Adaptive Tuning of PID Controller for a Nonlinear Constant Temperature Water Bath under Set Point Disturbances using GANFC

Avneesh Mittal, Avinashi Kapoor, T. K. Saxena

Abstract- Temperature control is an important task in the modern industries like chemical, pharmaceutical etc. considering the real time variations in their plants. The present work gives experimental results for the control of a constant level stirred nonlinear temperature water bath under continuous inlet and outlet flow. A real time PID controller taken with a fixed bias voltage has been used and tuned by Genetic Algorithm based Neuro Fuzzy Controller (GANFC) developed on the platform of Visual BASIC 6.0. The PID controller was designed and developed based on 89C51 microcontroller around MK-70 MLW bath. The constant level is maintained by keeping the outflow rate same as the inflow rate ranging between 100ml/min to 500ml/min. Fluke Hydra 2625A Data acquisition unit has been used. Different heaters, 500W, 1KW and 2KW, were operated between 0-240V ac with 256 different firing angles for the Triac. The set point variations between 40.00°C -70.00°C were taken for four combinations of water bath capacity, 5Litre and 20Litre, with different heaters to have 87 different cases. Set point variations also act as disturbances to the closed-loop stable system. Results for the GANFC tuning were compared with Fuzzy PID controller. The experimental result using GANFC shows a better rise time and settling time along with better overshoot and stability. GANFC provided a gain in the rise time between 4.6sec- 632.9sec and a gain in the settling time observed was between 124.9sec to 4055.5sec. GANFC also showed an overall stability of ±0.01°C for different flows and an overshoot of 0.03°C to 0.16°C as against 0.05°C to 2.74°C in fuzzy controller.

Keywords: PID, Adaptive Control, Temperature Control, TSK Fuzzy, GANFC, Step Disturbance.

1. INTRODUCTION

Temperature control is an important factor in many industrial process control systems like textile, polymer, paper, medicinal, biotechnological and chemical and pharmaceutical [1-3] as the product produced is seriously affected if the temperature variation persists during processing. The basic task of these controllers remains to achieve the optimum performance, specified mainly in terms of overshoot, rise and settling time, when faced with various types of unknown disturbances present in industrial applications [4]. Since the process-control systems are often nonlinear, as they tend to change in an unpredictable way by the disturbances, they are not easy to control accurately.

Mathematical model based classical control methods often degrades the controller performance because of the inaccuracies in the modeling especially for the complex or the nonlinear system [5]. The well established proportional integral derivative (PID) controller is by far the most commonly used controller in process control applications despite the huge development in control theory [6, 7]. The popularity of the PID controller is mainly because of its low cost, simplicity in terms of less numbers of parameters to be tuned and applicability on wide range of operating conditions [8]. Even complex industrial control
systems may comprise a control network whose main control building block is likely to be a PID control module. The key concept in designing a PID controller is the determination of three gains of the controller, i.e. Proportional gain $K_P$, Integral gain $K_I$ and Derivative gain $K_D$ as determined by operators based on their experience and knowledge of the undergoing process. Therefore, best values of the three gains were hard to pick for a desired output. Online auto tuning of PID controller was encouraged in the industry because of the development in the computer technology [2, 9]. Automated PID controller minimize the user expertise in the tuning process and allows the autonomous tuning of PID controllers using theory, algorithms and their implementations through computer software and developed hardware installed at the plant.

Ziegler-Nichols (ZN) [10-11] and Cohen–Coon (CC) [12] tuning methods have been used by many authors. O’Dwyer [8] presented a collection of tuning rules for PI and PID controllers. Yamamoto and Shah [13] had experimentally evaluated a multivariable self-tuning PID controller design scheme on a 2×2 level plus temperature control system. Yusof and Omatu [14] had presented a multivariable online self-tuning controller with a PID structure. In order to have a better control on the PID gain values, for processes with changing dynamic properties, automatic tuning [9] and adaptive control strategies [4] have been proposed by many researchers [15-18]. Liu and Daley and others [19-21] had also proposed an optimal tuning PID control strategy. Optimization has indeed proved to be a powerful tool for control design where chosen performance indices are optimized [6].

Several numerical approaches such as Fuzzy Logic Controller (FLC) algorithm [22, 23] and evolutionary algorithms [24-27] have been used for the optimum design of PID controller. Moreover combination of neural/fuzzy system with the traditional adaptive control has been usually demonstrated in the nonlinear control [28-29], due to their powerful nonlinear modeling capability and adaptability as mentioned by Feng et. al [30]. But the problem of designing of structural parameters and tuning of gains of conventional controller and complicated analytical tuning algorithms makes fuzzy controller to be of limited use.

Genetic Algorithm (GA) is one such parallel, global search optimization technique inspired on the natural selection mechanism first developed by Holland in 1962 [31]. Thereafter, a lot of literature and work has been reported by many authors [32-35] and has shown to be successfully used in several areas of science. GA offers an effective way for automatically searching or tuning of PID parameters [36] according to the dynamic behavior and signals of the measured system. Different aspects of GA tuning were discussed by Grefenstette [37]. Fan and Joo [38], have stated that, “. .It performs especially well when solving complex problems because it does not impose many limitations of traditional techniques..” They have obtained improved performance by the use of GA on second and third order control system. In their work Wang and Kwok [39] have mentioned the advantage of GA over conventional optimization techniques to fine-tune classical PID controllers. They had mentioned applicability of GA over a large range of practical plants including nonlinear ones. According to Pereira and Pinto [40], “...this technique has the capability to solve nonlinear and complex optimization problems..” Since GA is based on the coding of parameters rather than their exact value, it avoids requirement of parameter continuity and differentiability. Further GA can handle multiple objective measures such as mixing overshoot, rise time and settling time together as well as even knowledge-based performance indices, as it doesn’t require analytical performance evaluation. This way GA has the information driven feature which differentiate it from conventional derivative driven searching technology and avoids GA to be locked at the local optima. The efficiency of GA does not merely rely on the characteristics of plant under control. The better
performance is obtained because of global and robust nature of GA, its ability of locating high performance areas in complex domains without experiencing the difficulties associated with high dimensionality or false optima, and its computational efficiency. Thus, GAs, in this PID tuning case, can possibly work out the real optimal solution. The PID controllers based on GA have good performance and have been applied in practice. As a popular and successful optimization algorithm, GA had also been used by [41-44] to tune PID parameters.

Hybrid tuning involving neural network’s learning ability and fuzzy system with GA had also been used. Tuning the membership function parameters of FLC have been studied extensively in the literature [45-48]. A neural network based self-learning FLC had been presented by Jang [49] which was trained by temporal back propagation. Karr [50-51] and Varsek et. al. [52] had also applied GA in the automatic tuning of fuzzy MF. Zhou and Lai [53] describe the use of a GA with dynamic mutation rate to evolve the fuzzy MF as well as the consequent variable for a fixed set of fuzzy control rules. They have indicated that the method is effective and efficient, especially in comparison to the conventional trial-and-error design process for fuzzy logic controllers. Takagi–Sugeno–Kang (TSK) type of FLC [54] was also tuned by Lee and Takagi [55] by simultaneous MF and rule set design.

In the present paper, parameter tuning task of the conventional PID, with an initial offset, for a practical nonlinear process is assessed. In this work GA has been used to optimize the coordinates of the triangular membership functions (MF) and values of the PID controller gains $K_P$, $K_I$, and $K_D$ based on the ANFIS architecture developed by Jang [56] for TSK type fuzzy inference system. The consequent parameters of the MF were tuned in the forward pass using least squares estimate method [57-58].

2. GANFC ARCHITECTURE

The PID controller [4, 59-61] with a bias [62-63] of value $u_{bias}$ has been considered in the work presented. The control parameters in general represented as Eq. (1)

$$K_x = K_{x-1} + \Delta K_x$$

The evaluation of the RHS will give us the new values of gain parameters using the known values at the $n^{th}$ sampling instant. If different values of $K_P$, $K_I$, and $K_D$ are chosen, correspondingly various responses of the plants will be obtained. Therefore, the PID parameter tuning problem is equivalent to selecting these parameters to obtain the desired response of the plant. GA is a powerful search optimization algorithm. Because of the robustness, these are successfully applied to generate if-then rules and membership functions of fuzzy systems [50-51]. The presented neuro-fuzzy network (NFN) is based on Takagi-Sugeno-Kang (TSK) type model [54] and was tuned using GA.

A typical TSK based Neuro-fuzzy structure [56] is shown in Fig.1. This neuro-fuzzy system has six layers representing input layer, fuzzy layer, product layer, normalized layer, consequent-defuzzification layer and output layer [64-66]. In the present work input layer had two neurons representing error $e(t)$ and the derivative of error $de(t)$ and the membership function $\mu_A(x)$ was triangular shaped. The value of each input variable was described by one of the 5 fuzzy membership sets {NB, NS, ZE, PS, PB} representing Negative Big, Negative Small, Zero, Positive Small and Positive Big respectively. Every node in the layer 5 was an adaptive node connected to M normalization nodes and also received N initial inputs. Parameters $\{c_{i0}^h, c_{i1}^h, c_{i2}^h, ..., c_{iM}^h\}$ in this layer were referred as consequent parameters of $i^{th}$ rule at $k^{th}$ node and tuned during the corresponding learning procedure. These link weights were an indicator of the correlation strength between the input variables and output variables in the consequent part. Similar to competitive learning,
for simplification, only the significant \( \{ \text{max} \} \) component was considered among \( c_{ij}^k \) while smaller ones were eliminated by making them to be zero. \( O_1^5, O_2^5, O_3^5 \) correspond to three parameters \( K_P, K_I \) and \( K_D \) of PID controller respectively. The overall output was given by Layer 6 as per the standard PID equation. The net output goes to the feedback for necessary tuning as well as heater of the bath. Any disturbances either by changing the flow rate or changing the set point are denoted by ‘d’ in the Fig. 1. These set point changes also act as disturbances to the closed-loop system. The function of the feedback controller is to drive the controlled variable to match the set point. The significances of neuro-fuzzy system structure have been summarized in Table I.

All parameters of the network were initially randomized, and then tuned and optimized simultaneously. Initially, a population of chromosomes was randomly generated. In this population, each chromosome represented a potential solution to the problem. The population pool was sorted in accordance with a fitness function. Using a roulette wheel technique, pairs of candidates are selected from the initial population pool for breeding. This selection process typically favoured candidates with a better fitness, where the fitness function applied depends upon the particular problem under investigation. Following selection, a crossover operation was performed in which the original candidates were passed into a second-generation population pool or unchanged pairs of candidates breed to produce offspring which also joined the second-generation pool. These offspring were then mutated by randomly changing parts of their chromosome structure. The selection, crossover and mutation, elitism, operations ultimately produce a new population of chromosomes from the original population. The GA successively generated new

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**Fig 1: GANFC architecture based on ANFIS**
generations of chromosomes by repeatedly selecting two parents from one generation and performing crossover and mutation operations on their offspring until the genetic evolution was completed, i.e. the solutions were deemed to be sufficiently accurate. Different termination criteria can be used, iterating to achieve the desired fitness value, convergence of fitness value, particular sequence of consecutive generations or fitness of the least fit individual. In this work presented, prescribed numbers of maximum iterations have been considered. As the maximum numbers of iterations have been performed, the chromosomes of the best individuals in the final generation were decoded and used as the gain of the PID controller. Fig. 2 shows the block diagram of the GANFC controller where induced disturbances are represented by ‘d’

**Table 1: Significance of GANFC Layers**

<table>
<thead>
<tr>
<th>Layer</th>
<th>Significance</th>
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<tbody>
<tr>
<td>1</td>
<td>$O_{i}^{1} - x_{i}$; where $i = 1, 2$</td>
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<tr>
<td></td>
<td>$O_{a_{j}}^{2} = \mu_{a_{j}}(x_{i})$; where $i = 1, 2$ and $j = 1, 2, ... 5$.</td>
</tr>
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</table>
| 2     | $\mu_{a}(x) = \begin{cases} 0 & x \leq a \\
                              \frac{x-a}{b-a} & a \leq x \leq b \\
                              \frac{c-x}{c-b} & b \leq x \leq c \\
                              0 & x \geq c \end{cases} = \max \left( \min \left( \frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right)$ |
| 3     | $O_{j,k}^{3} = w_{j,k} = \prod_{i=1}^{2} \mu_{a_{j}}(x_{i}) = \mu_{a_{j}}(x_{1}) \mu_{a_{j}}(x_{2})$ with $j, k = 1, 2, ... 5$. |
| 4     | $O_{i}^{4} = w_{j,k} = \frac{w_{j,k}}{\sum_{j,k=1}^{N-1} w_{j,k}}$ |
| 5     | $P_{t,i} = c_{i,1} X_{1} + \sum_{i=2}^{N} (c_{i,2} X_{2} + \ldots + c_{i,2} X_{N})$ |
| 6     | $O_{i}^{5} = \sum_{i=1}^{N} P_{t,i} O_{s}$ where $X_{3}=1, N=1,2$ and $M=n_{1} \times n_{2}=25$ |
| 7     | $O_{i}^{6} = K_{p} X_{1} + K_{i} \sum X_{1} + K_{d} X_{2}$ |

**Fig. 2: Block diagram of the GANFC**
3. LEARNING ALGORITHM OF THE NETWORK

A step in the learning procedure has got two parts: In the first part the input patterns are propagated, and the optimal consequent parameters are estimated by an iterative procedure of eq. (2) while the premise parameters are assumed to be fixed for the current cycle through the training set. In the second part the patterns are propagated again and keeping the consequent parameters fixed GA uses fitness values to modify the premise parameters. This procedure is then iterated.

For two inputs, if we have $n_1$ and $n_2$ memberships function respectively, the designed neuro-fuzzy, has $n_1+n_2=n_3$ memberships. In the work presented here, the number of fuzzy rules thus becomes $5 \times 5 = 25$ as shown in Fig. 3. The triangular membership function (MF) is used for two of the inputs $X_1$ and $X_2$ with three variables each. As shown in Fig. 3 there are $(3n_1-3)$ and $(3n_2-3)$ parameters to determine in defining the MFs $A_1^1, A_2^1, \ldots, A_{n_1}^1$, and $A_1^2, A_2^2, \ldots, A_{n_2}^2$ respectively. Hence $24 (3 \times 5 + 3 \times 5 - 6)$ premise parameters of layer 1 are to be tuned. The consequent parameters were tuned during learning. In the forward pass, the algorithm uses least squares method to identify the consequent parameters using eq. (2)

$$c_{ij}^k(t + 1) = c_{ij}^k(t) + \alpha \cdot X_j(t) \cdot \delta(t)$$  

where $\alpha$ is the predefined learning rate, $\delta$ is the error. It runs for a maximum of 5 iterations, as another termination criteria for this loop. Three gain coefficients were further tuned during this training with a set of nearly 20 combinations each for one combination of capacity, heater and flow. Some of the training curves are shown in the Fig 4 for 100ml/min. Three setup variables the volume capacity $V$, heater used $Q_H$ and water flow $F$ have also been used as alleles of the chromosome and remain fixed for one particular learning epoch. The bias has been also tuned using the various DAC responses of the plant shown in the Fig 5 for 5Litre and 20 Litre capacity.

![Fig. 3: A set of 5 triangular membership functions with 12 parameters](image-url)
4. IMPLEMENTATION OF GANFC

In the present work PID controller to control the temperature of a water bath has been taken as an example for the controller. Variables of neuro-fuzzy that must be regulated are (i) Membership parameters of layer 2 (ii) Weights of layer 5, Parameters \( \{c_k^0, c_k^1, c_k^2, \ldots, c_k^N\} \) that acts as consequent parts of fuzzy rules (iii) three gain coefficients \( K_P, K_I \) and \( K_D \) (iv) \( u_{bias} \) for the known setup parameters. The numbers of alleles were 32 as determined from the total number of neuro-fuzzy sets used to partition the space of the input-output variables including an allele each for capacity (V), Heater (H) and Flow rate (F). The most crucial step in applying GA is to choose the objective function that is used to evaluate fitness of each chromosome. Integral of time multiplied absolute error (ITAE), eq. (3), is used as fitness

![Graph showing training data for PID parameters for four combinations considered under 100ml/min and set point of 50.00°C.](image-url)
function in the work presented. The chromosome thus will take the form as shown in Fig. 6. The numbers of alleles were 32 as determined from the total number of neuro-fuzzy sets used to partition the space of the input-output variables and rules number.

\[ ITAE = \int_0^t |e(t)| \, dt \]  

(3)

Fig 5: DAC response of 5Litre and 20 Litre bath under various heater and flow
GA has been implemented in Visual BASIC-6.0 using the parameters mentioned in Table II.

### Table II: Parameters used in implementation of GANFC

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>Maximum number of generations</td>
<td>maxgen = 75</td>
</tr>
<tr>
<td>Population size</td>
<td>psize = 25</td>
</tr>
<tr>
<td>Probability of crossover</td>
<td>p_c = 0.65</td>
</tr>
<tr>
<td>Probability of mutation</td>
<td>p_m = 0.03</td>
</tr>
<tr>
<td>Bounds of the parameter used</td>
<td>u_{bias} ∈ [20,120], K_p ∈ [0,25], T_i ∈ [0,1000] and T_d ∈ [0,30]</td>
</tr>
<tr>
<td>Universe and change of error</td>
<td>e ∈ [-100, 100] and de ∈ [-5, 5].</td>
</tr>
</tbody>
</table>

In the designed and developed controller, fuzzy rule are used initially to tune the membership function of the GANFC. A software was developed in Visual BASIC 6.0 for this purpose. The software uses 5 triangular membership functions. The software starts by taking 12 initial parameters and then ask user to start the learning as shown in Fig.7(a) for the two inputs viz e and de. The training was performed initially to tune the 12 parameters. The Fig 7(b) shows the change in the shapes of the membership functions for both the input variables after learning. It then ask user to start the PID algorithm. The training of Fig. 7 was performed for a set point of 50.00°C at a flow of 100ml/min.
5. EXPERIMENTAL SETUP

The block diagram of the experimental setup used in the present work has been shown in the Fig. 8. It was centered on an old East German 20 liter water bath MK-70 MLW. In this setup the cooling circuit of the bath was used, when required, while the heating portion was designed and developed around 89C51 microcontroller. In the present setup, water level was kept constant with the help of a separate circuitry based on 89C51 and a water level sensor which sends the water level signal continuously to the 89C51 microcontroller which controls the flow with the help of inlet motor based on the level in the bath. Although a built in pump was available in the bath for outlet but the same had not been used. Another circuit based on 89C51 had been designed and developed to vary the outflow of the bath. A controlled external stirrer was also used for maintaining the turbulent flow inside the bath. In the present work an inflow of 100ml/min to 500ml/min was allowed and the level is maintained constant by keeping the outflow rate equal to inflow rate. Block diagram of the triac firing circuit for the PID controller is shown in the Fig 9 and explained in [61].

Photograph of Practical experimental setup is shown in the Fig. 10. In this photograph one can clearly see the (1) Data acquisition unit Fluke Hydra 2625A, (2) developed 89C51 based Triac firing circuit, (3) External stirrer with its controller, (4) MK-70 MLW bath, (5) PRT, (6) heater and (7) water flow control system.
6. RESULTS AND DISCUSSION

The objective of this paper was to control the temperature of the water bath MK-70 MLW with a provision of variable flow. The process of the bath system can be represented by the Eq. (4) defined by Stephanopoulos [67] and used by many authors including [2,61,62,66,68].

\[
\frac{dT(t)}{dt} = \frac{T_H(t)}{RC} + \frac{T_o - T(t)}{RC} = \frac{F_H(t)}{C} + \frac{T_o - T(t)}{RC}
\]  

(4)

where \(T(t)\) was the instantaneous bath temperature at time \(t\), \(T_H(t)\) was the instantaneous temperature of the heating filament, \(F_H(t)\) was the instantaneous heat flowing inward the system, \(R\) and \(C\) were the equivalent thermal resistance and thermal capacity respectively, \(T_o\) be the inlet temperature of the water. The plant input (voltage to the heater) was limited between 0V\(_{ac}\) and 240V\(_{ac}\) and it is also assumed that the sampling time \(T_s\) is limited by \(T_s \cong 2s\).

The desired set point was obtained under induced disturbances. The disturbances were induced by varying the set point. The experiment was carried out for an inflow water at the rate of 100ml/min to 500ml/min at room temperature for four different combinations of heater wattage and capacity viz; I)500W-5lit, II)1KW-5lit, III)1KW-20lit and IV)2KW-20lit. The two types of control strategies have been compared in the present work i.e. Fuzzy and GANFC for all 87 cases presented here because of different set points of each combination.

Fuzzy controller was developed for a 5×5 rules shown in the Table III. One of the examples of online fuzzy tuning is shown in the Fig 8. Two horizontal lines in each of the window correspond to two inputs. Accordingly the output is generated for the heater.

![Table III: Fuzzy rules used for tuning](image)

<table>
<thead>
<tr>
<th>(de)</th>
<th>NB</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
<th>PB</th>
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<tr>
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<td>ZE</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
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![Fig. 13: Fuzzy tuning of PID parameters](image)

Figs 9a-9d show the 3D graphs obtained for I-IV combination, I)500W-5lit, II)1KW-5lit, III)1KW-20lit and IV)2KW-20lit respectively, under various flow rates (100ml/min to 500ml/min). The maximum overshoot, stability, rise time and settling time for these cases were listed in the Table IV, Table V, Table VI and Table VIII respectively and compared for both the control strategies. Comparing results of the two controllers, for all four combinations, it is observed that GANFC offers better overall results as compared to Fuzzy controller for each case.
Looking carefully Table IV, for 500W heater with 5liter capacity bath under 100ml/min flow rate, it is observed that for a set point of 45.00°C the overshoot for the fuzzy controller is quite high (1.84°C) as compared to GANFC (0.12°C). The result can be explained as follows, the small capacity and small wattage heater means low resolution of the firing angles. Therefore, the fuzzy controller gave large changes in the firing angle to control appropriate heat flow. Also the set temperature was near to initial temperature of the water in the bath (≅30°C) or the inlet temperature of the water (28°C). Consequently the high rise time and settling time were observed for fuzzy as compared to the GANFC. It is mainly because GANFC is a self-learning algorithm whereas the fuzzy controller limits itself to the given constraints after initial learning making it a little rigid system. The stability is also better in the GANFC when compared with fuzzy controller. In case of fuzzy controller stabilizing inaccuracy is 0.44°C±0.01°C. This is due to the reason that the fuzzy controller was unable to give large variation in the firing angle. In case of GANFC controller it was capable of self-learning and acts accordingly. So it was able to give large variations in the firing angles according to the environmental conditions. When the set point was increased
to 50.00°C, the overshoot decreases to 1.33°C and 0.10°C respectively for the two controllers. The resolution of the firing angle was able to control the bath better, resulting in a better rise & settling time and stability also. This was due to the reason that as the set point temperature is increased the bath has got the tendency to radiate more and more heat to the environment thereby forcing the system to stabilize early. At set point of 60.00°C the Fuzzy controller was not able to control the heater precisely and gives a high overshoot of 2.74°C whereas the GANFC control is much improved because of the better resolution for the heater and increased losses. For a high set point of 65.00°C and 70.00°C the increased losses results in high rise & settling time for both the controllers. The heat gradient suits the condition to give a better stability. Because the heater is of smaller wattage, comparatively high time was taken to reach the set point. The increased overshoot can be explained by the high response (7800sec) and dead time (240sec) of the system bath [61].

When these results were compared with the higher wattage results of Table V, higher rating of the heater is reflected in the higher overshoot, smaller rise & settling time for the fuzzy controller. The highest overshoot for the fuzzy controller was observed at 2.72°C as compared to GANFC at 0.01°C. The higher inaccuracy in the settling point is also explained by considering the higher heat flow. For a set point of 50.00°C, the system was able to bring down to 50.27°C as compared to 50.36°C as the training at 50.00°C helped. In
the 1KW case the GANFC was working accurately. The overshoot, rise and settling time of the GANFC were reduced as the respective chromosomes formed were able to control the system efficiently.

When the results of 20Lit capacity were compared, for 1KW and 2KW heater under a flow of 100ml/min, it was observed that the rise time is decreased for both the controllers but with a slightly more overshoot as a result of more heat flow by increasing the heater wattage. The increase was as high as 1.34°C and 0.16°C for fuzzy and GANFC controllers respectively. A marginally high rise time, by 1.4°C, was observed for 2KW GANFC system for a set point of 70°C but the lower overshoot of 0.09°C (against 2.13°C for fuzzy system) and better stability, in this case, was also observed. For a lower set point of 45.00°C and 50.00°C the settling time was high, means the 2KW fuzzy controller was not able to bring back the temperature, because the comparable temperature of the inlet water is aiding to the temperature of the system which results in lower losses or the lower rate of heat transfer. It also results in greater inaccuracy in the stabilizing temperature for 2KW at 0.07°C±0.01°C as compared to 0.02°C±0.01°C at 1KW. Results of IV combination mentioned in Table VII shows that GANFC also gives slightly more (56.60sec) but comparable settling time only for the 45.00°C as compared to fuzzy controller, while for other set points the GANFC gives better result in terms of rise and settling time.

<table>
<thead>
<tr>
<th>Flow (m/min)</th>
<th>Set Point</th>
<th>Rise Time</th>
<th>Setting</th>
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<tr>
<td>100</td>
<td>45.00</td>
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<td>55.05</td>
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<td>45.05</td>
<td>45.16</td>
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<tr>
<td></td>
<td>60.00</td>
<td>60.05</td>
<td>60.16</td>
</tr>
</tbody>
</table>
Let us now compare the 100ml/min flow results of same wattage heater of 1KW with different bath capacity of 5Lit and 20Lit given in the Table V and Table VI respectively. The rise time was slightly increased as same heat is to be pumped in a larger volume. The increased distribution of heat results in reduced overshoot and better stability. The decrease in the overshoot was in the range 0.04°C to 1.57°C for the fuzzy controller whereas by 0.01°C for GANFC. It is mainly because of the enhanced dissipation in the larger volume. Lowest gain of 35.1sec and 107.10 sec were obtained in the rise time of the two controllers respectively for 20Lit bath. For the fuzzy controller, highest stability observed to be 0.02°C±0.01°C for 20Lit bath as against the best stability of 0.08°C±0.01°C in the 5Lit bath. GANFC was able to achieve consistently a stability of 0.00°C±0.01°C with respect to set point in both the cases. The error in the stability for fuzzy controller was still slightly higher as compared to GANFC. The increased accuracy in the stability was though compensated by the increased settling time for both the controllers. The comparable settling time, with 5lit volume, was also obtained for 20lit volume fuzzy controller at set point of 70.0°C. This is due to the reason that the fuzzy system reduces the energy in controlled way so that the oscillatory behaviour around set point is avoided.

Analyzing Table IV for the change of flow from 100ml/min to 200ml/min for a 500W-5Lit bath system, it is observed that the overshoot is reduced for both the control mechanisms. It is expected as the greater flow enhances the grater heat loss or lower heat accumulation. Rise time was also observed to be higher for fuzzy as well as GANFC as greater efforts were needed to reach a higher temperature. Slightly lower rise time was observed for 200ml/min fuzzy system, at a lower set point of 45.00°C can be explained as the comparable heat of the inlet water is pumped more in to the system at a higher rate. This contribution though becomes insignificant at higher set point and higher flow rate. Same factor contributes in settling time as the increase in settling time for the 200ml/min fuzzy system was observed. This increase in settling was compensated in such a manner that the system settles at a much better point that too in a higher flow disturbance. It results in a reduced inaccuracy of 0.16°C±0.01°C against 0.44°C±0.01°C at 45.0°C set point. The reduced settling time for 50.0°C set points GANFC controller can be explained by considering its self-learning feature.

When results under a flow of 200ml/min for increased wattage but a constant capacity were analyzed i.e. Table IV with Table V and Table VI with Table VII, a reduced rise was observed but with a slightly higher overshoot which was though compensated by much better settling time with comparable stability change.

All four combinations when compared for two control strategies, under 200ml/min flow rate, GANFC was consistently giving better settling time and overshoot. The rise time was also improved with a highest advantage of 632.9sec, but it is also coming to be greater but comparable with fuzzy controller in four cases (by 14.5sec, 23.2sec, 21.4sec and 6.8sec). It is to be pointed again that because the training was done at 50.00°C the fuzzy tuner was better at this set point.

When the same analysis was done for 300ml/min, 400ml/min and 500ml/min the pattern of reduced overshoot, increased rise and settling time with comparable stability was observed when higher rating heater was used in the same capacity of water bath. The overshoot in the respective set point was decreased under higher flow rate mainly because of the better thermal energy distribution. Two cases of higher settling time for 2KW-20Lit system under 300ml/min, as compared to 1KW-20Lit system, were resulting in a better stability. For 400ml/min-20Lit case of higher settling time(by 110.9sec) with greater stability error(0.06°C), in 2KW as against 1KW system at set point of 45.00°C, is due to the reason that the fuzzy system reduces the energy in controlled way to the system with sufficiently
large volume as well as slightly large flow rate. The large volume takes more time to reduce its temperature though the heat is also utilized in raising the temperature, reduced by the water inflow. The high rise time and stability error is still better as compared to the oscillatory behavior, if exists.

Keeping the heater same but increasing the bath capacity i.e. comparing Table V and Table VI for 200ml/min results in reduced overshoot. This came along with an increased rise time and settling time. Same trend was observed under 300ml/min, 400ml/min and 500ml/min flow rate. Better settling time for the fuzzy controller at higher set point were observed for various flow rates. It can be understood considering that by increasing the system capacity volume, the gradient of the heat supplied in to the system is decreased also aided by the increased heat loss in the environment at higher temperatures. It is to be mentioned here that the set point are different for 500W heater as being a smaller rating heater it was not able to reach the higher set point even with its maximum power delivered to the bath.

While analyzing Table IV for a flow rate of 100ml/min to 500ml/min it was observed that a highest flow rate considered here results in a lowest overshoot at 0.31°C for a fuzzy

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| Table VI: Comparison of 1KW 20Litre results for Fuzzy and GANFC Controller (Combination III) |
|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| Flow (m³/min) | Temp (°C) | Overshoot | Stability | Rise | Setting |
| 100 20Litre |
| Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC |
| 45.00 | 46.35 | 45.00 | 45.02±0.01 | 45.00±0.01 | 5422 | 402.08 | 1098 | 70 | 544.20 |
| 50.00 | 51.46 | 50.01 | 50.02±0.01 | 50.00±0.01 | 2100 | 199.40 | 800 | 20 | 300.40 |
| 60.00 | 61.11 | 60.00 | 60.02±0.01 | 60.01±0.01 | 2479 | 448.50 | 774 | 00 | 618.60 |
| 70.00 | 70.78 | 70.01 | 70.02±0.01 | 70.00±0.01 | 3235 | 298.30 | 632 | 90 | 409.30 |
| 200 20Litre |
| Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC |
| 45.00 | 46.35 | 45.00 | 45.02±0.01 | 45.00±0.01 | 5030 | 478.60 | 665 | 50 | 677.30 |
| 50.00 | 51.46 | 50.01 | 50.02±0.01 | 50.00±0.01 | 2140 | 435.30 | 585 | 00 | 378.90 |
| 60.00 | 61.11 | 60.00 | 60.04±0.01 | 60.00±0.01 | 6650 | 612.80 | 1187 | 20 | 811.30 |
| 70.00 | 70.78 | 70.01 | 70.04±0.01 | 70.02±0.00 | 6589 | 595.40 | 1112 | 70 | 818.30 |
| 300 20Litre |
| Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC |
| 45.00 | 46.35 | 45.00 | 45.02±0.01 | 45.00±0.01 | 6029 | 501.90 | 1142 | 90 | 600.70 |
| 50.00 | 51.46 | 50.01 | 50.02±0.01 | 50.00±0.01 | 2943 | 379.10 | 653 | 20 | 390.80 |
| 60.00 | 61.11 | 60.00 | 60.04±0.01 | 60.00±0.00 | 7692 | 785.50 | 1177 | 90 | 1096.50 |
| 70.00 | 70.78 | 70.01 | 70.04±0.01 | 70.02±0.00 | 6456 | 638.90 | 1112 | 20 | 844.50 |
| 400 20Litre |
| Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC |
| 45.00 | 46.35 | 45.00 | 45.02±0.01 | 45.00±0.01 | 5422 | 493.90 | 553 | 40 | 576.50 |
| 50.00 | 51.46 | 50.01 | 50.02±0.01 | 50.00±0.01 | 2943 | 379.10 | 653 | 20 | 390.80 |
| 60.00 | 61.11 | 60.00 | 60.02±0.01 | 60.00±0.01 | 1316 | 209.10 | 581 | 00 | 1134.80 |
| 70.00 | 70.78 | 70.01 | 70.02±0.01 | 70.00±0.01 | 9940 | 707.50 | 1508 | 00 | 951.40 |
| 500 20Litre |
| Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC | Fuzzy | GANFC |
| 45.00 | 46.35 | 45.00 | 45.02±0.01 | 45.00±0.01 | 4950 | 446.70 | 1093 | 20 | 653.10 |
| 50.00 | 51.46 | 50.01 | 50.02±0.01 | 50.00±0.01 | 2743 | 296.40 | 864 | 70 | 392.20 |
| 60.00 | 61.11 | 60.00 | 60.02±0.01 | 60.00±0.01 | 1395 | 925.40 | 1949 | 10 | 1255.70 |
| 70.00 | 70.78 | 70.01 | 70.02±0.01 | 70.00±0.01 | 1002 | 778.00 | 1593 | 10 | 1034.00 |
controller. For the same system the highest overshoot was observed to be 2.74°C for the lowest flow rate considered here. Similar inferences can be drawn from the Tables V, VI and VII respectively of each combination. The fuzzy controller results in an overshoot ranges between 0.2-2.72°C for 1KW 5Lit, 0.05-1.46°C for 1KW 20Lit and 0.75-2.30°C for 2KW-10Lit system were observed. In comparison GANFC controller results in a maximum overshoot at 0.12°C, 0.03°C, 0.02°C and 0.16°C respectively for I to IV combination. Hence in most of the cases the overshoot observed for GANFC is negligible. Similar results were obtained when one analyzed the obtained stability of the two controllers for four combinations under various flows. In these combinations the lowest accuracy observed for Fuzzy controller was 0.44°C, 0.75°C, 0.14°C and 0.14°C respectively with respect to the set point with ±0.01°C to ±0.02°C tolerance mainly at lower flow rate of 100ml/min or 200ml/min. In comparison the GANFC controller consistently gives an accuracy of ±0.01°C with respect to the set point.

### Table VII: Comparison of 2KW 20Litre results for Fuzzy and GANFC Controller (Combination I’)

<table>
<thead>
<tr>
<th>Flow (m/min)</th>
<th>Set Point</th>
<th>Max Overshoot</th>
<th>Stability</th>
<th>Rise</th>
<th>Setting</th>
<th>2KW 20Litre</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow (m/min)</td>
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<td>2KW 20Litre</td>
</tr>
<tr>
<td>100</td>
<td>45.00</td>
<td>45.56</td>
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<td>GANFC</td>
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<td>50.01=0.01</td>
<td>50.00±0.01</td>
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<td>60.00±0.01</td>
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<td>GANFC</td>
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<td>45.10±0.01</td>
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<td>46.33</td>
<td>Fuzzy</td>
<td>GANFC</td>
<td>45.02=0.02</td>
<td>45.00±0.01</td>
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<tr>
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<td>51.07</td>
<td>50.02=0.01</td>
<td>50.00±0.01</td>
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<td>65.02±0.01</td>
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<td>70.08</td>
<td>70.01±0.02</td>
<td>70.00±0.01</td>
<td>930.20</td>
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It was also observed that the rise time and settling can be further improved using GANFC controller. The lowest gain in the rise time is 4.6sec for 100ml/min flow at a set point of 50°C for IV combination. The highest difference in the rise time is 632.9sec for 200ml flow at a set point of 60°C for I combination. For some instances the rise time is more for GANFC controller where the difference varies between 0.9-55.10sec. Obviously the difference is not too high. It can be explained as the chromosome formation is a random formation and sometimes it takes more iteration to reach the optimum solution having the desired results. The smallest gain for settling time was 124.9sec at a flow of 500ml/min at a set point of 50.00°C for IV combination whereas the highest gain for settling time was 4055.5sec at a flow of 200ml/min at a set point of 60.00°C for I combination.

6. CONCLUSION

It was observed that the rise time and settling can be further improved using GANFC controller. When the inlet temperature becomes comparable to the desired set point their effect becomes that much prominent in terms of rise time, overshoot and short term stability. The energy given to the plant varies at the same firing angle because of the fluctuation in the ac mains, a common feature in the industries. It also contributes in the short term stability of the system at a desired set point. It is also to be mentioned that the system desires a constant level to be maintained. It is achieved by keeping the outflow rate to be same as the input flow rate. Still a variation in the input flow rate, because of the changes in liquid level in its reservoir, can cause the level to change. It leads to change in the heat gradient in the system and equivalently taken as the disturbance to the system.

REFERENCES


