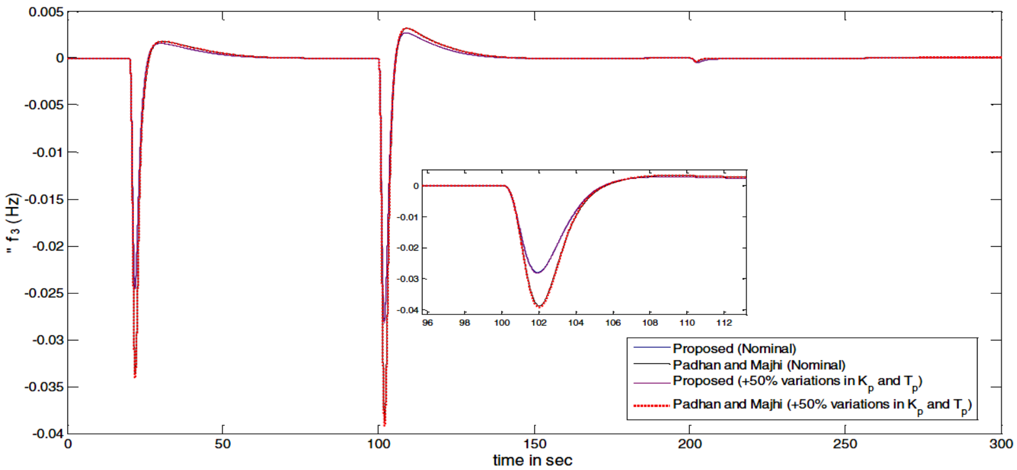

Fig.13 Frequency deviation in area 4 following a small change in loads *ΔPdi*

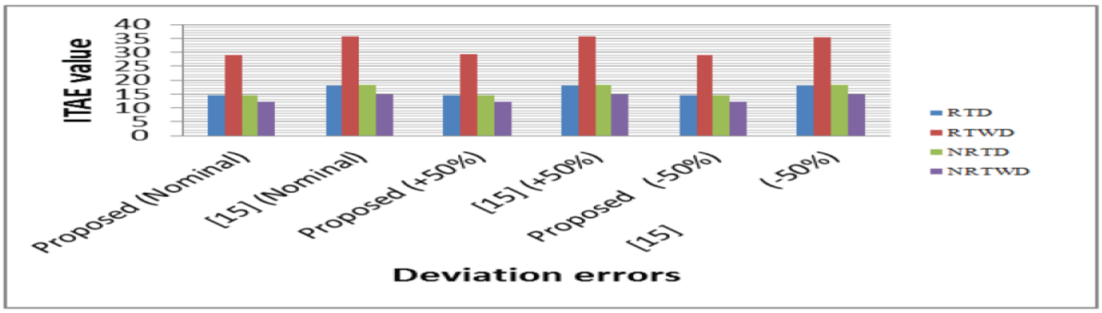

Fig.14 Frequency deviation errors (ITAE) in different areas

From Fig.14, it can be revealed that the presented hybrid controller gives less frequency deviations compared to the method in (Padhan, D.G. *etal.* 2012) for both nominal and perturbed systems.

12. CONCLUSION

A hybrid configuration for PID type controller has been presented, implemented and examined which will improve the performance of the conventional PID approach. The characteristic of LFC in a single-area power system consisting of reheat and non-reheat turbine has been examined. The designing of the new hybrid controller based on fuzzy logic theory is simple to implement and verify. The results have shown that the suggested design has a better performance and is robust than the recently reported approaches. The proposed optimization procedure found more effective for evaluating the multiple performance characteristics and significantly improve the economic production of quality components in turning Al/SiCp metal matrix composites.

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