Design and Analysis of GA based Neural/Fuzzy Optimum Adaptive Control.

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Abstract: Process changes, such as flow disturbances and sensor noise, are common in the chemical and metallurgical industries. To maintain optimal performance, the controlling system has to adapt continuously to these changes. This is a difficult problem because the controller also has to perform well while it is adapting. The Adaptive Neural Controller (ANC) developed in this paper satisfies these goals. Using a neural network controller, ANC modifies the network parameters through Genetic Algorithms. Along with this a Fuzzy logic Controller is also implemented for the on-line tuning of PID controller even in the presence of noise. The performance of these approaches has been evaluated using data of different plants on a common set of performance indices. The simulations results show that identified GA based Adaptive neuro-controller along with PID controller was able to adapt to process changes while simultaneously avoiding hard constraints. The identified ANC balances the need to adapt with the need to preserve generalization, and constitutes a general tool for adapting neural controllers on-line. While the fuzzy system which is rather simple to build and implement (because of small computational efforts) considerably improves the system dynamics.

Index Terms: Proportional-Integral-Derivative controller, Adaptive Neuro Controller, Genetic Algorithms

1. INTRODUCTION

PID controllers are important type of controller and provide good static and dynamic response, for this its parameters must be properly tuned. Tuning the controller parameters is a crucial issue and among the various tuning methods, the most widely used is Ziegler-Nichols, which provides good load disturbance attenuation [1]. The system gives desired performance under load disturbance. But have a distributed dynamics under the influence of external/environmental factors and noise. PID controllers are not tuned for the disturbances (or noises) which are due to the change in the ambience conditions which affects the process/plant or are due to the sensor noise. They can't compensate the parameter variation in the plant and can't adapt the changes in the environment [2, 3]. So, it was desired to deal with these problems and various non-linearities such as high order, non-linearities, and dead time. Fuzzy logic has been widely used with application to PID controllers. A FL-based nonlinear PID controller was developed in which fuzzy rules were developed to change the controller parameters based on the error & its rate of change at each step point change [4]. A methodology was developed that consist of parameterizing Zeigler-Nichols-like formulae by a single parameter & then self tuning this parameter by means of an on-line fuzzy inference mechanism. Many Neuro-Fuzzy models have also been proposed [5-8]. Parameter fitting was done on an array of linear networks. The local model used was basically a non-linear auto regressive moving average (NARMA) model. The system was trained to serve the non-linear models [9]. A better adaptive controller for linear and non-linear plants was proposed using back propagation algorithm [10].

Ziegler-Nichols method of tuning PID controllers is beset with drawbacks: (i) it doesn't guarantee tuned parameters optimally. The very concept of optimality needs be linked with some performance index, which this method misses woefully; (ii) generally, the parameters tuned by it stand improved upon through trial & error. [11]. A GA based method doesn't suffer from above drawbacks .GAs was employed to find out the optimum tuned PID parameters and the results/response was better in comparison to conventional Ziegler-Nichols [12-13].

In this paper a methodology is proposed to make the system perform well under the abnormal conditions, for this the controller must be able to adapt its parameter in accordance with the changing environment. The intelligent techniques are used for adaptation. For this Fuzzy set-point weighting (FSW) is used for tuning of PID controller and its adaptability to parametric variations will be discussed. Also an Adaptive Neuro-controller (ANC) will be identified which will adapt to the parametric variation which are due to external/environmental factors and noise. The proposed controller shall meet the following objectives:

a. Make the system adapt to the optimal set point (reject the presence of noise),
b. Maintain the system dynamics, and
c. Maintain the system stability.

A hybrid technique will also be used to generate the ANC parameters using genetic algorithms.

This paper is organized in five sections. The first section introduces the role of intelligent adaptive control for noise rejection. The second section deals with the overall methodology for the synthesis of adaptive controller using fuzzy logic, artificial neural network and evolutionary operation. The validation of identified adaptive controllers is done for various case studies is presented in the third section. The results are discussed in the penultimate section. The Concluding remarks are drawn in the last section.

2. Synthesis of Adaptive Controller Identification Tool

A process operating point (i.e. the process state) determines the product purity and production rate. The operating point thus has an intrinsic economic value. The fixed operating points (i.e. set points) are based on the economic value. Process changes, due to process disturbances and drifting dynamics, cause deviation from the set points, requiring corrective action. Optimal set points and effective corrective action yield greater economic return. Typically, linear controllers (e.g. PID controllers) maintain the set points and provide corrective action to process changes [14]. PID controller typically utilizes both set points and fixed controller parameters. The PID controller parameters govern the corrective action (i.e. the control response) to process changes.

Non-linear processes are common in the process industries. In such cases, PID controller parameters are optimal only over a limited operating region. Process changes may cause the operating point to stray far from the set point, whereupon PID controllers may implement sub-optimal corrective actions. Sub optimal performance may be avoided only by adapting the controller parameters. As the set points largely determine the economic return, the set points must also adapt to process changes. Tracking the economic optimum therefore requires adapting both the controller parameters and the set points [15].

Effective generalization and adaptability during process changes are essential to tracking a process economic optimum. Generalization tools, as fuzzy logic & neural networks, are invaluable in creating non-linear controllers for non-linear processes. Non-linear controllers are near optimal over wider operating.

On-line information contains inaccuracies due to sensor noise and short-lived disturbances. Adapting controller parameters based on imperfect process information involves operational risk. The process may become unstable. On-line adaptation on to control parameters faces numerous challenges:

i. Balancing the use of past and present information,
ii. Supervising process stability,
iii. Implementing emergency procedures should the process become unsafe, due to on-line adaptation [15].

The following two sub-sections illustrate the aims of conventional methods for adapting controller parameters and process set points. The proposed adaptive controller has the same aim, though its methodology is dissimilar.

2.1 Fuzzy Set Point Weighting (FSW)

The PID controller has the following standard form in time domain:

$$u(t) = K_p[e(t) + T_d \frac{de(t)}{dt} + \frac{1}{T_i}\int e(t)dt] \qquad (1)$$

where e(t) is the system error, while K_P is the proportional gain, T_d is the derivative time constant & T_i is the integral time constant. We can also write (1) as

$$u(t) = K_p e(t) + K_d \frac{de(t)}{dt} + Ki\int e(t)dt \qquad (2)$$

where $K_d = K_P T_d$ and $K_i = K_P/T_i$

The tuning problem consists of selecting the values of K_P, T_d & T_i. The Zeigler Nichols method of tuning is widely accepted in order to meet different control specifications such as set-point following, load disturbance attenuation. But it also has a large overshoot and settling time for a step response that might not be accepted for a number of processes moreover it shows varied/distributed performance due to model uncertainties and parametric variation affecting the process & the system.

The FSW approach consist of fuzzifying the set-point weight, leaving fixed the other three parameters (determined with Ziegler-Nichols method to preserve good load disturbance attenuation) but the added effect is in a large overshoot and settling time for a step response. Increasing the analog gain K_P, highlights these aspects. A way to cope with this problem is to weight the set point for the proportional action by means of a constant 'b' so that we get

$$u(t) = K_p e_p(t) + K_d \frac{de(t)}{dt} + Ki\int e(t)dt \tag{3}$$

Where $e_P(t) = bY_{SP} - Y$

In this way a simple two degree of freedom scheme is implemented, one devoted to the attenuation of load disturbances, the other to the set-point following as shown in Figure 1, where it is

$$G_{ff} = K_P(b + \frac{1}{sT_i} + sT_d)$$

$$G_C = K_P(1 + \frac{1}{sT_i} + sT_d)$$

In this a fuzzy map is formed in such a way that it updates 'b' in accordance with the current regulation error and error rate. Specifically, it changes the value of set point for the proportional action in order to speed up the convergence of the process output Y to Y_{SP} and to slow down the divergence trend of Y from Y_{SP}. More precisely, the output of fuzzy

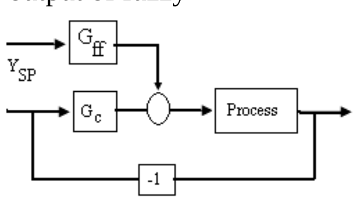


Fig. 1 The two degree of freedom structure of the PID controller with set point weighting.

module is 'b', which is multiplied by set point. The proposed control system that uses fuzzy logic for tuning of proportional gain of PID controller is shown in figure 2.

2.1.1 Fuzzy System

Fuzzy logic is a natural way of making decision and is very close to the way the human being think and makes decision. Fuzzy logic is a natural way of decision making as it allows to expressing the requisite Knowledge required for arriving at a decision with subjective concepts. Any fuzzy system consists of following four major modules (i). Fuzzification module, (ii). Inference engine, (iii). Knowledge base and (iv). Defuzzification module [16].

2.1.2 Design of Fuzzy System

To design a fuzzy logic based embedded controller, the following steps are usually followed:

- Structure specification:
  1. Identify the inputs and outputs variable
  2. Assigning membership functions to the variables
  3. Building a rule base
  4. Reducing the rule base if possible
- Choosing an inference strategy.
- Selecting defuzzification scheme.

For the simulation, we use the following operators

- Rule Composition Operator: MIN
- Implication Operator: MIN (Mamdani mode)
- Aggregation Operator: MAX
- Defuzzification Technique: Weighted Average

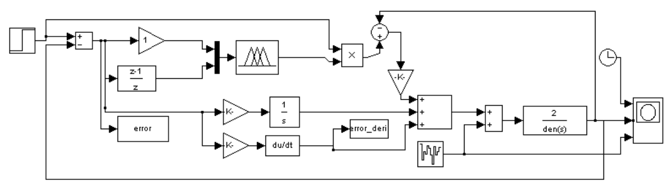


Fig. 2 Fuzzy logic based controller (Simulink)

2.2 Adaptive Neurocontroller (ANC)

2.2.1 Conventional Adaptive Control

An adaptive linear controller Figure 3 maintains a specified control response (i.e. corrective action) around a set of PID controller parameters can only maintain the specified control response for a limited range of process conditions. Process changes in non-linear processes may cause the control response to become oscillatory around the set point.

Adaptive linear control tunes the PID controller parameters, which corrects the oscillatory response to the specified response. Conventional adaptive control relies on on-line process modeling (i.e. Model Reference Adaptive Control) and heuristic methods (i.e. Ziegler-Nichols) for adapting controller parameters [17]. The proposed adaptive neural controller must ensure that a specified control response is maintained.

Neuro-controllers may originate from various sources. Neural networks may be trained to mimic the control action of existing PID controllers, thereby distributing the PID functionality over several neurons. Neuro-controllers are also developed utilizing evolutionary reinforcement learning techniques [18]. Neural networks are beneficial to an adaptive scheme, such as generalization and graceful degradation.

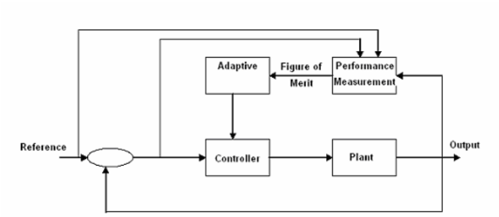


Fig. 3. A Conventional Adaptive Control Scheme

Once a PID controller is adopted, the small number of control parameters prohibits effective generalization to past process conditions. Neural network controllers are collections of neurons, with each neuron specifying the weights from the input layer (process states) to output layer (control actions). Neuro-controller parameters are the neural network weights. In the present paper, the adaptive controller works in unison with the PID controller, so that both under the normal working conditions (e.g. load disturbances) and under the effect of changing ambience condition the proposed adaptive controller works for desired control and performance. During adaptation, a neural network's distributed functionality preserves greater generalization to past process conditions. The need for effective generalization justifies the use of neural networks. Process stability is preserved during adaptation.

2.2.3 *Block Representation of Adaptive Neuro-Controller*

ANC maintains a population of possible neuro-controller solutions that serve as reinforcement learning evaluations, similar to EVOP experiments [19]. The neuro-controller is evaluated individually over a number of sensor sample periods while interacting with a dynamic process as in Fig. 4.

Initially, the process may be at an arbitrary operating point (state, s_t). The neuro-controller observes the current process operating point at sample, t, and selects a control action, a_t. The control action changes the operating point to s_{t+1}. A reward, r_t, is assigned based on the economic value of this new operating point. The objective is to maximize the total reward over a series of control actions, while maintaining a specified control response.

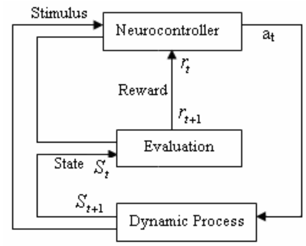


Fig. 4 Proposed Adaptive Neuro Controller

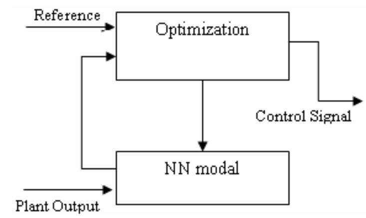


Fig. 5 The Adaptive Neuro Controller

An optimization algorithm adapts the neural network weights based the reward feedback from each evaluations. The above controller can also be represented as shown in Fig. 5 while maintaining the above explained generality.

The neural network model and the simulation block of above said ANC is shown below in Fig. 6 and Fig. 7 respectively

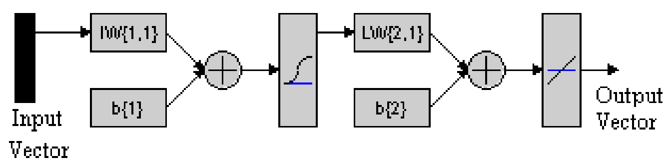


Fig. 6 ANC Network Representation

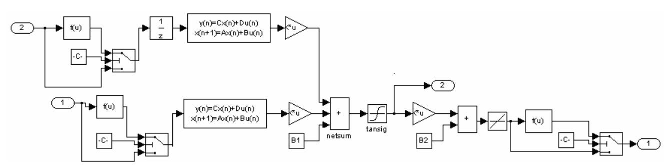


Fig. 7 Simulation Block of ANC

The above shown network can be trained for a given set of plant parameter data-base. The training will result in optimum set of weights and bias, for a predefined number of neurons, selected for achieving the selected/ or the defined performance and the control criterion.

2.2 Evolutionary Operation

Adaptive control (even the one proposed above) does not change the set points that largely determine the economic return. Set points are selected during design based on an optimization of dynamic model equations. The optimization considers both economic return and controllability. However, process changes during operation may make the current set points economically sub-optimal.

Evolutionary operation (EVOP) challenges the use of constant set points in a continuously changing process. EVOP monitors the process and improves operation by changing the set point towards the economic optimum. EVOP makes a number of small set point changes that do not disrupt production. However, the set point changes need to be sufficiently large to discover potential improvements in the operating point. EVOP uses an experimental design to determine the number of set point change experiments. Pattern search methods use the experimental results to determine whether and in which direction the set points should be changed [20].

EVOP does not adapt the PID controller parameters for each of the set point experiments. As explained in previous section using the same controller parameters for all the set point experiments may give oscillatory responses.

Adaptive control and EVOP may be combined in a two-step methodology to track a changing economic optimum. EVOP selects a number of set point experiments. An adaptive control method establishes a specified control response for each set point experiment. The system performance evaluations for each experiment will consequently be comparable, whereupon EVOP adjusts the current set point. This cumbersome two-step process is repeated until the optimal set point is found. Ideally, a single off-line experiment should provide information on the control response.

2.3.1 GA Based Network

Genetic algorithms are a part of EVOP which use a direct analogy of natural behavior, work with a population of individual strings, each representing a possible solution to the problem considered. Each individual string is assigned a fitness value which is an assessment of how good a solution is, to a problem. The high fit individuals participate in "reproduction" by cross breading with other individuals in the population. This yields new individual strings as offspring which share some feature with each parent. The least-fit individuals are kept out from reproduction and so "die out". A whole new population of possible solution to the problem is generated by selecting the best (high fit) individuals from the current generation. This new generation contains characteristics which are better than their ancestors [21].

Progressing in this way, after many generations, owing to mixing and exchange of good characteristics, the entire population inherits the best characteristics and therefore turns out to be fit solutions to the problem. For a well designed GA problem, then most promising areas of search space are explored, resulting in the population converging to an optimal solution [22].

2.4 IMPLEMENTATION BY GA

2.4.1 Automatic Fuzzy Controller Tuning With Genetic Algorithms.

Genetic Algorithm is an idea to search the optimal values of the parameters of the fuzzy logic based system. Specifically we search for the values of scaling factors for the inputs i.e. error and its derivative for defining the membership grade along with for the output that is also scaled for the same in order to minimize the following objective function:

$$IAE = \int \left| Y_{SP}(t) - Y(t) \right| dt$$

A program is written in Matlab with the help of GA toolbox to minimize IAE. At the end of generation, we get optimal result. For the problem, real coding and stochastic universal sampling as fitness is used for GA. Single-point crossover is used with crossover probability of 0.8. Population size is 10. Maximum numbers of generation chosen are 25. The procedure consists of evaluating a series of step response in order to permit the genetic algorithm to converge to the optimal solution.

2.4.2. Genetic Algorithm Based Adaptive Neuro Controller

GA based Backpropagation is a Neuro-Genetic hybrid which makes use of GAs to determine the weights of a multilayer feed forward network with backpropagation learning. Conventional back propagation networks make use of gradient descent learning to obtain their learning to obtain their weights. But some time networks get struck in local minimum. On the other hand, GA based backpropagation though not guaranteed to obtain global optimum solution, has been found to obtain 'acceptably good' solutions 'acceptably quickly'. The discussed is a backpropagation network architecture in which the GA makes use of real coded Chromosomes to determine its weights [22].

The weights and biases for the given layer (Fig. 6) are then obtained using EVOM (GA based) and are then tested on the network shown in Figure 7.

GA based methodology developed to solve the problem uses real coding and stochastic universal sampling as fitness is used. The GA also uses two point crossovers with crossover probability of 0.8, real value mutation and generation gap of 0.8. The objective function used was IAE. The population size was 10 and maximum numbers of generation chosen are 25.

3. Validation and Case Studies

The PID controller parameters are fixed for the given process and then the system response is observed. (Ziegler-Nichols tuning method). The tuned system's performance is observed under the presence of the noise condition. The Off-line training of adaptive neuro-controller is done. The system is trained for a set of input-output data. The input data pertains to the plant output as well as the band limited noise and output data pertains to the set point. The trained Adaptive Neuro-controller (ANC) is then made online and system response is observed. Weights of the trained network are optimized using GAs. The system with new weights and biases is made to perform under the disturbed conditions and the performance is analyzed.
In order to evaluate effectiveness of our proposed model we choose the following systems [23].

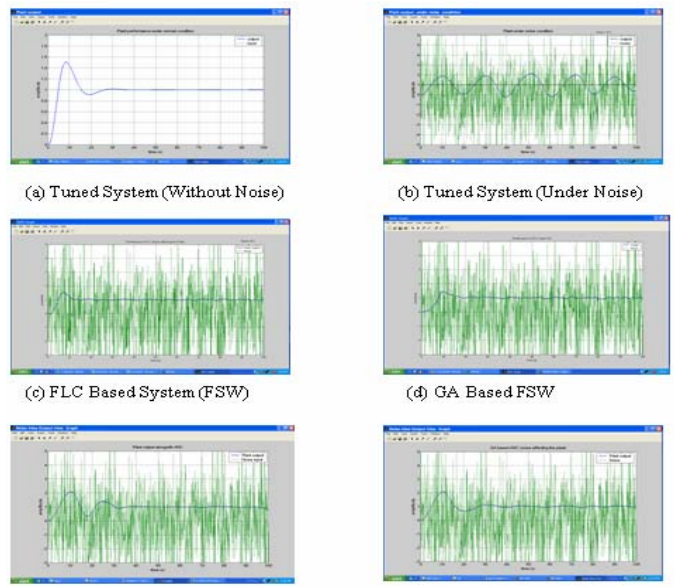
(i) $$G_1(s) = \frac{2}{(10s^3 + 21s^2 + 12s + 1)}$$

(ii) $$G_2(s) = \frac{1}{(s+0.1)(s+2)(s+3)}$$

The Simulation results of the cases discussed are tabulated in the Table 1 & 2 respectively and the performance graph are shown in figure 8 & 9 respectively. The comparison is done between the transient response of the plant obtained when subjected to a uniform load, which are handled by the PID controller (Zeigler-Nichols tuning method) and affected by the noise. The same indices are compared under the effect of noise with the inclusion of fuzzy controller, Adaptive neural controller and GA based fuzzy & neural controller.

4. Results and Discussion

The tabulated results shows that the rise time, peak time & the peak overshoot for the system using ANC improves remarkably in comparison with the system using Zeigler-Nichols tuned PID controller, which becomes unstable under noise condition. The use of ANC in whole makes a system stable and the system transient behavior is almost preserved even in the presence of noise as it was under no noise condition. The fuzzy system is too able to control the system dynamics but has rather slow dynamics in comparison to the ANC (as depicted by the values of rise time & peak time) but it is capable enough to lower down the peak overshoot even in comparison to the Zeigler-Nichols tuned PID controller along with ANC. The same can be observed in terms of objective function i.e. IAE (and ISE). The Evolutionary approach using Genetic algorithms greatly improves (or significantly reduces) the performance indices whether it be a Fuzzy system or a neural network.



(a) Tuned System (Without Noise) (b) Tuned System (Under Noise)
(c) FLC Based System (FSW) (d) GA Based FSW
(e) ANC Based System (f) GA Based ANC

Figure 8. Simulation result showing performance of $G_1(s)$

Table: 1 Result of $G_1(s)$

	Rise Time (s)	Peak Time	Peak Overshoot	IAE	ISE
Z-N	4.90	8.40	50.52	7.380	4.17
Under Noise	UNSTABLE				
Fuzzy	7.88	9.75	42.09	10.65	4.91
GA based Fuzzy	7.74	9.7	44.8	10.25	4.74
ANC	4.90	10.4	108.73	17.26	10.93
GA based ANC	4.90	8.4	51.6	15.90	9.46

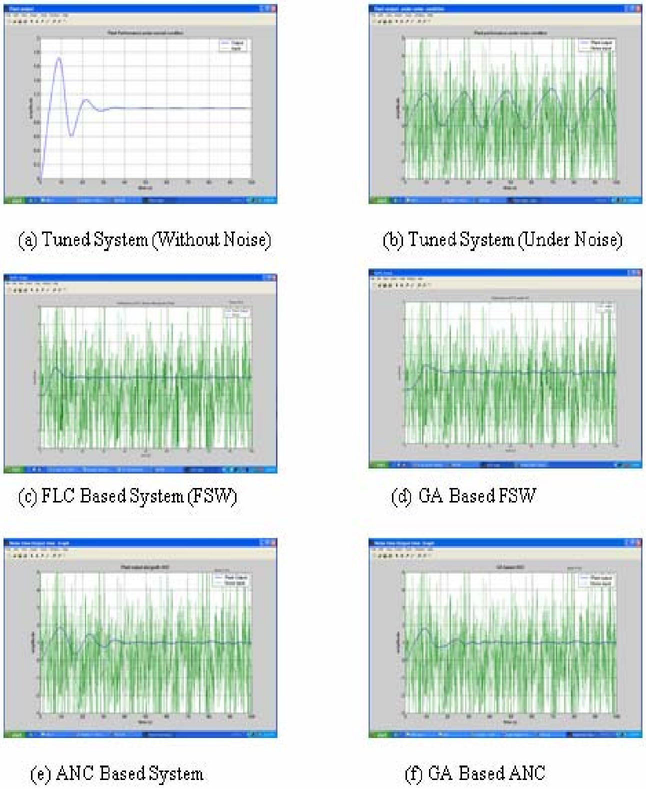


Figure 9. Simulation result showing performance of $G_2(s)$.

Table:2 Result of $G_2(s)$

	Rise Time (s)	Peak Time	Peak Overshoot	IAE	ISE
Z-N	4.41	8.76	71.2	8.83	4.79
Under Noise	UNSTABLE				
Fuzzy	4.87	7.5	54.2	7.59	3.56
GA based Fuzzy	4.8	7.3	53.7	7.31	3.38
ANC	4.41	9.6	85	16.417	8.06
GA based ANC	4.418	9.23	79.4	18.17	7.39

5. Conclusion

In this paper, a design method of an Adaptive controller has been identified, using fuzzy system & artificial neural network. Hybrid Intelligent System Based Controller augments fuzzy set-point weighting for tuning of PID controller. The set point for the proportional action is weighted by means of fuzzy logic The constant control gains (scaling factor) of these controllers are tuned manually; these being a tedious process generally do not achieve their best possible performance due to lack of optimization. For optimization, one has to look for some intelligent techniques such as Genetic algorithms.

The Adaptive neuro-controller augments weights on backpropagation and on GA basis, thereby garnering greater economic return from the changing process. ANC balances the need to adapt with the need to preserve generalization. Neural networks maintain process stability and exhibit the property of graceful degradation that allows small changes to the weights without causing catastrophic loss in control performance. A genetic algorithm was used in integration with the adaptive neuro-controller for determining the weights and biases of the neural network.

The proposed methodology is suitable for application in an industrial environment because of its simplicity and because only a small computational effort is required for its implementation. Further the use of GA automates the search process and provides with the global best result for noise reduction. The simulation result indicates that inclusion of fuzzy & neural controller results in a remarkable improvement in the system response by reducing the overshoot and IAE, and maintaining the system dynamics even in the presence of noise.

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