

Determination of Optimal PI Gains For Fuzzy-PI Controller Using Bacterial Foraging Algorithm (BFA)

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Abstract: This Paper Presents A Method Of Obtaining Optimal Pi Gains For A Fuzzy-Pi Controller To Control The Frequency Of Micro Hydro Power Plant (Mhpp). Conventional Control Techniques Such As Proportional, Integral And Derivative (Pid) Controllers Have Been Used As Controllers To Control The Frequency Of Mhpp, But These Controllers Attain Poor Control Performances, Such As High Overshoots And Long Settling Times. The Purpose Of The Study Is To Obtain Optimal Pi Gains For A Fuzzy-Pi Controller By Use Of The Bacterial Foraging Algorithm (Bfa) In Matlab/Simulink Environment. The Results Are Then Compared With Conventional Pi And Fuzzy-Pi Controller. This Is To Verify Which Controller Give The Best Control Performance (Pi Gains) In Terms Of Overshoot And Settling Time. It Is Shown That The Optimised Fuzzy-Pi Controller Is Superior In Terms Of Overshoot And Settling Time. This Clearly Depicts That Using Intelligent Techniques Such As Fuzzy Logic And Optimizing The Membership Functions Using Stochastic Optimization Algorithms Can Greatly Improve The Control Performance In The Frequency Control Of Mhpp.

Keyword: Pi, Fuzzy-Pi, Bfa, Mhpp, Frequency, Synchronous Generator

I. Introduction

PI controllers are commonly used infrequency control of Micro Hydro Power Plants (MHPPs). This is because of their various merits: They can be easily understood by plant operators, they have near optimal performance, they can be applied in a wide range of application and are relatively low in cost [1]. PI controllers are widely used in most applications due to the inherent stability of proportional controller and the steady state error elimination ability of integral controller. PI controllers can be tuned using various methods such as Ziegler-Nichols method. However, the drawbacks of using PI controllers are that they require frequent tuning and give poor performance for systems which are nonlinear or subject to disturbances [2],[3].

In this paper, optimal PI gains are determined to control the frequency of MHPP. In the determination of the optimal PI Gains, a fuzzy-PI controller is first designed. The peaks of the fuzzy membership functions are then optimized using Bacterial Foraging Algorithm (BFA), an optimization algorithm inspired by the social foraging behavior of Escherichia Coli bacteria present in the human intestine. This optimization algorithm has proven to be superior over the other optimization algorithms such as genetic algorithm, particle swarm optimization etc. in terms of faster convergence speed to global optimal solution, better response and less computational time requirement. [4], [5],[6].

II. Transfer Function for the MHPP

Micro-hydro is the small scale harnessing of energy from falling water such as steeped mountain rivers generating typically less than 100 kW using the run-off-river type flow of water hence it does not require the construction of expensive dams. For experimental purposes, the MHPP is a 3-phase synchronous generator of the following specifications: 350 VA, 415V, 50 Hz, 3000 rpm, 2-pole. The synchronous generator is by definition synchronous, meaning that the electrical frequency produced is locked in or synchronized with mechanical rate of rotation with the generator [7]. The frequency of the generated voltage is dependent on the speed of rotation of the rotor and the number of poles of the machine as given by (1).

$$F_e = \frac{n_m P}{120} \quad (1)$$

where F_e = electrical frequency (Hz), n_m = mechanical speed of magnetic field, and P = number of poles.

From the swing equation and the synchronous generator rotor mechanical model, the closed-loop transfer function relating the output and the input of the synchronous generator is modelled as shown in (2) [7].

$$G(s) = \frac{Y(s)}{U(s)} = \frac{\Delta \omega}{T_m - T_e} = \frac{1}{2Hs + D} \quad (2)$$

where, H = inertial constant, and D = damping constant.

The H and D parameters for our synchronous generator are calculated to be 0.038 and 1.3 respectively.

III. Simulation of the Conventional PI Controller

A PI controller is the most commonly used feedback controller. In essence, PI controller calculate the error values as a difference between measured and desired set point. The controller attempts to minimize error the by adjusting the process control inputs. The proportional part is responsible for following the desired set-point, while the integral part account for the accumulation of past errors. The PI controller is described by the following transfer function in continuous s-domain as shown in (3).

$$G(s) = K_p + \frac{K_i}{s} \quad (3)$$

A conventional PI controller is simulated for the MHPP with a unit step as reference and PI block in MATLAB/SIMULINK as shown in Fig. 1. The initial gains of the PI controller are calculated to be $K_p = 0.22$ and $K_i = 30.4$ respectively.

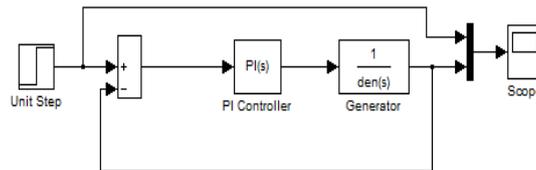


Figure1: Conventional PI Controller

IV. Design and Simulation of Fuzzy-PI Controller

The block diagram of the designed Fuzzy-PI controller is shown in Fig. 2. It basically measures the system output (y) and then calculates error (e) and change in error (Δe) based on y and the input (r). The fuzzy controller then tunes the PI parameters using the fuzzy control rules in order that the synchronous generator achieves better dynamic PI performance in different situations. This is necessary since the fixed gains of the conventional PI controllers are not suitable for isolated MHPP due to its nonlinear nature [8].

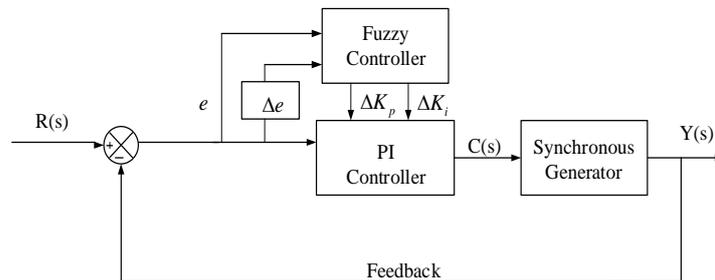


Figure 2: Block Diagram of the Fuzzy-PI Controller

Triangular membership function with seven partitions is used for the design of the Fuzzy PI controller because of its simple formulae and computational efficiency. In the design, two inputs to the fuzzy controller named the error (e) and change in error (Δe) and two outputs named change in K_p (ΔK_p) and change in K_i (ΔK_i) are used. The input and output variables are fuzzified into seven triangular membership functions as shown in Fig. 3 and Fig. 4 respectively. where NB = Negative Big, NM= Negative Medium, NS= Negative Small, Z= Zero, PS= Positive Small, PM= Positive Medium, PB= Positive Big. The ranges of input variables e and Δe are 49.5 to 50.5 and -10 to 10 respectively.

The ranges of output variable ΔK_p and ΔK_i of the controller are 0 to 0.1 and 0 to 5 respectively.

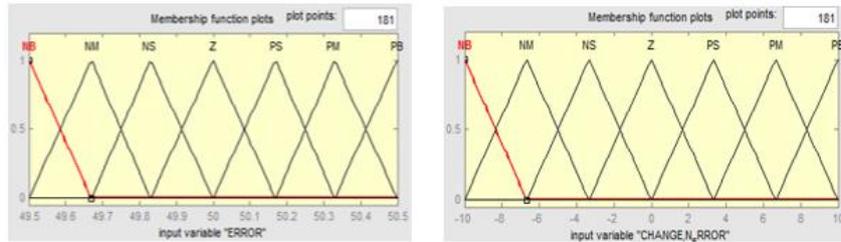


Figure 3: Membership Functions for the Inputs e and Δe

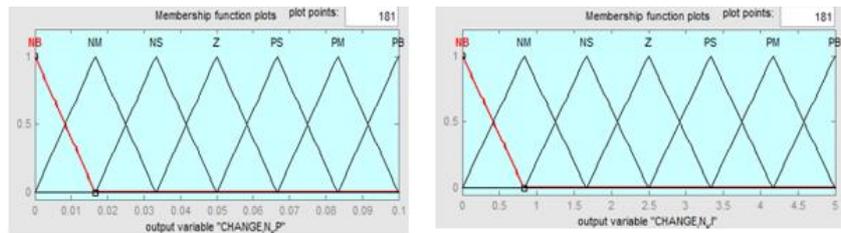


Figure 4: Membership Functions for the Outputs ΔK_p and ΔK_i

The fuzzy inference system used is Mamdani fuzzy inference system. The fuzzy control rules of the fuzzy-PI controller are written based on the control approach of the PI controller. The operation of the PI controller is such that the K_p provides the control action effectively when the error is more and K_i delivers efficiently when the system is operating near the set point value [3]. This means that K_p must be maximum when the error is large and should start varying to the minimum when the system is near the set point. The K_i is varied such that its value will be minimum when the system operates away from the set point and attains maximum value when it operates near to the set point[3], [9], [10].

With the input variables having seven memberships functions, the total number of rules for the output variables are $7^2 = 49$ rules. The rules are in the if-then format as illustrated below.

- If error is NB and change in error is NB, then ΔK_p is PB and ΔK_i is NB
- If error is Z and change in error is Z, then ΔK_p is Z and ΔK_i is Z
- If error is PM and change in error is PM, then ΔK_p is NM and ΔK_i is PM

With these analogy, the control rules for the input and output variables are shown in Fig. 5. The center of gravity defuzzification method is applied to obtain crisp output.

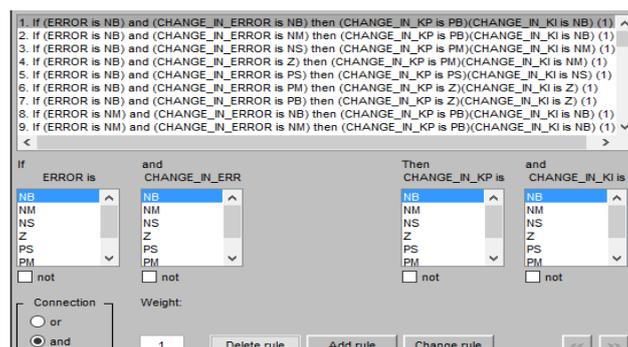


Figure 5: Fuzzy Rule Editor for Input and Output Variables

A. Tuning the Fuzzy-PI Controller

Generally, the purpose of tuning the gains of the PI controller is to adjust the control parameters K_p and K_i to the optimum values for the attainment of desired control response. The final K_p and K_i values for the Fuzzy-PI controller are determined using the simulation model shown in Fig. 6.

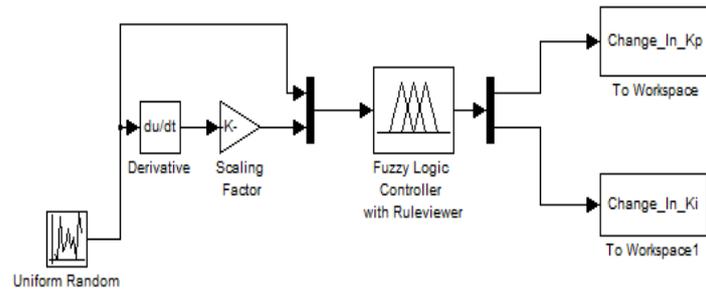


Figure 6: Simulation Model of the Fuzzy-PI Controller

To mimic the dynamic behaviour of the MHPP, the system is simulated using a random number generator producing values between 49.5 and 50.5 which is the frequency tolerance for the Kenya power grid [11]. The fuzzy controller inputs are e and Δe . The outputs are ΔK_p and ΔK_i . The final values are $\Delta K_p = 0.3906$ and $\Delta K_i = 2.4739$ respectively. Finally, the new PI gains are obtained using the adaptive gain updating equation as shown in (4) [10], [12].

$$K_p = K_p \text{ initial} + \Delta K_p \quad (4)$$

$$K_i = K_i \text{ initial} + \Delta K_i$$

Where $K_p \text{ initial}$ and $K_i \text{ initial}$ = Initial value of the PI parameters, ΔK_p and ΔK_i = tuned values from the fuzzy logic controller.

V. Design and Simulation of Optimized Fuzzy- PI Controller

A. Bacterial Foraging Algorithm

Bacterial Foraging Algorithm (BFA) has been widely accepted as a global optimization algorithm of current interest by researchers because of its efficiency in solving real-world optimization problems arising in several application domains [4], [13]. BFA is inspired by the social foraging behaviour of Escherichia Coli bacteria present in the human intestine. These unique features of this algorithm overcome the premature convergence problem encountered in GA and PSO. Foraging theory introduced by Passino [13] is based on the assumption that animals search for and obtain nutrients in a way that maximizes their energy intake E per unit time T spent given the constraints of its own physiology and environment. Hence, they try to maximize a function $\frac{E}{T}$ [13].

The optimization technique consists of determining the minimum of a function $J(\theta)$, where θ is the position of a bacterium in n -dimensional space i.e. $\theta \in \mathbb{R}^P$. J can be denoted as the nutrient surface. If $J(\theta)$ is negative, it indicates that the bacterium is in nutrient-rich environment, 0 indicates a neutral environment and a positive value indicates a noxious environment at location θ . The objective will be to try and implement a biased random walk for each bacterium where it will try to climb up the nutrient concentration, avoid noxious substances and will attempt to leave a neutral environment as soon as possible. These actions undertaken by the bacterium can be described as chemotaxis, swarming, reproduction, and elimination and dispersal.

Chemotaxis

This process simulates the movement of an E. coli cell through swimming and tumbling via flagella. Biologically an E. coli bacterium can move in two different ways. It can swim for a period of time in the same direction or it may tumble and alternate between these two modes of operation for the entire lifetime. Suppose $\theta^i(j, k, l)$ represents i -th bacterium at j -th chemotactic, k -th reproductive and l -th elimination-dispersal step. $C(i)$ is the size of the step taken in the random direction specified by the tumble (run length unit). Then in the computational chemotaxis the movement of the bacterium may be represented by (5):

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (5)$$

where Δ is a vector in the random direction whose elements lie in $[-1, 1]$.

Swarming

A group of E.coli cells arrange themselves in a traveling ring by moving up the nutrient gradient when placed within a semisolid matrix with a single nutrient chemo-effector. The cells when stimulated by a high

level of succinate, release an attractant aspartate, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. The cell-to-cell signaling in E. coli swarm may be represented by the objective function in (6):

$$J_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^S J_{cc}(\theta, \theta^i(j, k, l)) \tag{6}$$

$$= \sum_{i=1}^S [-d_{attractant} \exp(-w_{attractant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)] + \sum_{i=1}^S [h_{repellant} \exp(-w_{repellant} \sum_{m=1}^P (\theta_m - \theta_m^i)^2)]$$

where $J_{cc}(\theta, P(j, k, l))$ is the objective function value to be added to the actual objective function to be minimized to represent a time varying objective function, S is the total number of bacteria, p is the number of variables to be optimized, which are present in each bacterium and $\theta = [\theta_1, \theta_2, \dots, \theta_p]^T$ is a point in the p -dimensional search domain. $d_{attractant}$, $w_{attractant}$, $h_{repellant}$, $w_{repellant}$ are different coefficients that should be chosen properly.

Reproduction

The least healthy bacteria eventually die while each of the healthier bacteria, those yielding lower value of the objective function asexually split into two bacteria, which are then placed in the same location. This keeps the swarm size constant.

Elimination and Dispersal

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons. For example, a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space [13]. The flowchart for BFA is shown in Fig. 7 [14].

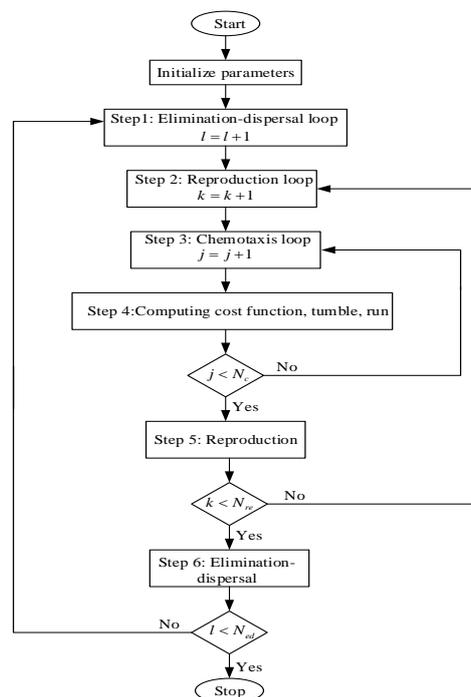


Figure 7: Flow Chart for BFA

B. Optimized Fuzzy-PI

The optimized Fuzzy-PI controller is an extension of the Fuzzy PI controller. Research has shown that in spite of the significant improvement in the of design of Fuzzy-PI controllers over their conventional counterparts, they still have some major disadvantage in that the location of the peaks of the membership functions are fixed and not adjustable [15]. Therefore, in order to improve the control performance of the Fuzzy-PI controller and to overcome the challenge mentioned above, the peak of the triangular membership functions

for all the fuzzy input and output variables of the designed Fuzzy-PI controller are optimized or tuned using BFA to solve the frequency control of MHPP. Fig. 8 shows the schematic diagram of the optimised Fuzzy-PI controller using BFA.

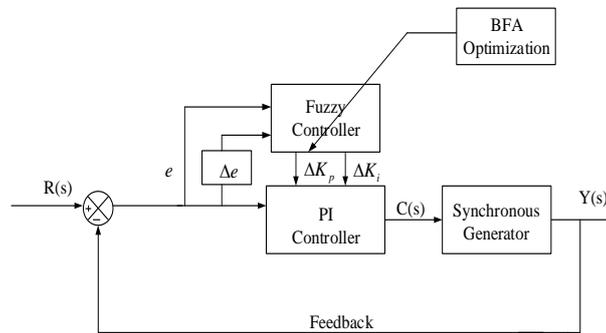


Figure 8: Schematic Diagram of the Optimized PI Controller

The triangular membership function for the designed BFA optimised Fuzzy-PI controller is characterised by the the cost function or the performance index as shown in (7) [16].

$$f(x; a, b, c) = \begin{cases} 0, & x \leq a, \\ (x-a)/(b-a), & a \leq x \leq b, \\ (c-x)/(c-b), & b \leq x \leq c, \\ 0, & c \leq x, \end{cases} \quad (7)$$

$a < b < c.$

In the optimization process, the cost function or the performance index is defined in such a way that the centers or the peaks b of the triangular membership functions for all the fuzzy control rules are selected as the parameter to be determined while the coordinates a and c are held constant. The criteria for BFA initialization parameter choices is necessary so as to determine the global minimum point of the nutrient media. The global minimum point is the place which has the highest nutrient level, hence regarded as a minimization problem. In this work, the bacteria are initially spread randomly over the optimization domain with the probability that a part of them will fall near the food.

The effects of BFA initialization parameters on the nutrient media or the cost function is based on the assumption that more bacteria searching the nutrient media means that they can search and explore more part of the nutrient media hence converging to global minimum quickly. But the drawback is that it normally results in computational complexity and computational time. However, with small population size, the bacteria risk the possibility of been trapped at the local minima [13]. Hence in the simulation, the BFA used the following initialization parameters: $P=2, S=80, N_c=10, N_s=3, N_{re}=3, N_{ed}=3, P_{ed}=0.25, C(i)=0.005$. The optimised membership function for both the fuzzy input and output variables using BFA are shown in Fig. 9 and Fig. 10 respectively.

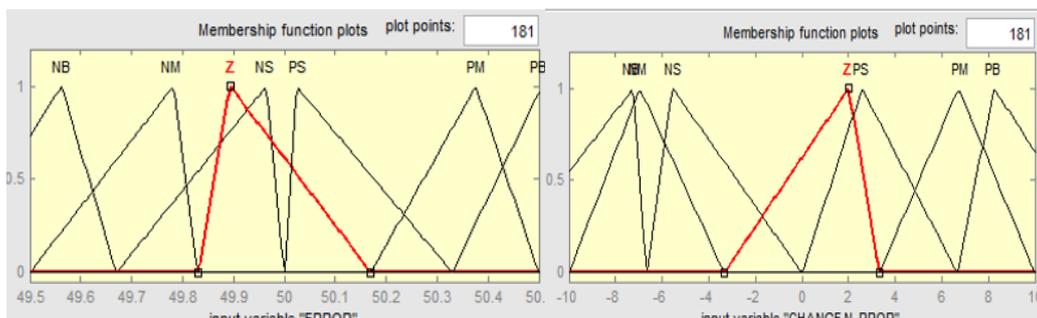


Figure 9: BFA Optimized Membership Function for the Inputs e and Δe

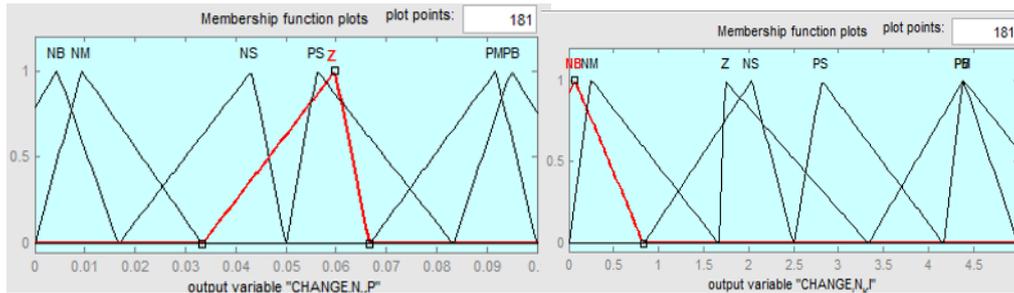


Figure 10: BFA Optimized Membership Function for the Outputs ΔK_p and ΔK_i

The same procedure for the obtaining the gains for the fuzzy-PI controller is also used for the BFA optimized Fuzzy-PI controller after the membership functions have been optimized. The final values are $\Delta K_p=0.6968$ and $\Delta K_i=2.0739$ respectively.

VI. Results and Discussion

The performance of the MHPP Synchronous generator using a unit step under conventional PI, Fuzzy-PI, BFA optimised Fuzzy-PI and the combined control response of the three controllers are shown in Fig. 11, Fig. 12, Fig. 13 and Fig. 14 respectively.

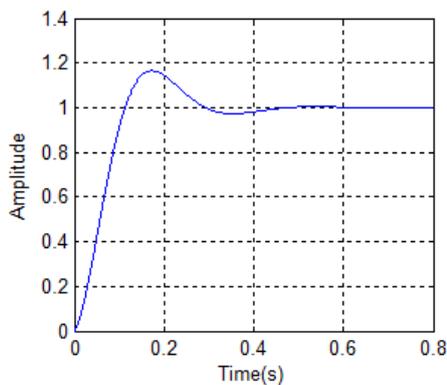


Figure 11: Conventional PI

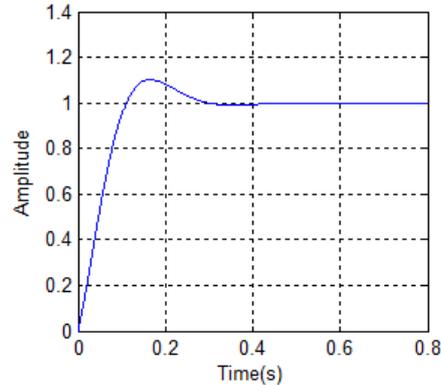


Figure 12: Fuzzy-PI

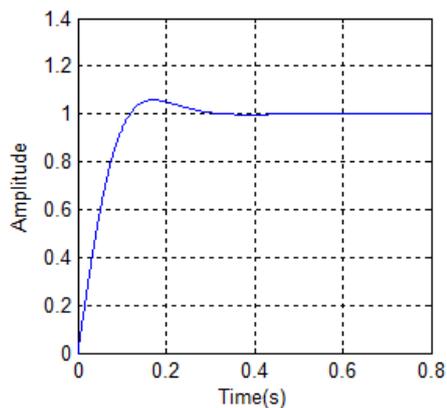


Figure 13: BFA Optimized Fuzzy-PI

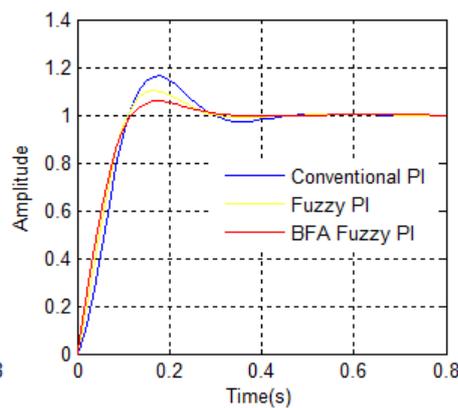


Figure 14: Combined Control Response

The time response for the conventional PI controller, Fuzzy-PI and BFA optimised Fuzzy-PI controller in terms of rise time, settling time and the percentage overshoot are shown in table 1.

Table 1: Time Response of the Various Controllers

| Parameter | Gains | | System Response | | |
|------------------------|--------|---------|-----------------|--------|---------|
| | Kp | Ki | Rr (s) | Rs (s) | %OS |
| Conventional PI | 0.22 | 30.4 | 0.0807 | 0.3969 | 16.4914 |
| Fuzzy-PI | 0.6106 | 32.8739 | 0.0811 | 0.2658 | 10.1801 |
| BFA Optimized Fuzzy-PI | 0.9168 | 32.4739 | 0.0842 | 0.2603 | 5.7992 |

It can be observed that the BFA optimized Fuzzy-PI controller gives the best control response in terms settling time and percentage overshoot. Hence the problem encountered in the conventional PI controllers such as high overshoots and long settling times is minimized hence improving the performance of PI controller and thus will ensure a stable frequency control of MHPP.

VII. Conclusion

The paper presented a method used in the determination of optimal PI gains for Fuzzy-PI controller using BFA. As demonstrated the performance of the BFA optimised Fuzzy-PI controller is superior in terms of overshoot and settling time compared to the conventional PI controller and fuzzy-PI controller. This clearly depicts that using intelligent techniques such as fuzzy logic and optimizing the membership functions using stochastic optimization algorithms can greatly improve the control performance in the frequency control of MHPP. The optimal PI gains obtained are used as PI control parameters to control the frequency of MHPP.

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