

HYBRID SYSTEM BASED FUZZY-PID CONTROL SCHEMES FOR UNPREDICTABLE PROCESS

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Abstract

In general, the primary aim of polymerization industry is to enhance the process operation in order to obtain high quality and purity product. However, a sudden and large amount of heat will be released rapidly during the mixing process of two reactants, i.e. phenol and formalin due to its exothermic behavior. The unpredictable heat will cause deviation of process temperature and hence affect the quality of the product. Therefore, it is vital to control the process temperature during the polymerization. In the modern industry, fuzzy logic is commonly used to auto-tune PID controller to control the process temperature. However, this method needs an experienced operator to fine tune the fuzzy membership function and universe of discourse via trial and error approach. Hence, the setting of fuzzy inference system might not be accurate due to the human errors. Besides that, control of the process can be challenging due to the rapid changes in the plant parameters which will increase the process complexity. This paper proposes an optimization scheme using hybrid of Q-learning (QL) and genetic algorithm (GA) to optimize the fuzzy membership function in order to allow the conventional fuzzy-PID controller to control the process temperature more effectively. The performances of the proposed optimization scheme are compared with the existing fuzzy-PID scheme. The results show that the proposed optimization scheme is able to control the process temperature more effectively even if disturbance is introduced.

Keywords:

Fuzzy-PID Controller, Genetic Algorithm, Q-Learning, Exothermic Batch Reactor, Thermal Control

1. INTRODUCTION

In polymer industries, resin adhesives are produced by mixing two reactants together, i.e. phenol and formalin. However, a large amount of heat will be released during the process due to its exothermic behavior and auto-catalyst nature. This sudden and unpredictable increase in temperature will cause the reaction becomes unstable, and consequently affect the quality and purity of final product [1]. If the generated heat exceeds the reactor cooling capacity, the unwanted exothermic heat has the potential to cause substantial harm workers, public and the environment [2]. Therefore, it is vital to control the process temperature during the polymerization process.

In today's modern industry, fuzzy logic has been used to auto-tune PID controller parameters because fuzzy logic is a simple artificial intelligent system [3,10]. Normally, the fuzzy membership function and the universe of discourse are manually adjusted and tuned by trial-and-error method. However, manually setup is not adequate due to the inherent nonlinearity and complexity of the process since the optimum membership function range is difficult to obtain. Besides that, the rapid changes in process parameters also increase the complexity of the process. Hence, these cause an increasing in difficulty on implementation of the conventional pre-defined fuzzy-PID

controller to control the process temperature.

In order to overcome these issues, an auto-optimize fuzzy membership function range approach is necessary for fuzzy-PID controller. Numerous methods have been developed to auto-tune fuzzy membership function range [1,4,5]. As shown in [6], an evolution technique is proposed to optimize the fuzzy membership function range. However, this method is unable to adapt itself into a dynamic change environment due to the pre-defined of its fitness function.

In order to increase the effectiveness in controlling the process temperature, an approach of hybrid QL-GA optimization scheme is proposed in this paper to optimize the fuzzy membership function of the fuzzy-PID controller. The aim of this paper is to design an effective auto-tuning method for fuzzy-PID controller to control the nonlinear and complex process temperature effectively.

The organization of this paper is described as follows. Section 2 describes the exothermic plant modelling. Section 3 explains the proposed optimization scheme. Section 4 shows the performance of the proposed control strategy. Finally, Section 5 summarizes all the findings of this paper.

2. EXOTHERMIC PLANT MODELLING

Basically, the conventional exothermic plant modelling can be divided into four elements: reference temperature profile, heating process plant, exothermic heat profile, and fuzzy-PID controller model. Fig.1 shows the conventional process plant with fuzzy-PID controller.

2.1 REFERENCE TEMPERATURE PROFILE

In practice, the polymerization of resin adhesives has shown that a specified quality of products can be obtained by controlling the reactor temperature [7]. Hence, a reference temperature of the process should be determined in order to obtain a pre-specified product quality.

According to [8], the target temperature for this polymerization process is set as 65°C. Due to the reactor thermal energy transfer limitation, the operation temperature has to be increased linearly from ambient temperature until the target temperature during the first 2400s, as shown in Fig.2.

2.2 HEATING PROCESS PLANT

The heating process plant model can be described as a first-order system with time delay, which is described in Eq.(1):

$$G(s) = \frac{K}{\tau s + 1} e^{-\tau_d s} \quad (1)$$

where K is the process gain, τ is the time constant and τ_d is the

time delay.

The value of K depends on the number and model of heater used. According to the industrial reaction curve method as described in [8], the process gain, K is $0.011^{\circ}\text{C}/\text{kW}$. In order to create a plant which is similar to the actual environment, a variable time constant is used instead of a fixed value. In this paper, the time constant, τ , is assumed to be varied from 500s to 1000s.

Due to dynamic in nature, the time delay of the process may not be constant all the time. Hence, this paper modelled a variable time delay, τ_d , which is varied from 10s to 40s.

2.3 EXOTHERMIC HEAT PROFILE

During the mixing of the reactants, a sudden increase in temperature is caused by the unpredictable exothermic heat. The exothermic heat is unpredictable and varies even though same volume of phenol and formalin are used. In this paper, two sets of exothermic heat profile are modelled, as shown in Fig.3.

2.4 FUZZY-PID CONTROLLER

Fuzzy logic is the common auto-tuning method for PID controller in modern industries because fuzzy logic is user-friendly since fuzzy rules can be set in terms of linguistic rules

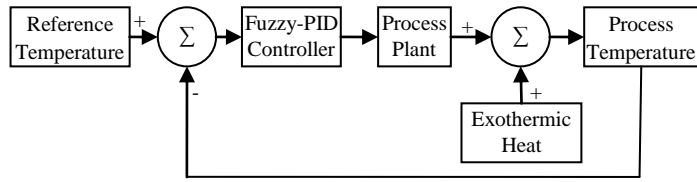


Fig.1. Conventional Exothermic Process Plant with Fuzzy-PID Controller

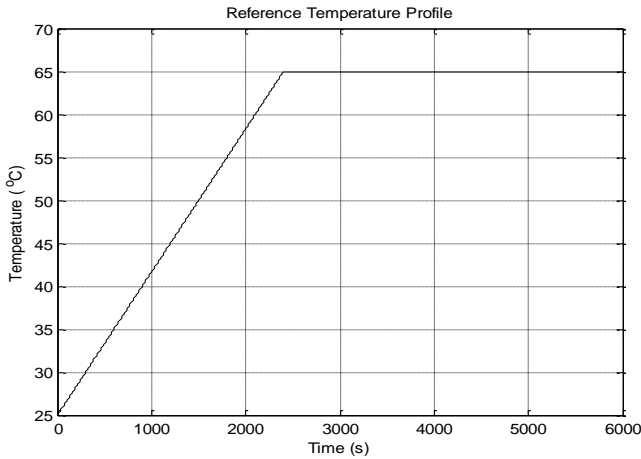


Fig.2. Reference Temperature Profile

using human expertise in tuning PID parameters. The fuzzy controller involves 4 basic operations: fuzzification, rule base, inference engine, and defuzzification [9], as shown in Fig.4.

The fuzzification is comprised of finding appropriate membership functions to describe the crisp data. A membership function is a curve that defines how each point in the input space is mapped to a membership value. The input space is referred to as the universe of discourse. The fuzzy controller in this paper

consists of two inputs: error, e and change in error, ce , and three outputs: proportional, P , integral, I and derivative, D parameters.

Fuzzy rule base is a collection of if-then rules. These rules contain all the information about the PID parameters tuning, as shown in Table.1. The function of inference engine is to deduce a logical conclusion using the rule base. Inference engine formulates the mapping from the given inputs to an output using fuzzy logic [10].

The function of defuzzification is to resolve a single output value from the fuzzy set. The defuzzification method used in this paper is the centroid method, which returns the center of area under the curve.

PID controller model is based on PID control algorithm, as described in Eq.(2).

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (2)$$

where $u(t)$ is the control variable, $e(t)$ is the error, K_p is the proportional parameter, K_i is the integral parameter, K_d is the derivative parameter.

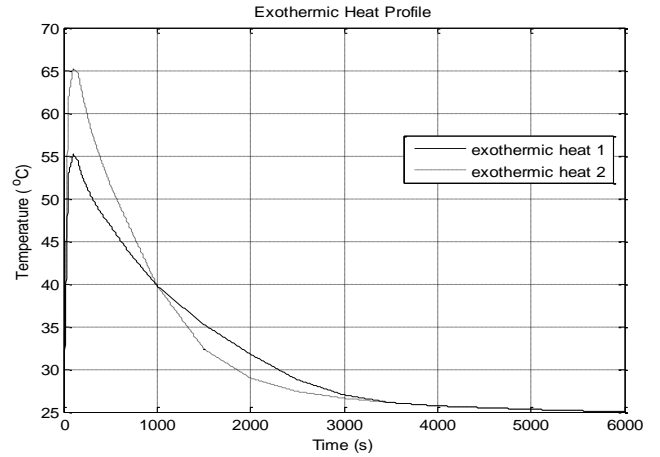


Fig.3. Exothermic Heat Profile

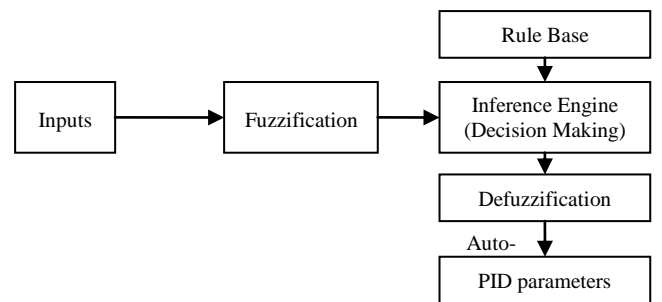


Fig.4. Basic Operations of Fuzzy Tuning Method

3. PROPOSED OPTIMIZATION SCHEME

In this paper, it is assumed that the whole process is a black box. The proposed hybrid optimization scheme of QL-GA needs to optimize the fuzzy membership function range of the fuzzy-PID controller in order to maintain the process temperature in the desired trajectory. The proposed optimization scheme can be divided into two modules: observation and learning module, and optimization module.

In the observation and learning module, QL is proposed to observe and learn the input-output characteristics of the process, and then it will estimate the process parameters for the optimization module, whereas for the optimization module, GA is proposed as controller optimizer, which is used to optimize the fuzzy membership function range.

The process controller will be the existing fuzzy-PID controller. Fig.5 shows the modification of the conventional fuzzy-PID control system using the proposed optimization scheme.

3.1 OBSERVATION AND LEARNING MODULE

In this module, it is assumed that the process is a black box. Therefore, QL is proposed to observe and learn the input-output characteristics of the process and then estimates the process parameters.

QL is an unsupervised machine learning algorithm that seeks to maximize a numerical reward signal [11]. QL is able to negotiate with a system’s problem by learning the system’s behavior through trial-and-error method and then evaluate an action by reward and penalty functions [12]. This paper modified the conventional QL equation, as described in Eq.(3).

$$Q_i = (1 - \alpha)Q_{i-1} + \alpha \cdot R \tag{3}$$

where α is learning rate, which is a set as 0.8 in this paper. R is the reward obtained after executed an action, i is the number of iteration, Q is the experience gained.

The framework of the proposed observation and learning module consists of two stages: observation stage and learning stage, as shown in Fig.6. In the observation stage, QL observes the input-output characteristics of the process, as shown in Fig.5.

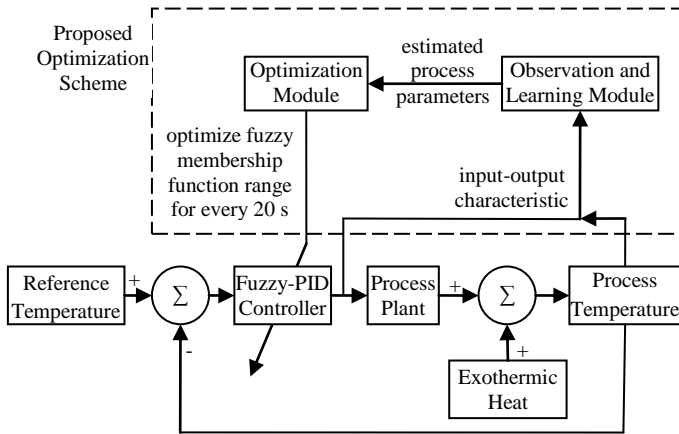


Fig.5. Proposed Optimization Scheme for Conventional Fuzzy-PID Control System

The learning stage can be divided into three sub-stages, as shown in Fig.6. In the first sub-stage, the QL estimates the process parameters through trial-and-error method. After that, the estimated process parameters are evaluated by the following sub-stage, reward and penalty calculation. A higher reward is awarded to the estimated process parameters which have the closest characteristics to the observed characteristics in the observation stage. The reward calculation is described in Eq.(4).

$$R = \frac{1}{(p - p_e)^2} \tag{4}$$

where R is the reward gained, p is the observed characteristics, and p_e is the characteristics of the estimated process parameters.

The stopping criterion of this QL is whenever the maximum learning iteration is reached. In this paper, the maximum learning iteration is set to be 40,000 in order to ensure that the QL has gained enough experience before it makes any decisions.

After the learning stage, the estimated plant parameters with the highest experience gained, Q will be the best solution to describe the actual process plant. These estimated plant parameters will be fetched to the fitness function in GA in order to calculate the fitness value for each of its chromosomes, as discussed in the following sub-section.

3.2 OPTIMIZATION MODULE

GA is a stochastic global search method based on natural selection and genetics [13]. In this module, GA is working as controller optimizer to optimize the fuzzy membership function range through evolution process for every 20s. However, the fuzzy rules base is pre-set in advanced, as shown in Table.1.

The framework of the GA is shown in Fig.7. First, an initial population of solutions is randomly generated with a population size of 50. Since the output of this GA function are optimum fuzzy inputs and outputs membership function range, the solutions of GA are strings of just five parameters, which is able to completely characterize all the input and output membership function range, as shown in Fig.8.

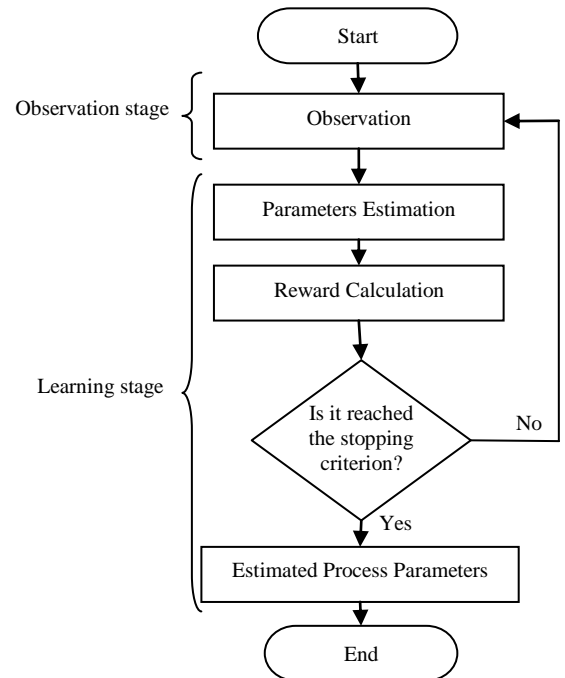


Fig.6. Framework of Q-Learning Algorithm

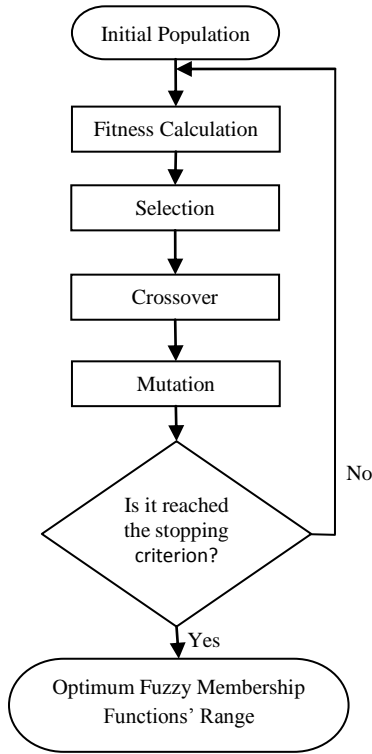


Fig.7. Framework of Genetic Algorithm

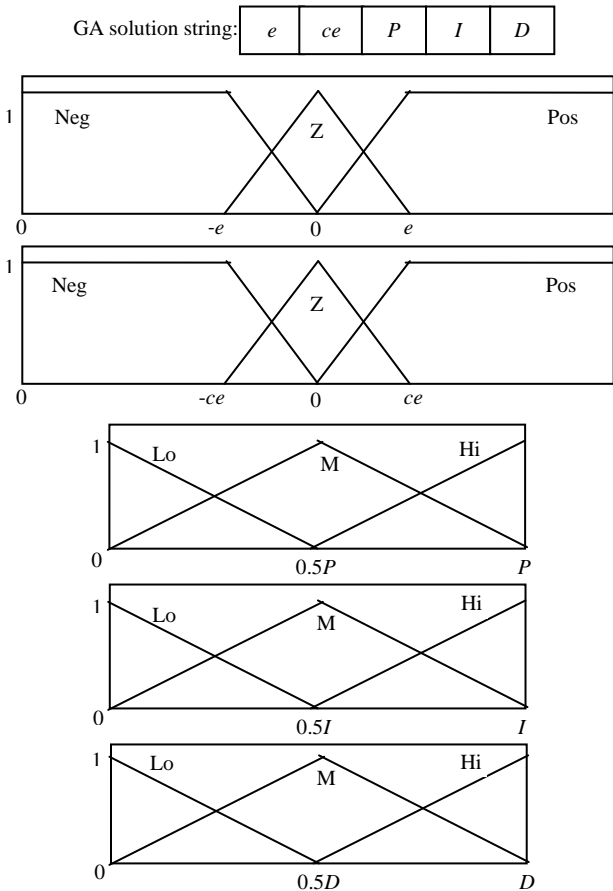


Fig.8. Fuzzy Membership Functions Represented by GA Solution String

Then, the fitness of each solution is calculated by using the estimated plant parameters. The best solution obtains highest fitness value; otherwise, it will obtain low fitness value. The equation of fitness function is described in Eq.(5).

$$Fitness = \frac{1}{(T_{ref} - T_e)^2} \quad (5)$$

where T_{ref} and T_e are the reference temperature and the estimated process temperature respectively.

In selection operation, ranking selection method is used. This operation emphasizes the fittest solution in the population by duplicating those solutions in mating pool and hoping that their offspring will in turn have even higher fitness value, while keeping the population size constant [14].

In crossover operation, blending method is used with a rate of 0.9. This operation will randomly pick two solutions, called parent solutions, from the mating pool. Some portions of the solutions are exchanged between the solutions and create two new solutions, called offspring. This method combines variable values from the two parents into new variable values in the offspring. The first offspring variable value comes from a combination of two corresponding parent variable values. The second offspring is merely the complement of the first offspring. Eq.(6) and Eq.(7) are used to create offspring solutions.

$$x_{n1} = \beta \cdot x_{p1} + (1 - \beta) \cdot x_{p2} \quad (6)$$

$$x_{n2} = \beta \cdot x_{p2} + (1 - \beta) \cdot x_{p1} \quad (7)$$

where x_n is the offspring, x_p is the parent, β is a random number, which is in between of 0 and 1.

The mutation operator helps in randomly searching other areas of the solution spaces that may be unexplored and might containing global maxima. However, the probability of mutation must be kept low to prevent the loss of too many fit solutions and affect the convergence of solutions. Hence, the mutation rate in this paper is set as 0.01.

The stopping criterion of GA in this paper is whenever the maximum number of generation is reached. The maximum number of generation is set to 10. Hence, the GA will stop after 10 generations and returns the optimal fuzzy membership range to fuzzy-PID controller.

Table.1. Fuzzy Rules Base

Error, <i>e</i>	Change in Error, <i>ce</i>	Parameter, <i>P</i>	Parameter, <i>I</i>	Parameter, <i>D</i>
Neg	Neg	Hi	Lo	Hi
Neg	Z	Hi	Hi	Lo
Neg	Pos	M	Lo	M
Z	Neg	M	Lo	Hi
Z	Z	Lo	M	Lo
Z	Pos	M	Lo	Hi
Pos	Neg	M	Lo	M
Pos	Z	Hi	Hi	Lo
Pos	Pos	Hi	Lo	Hi

4. PERFORMANCE OF PROPOSED OPTIMIZATION SCHEME

The proposed optimization scheme was programmed in MATLAB-SIMULINK 7.10.0 (R2010a). Then, the simulation was run for 6000 s on Intel® Core™ i5 CPU M480 processor based 2.67 GHz with 4.0 GB RAM. The performance of the optimization scheme for fuzzy-PID controller has been compared with the conventional fuzzy-PID controller and GA optimization scheme for fuzzy-PID controller.

Fig.9, Fig.10 and Fig.11 show the performances of conventional fuzzy-PID controller, GA optimization scheme fuzzy-PID controller, and the proposed optimization scheme (hybrid of QL-GA) fuzzy-PID controller respectively.

From the results, it can be noted that the conventional fuzzy-PID controller has greatest undershoot and overshoot, whereas the proposed optimization scheme for fuzzy-PID controller has the lowest undershoot and overshoot during the first 1000s of the polymerization process.

In order to stress the effectiveness of the proposed optimization scheme, performances of various controllers are examined under disturbances. This paper assumed the disturbance refers to a short period malfunction at input coolant valve, which is occurred at time 1000s and 3000s for duration of 60s and 120s respectively. The simulation performances of the conventional fuzzy-PID, GA optimization scheme fuzzy-PID and the proposed optimization scheme fuzzy-PID controllers are shown in Fig.12, Fig.13 and Fig.14 respectively.

From the results can be noticed that the malfunction of input coolant valve at the time 1000s are not affecting the three different controllers because the duration of the malfunction is too short. However, when the duration of the malfunction is long, e.g. 120s, the conventional fuzzy-PID control system needs more time to maintain the process temperature to the desired trajectory. Once again, the proposed optimization scheme shows the best performance in controlling the process temperature because it is able to control the process temperature to the desired trajectory in a short period of time and also has the minimum absolute error throughout the whole process.

5. CONCLUSION

In this paper, an exothermic plant model with hybrid control system has been developed based on the characteristic of polymerization of resin adhesives. The proposed optimization scheme consists of two modules: observation and learning module, and optimization module. QL has been employed to observe and learn input-output characteristics, and then estimate the process parameters. On the other hand, GA is used in the optimization module to optimize fuzzy membership function range using the estimated process parameters based on the observation and learning module. From the simulation performances, it can be concluded that the proposed optimization scheme provides an acceptable temperature control due to its robustness against the variable time delay, inconsistent exothermic heat and disturbances. In future, the hybrid of QL-GA can be used to modify the fuzzy rules to improve the computational time of the artificial intelligent algorithm.

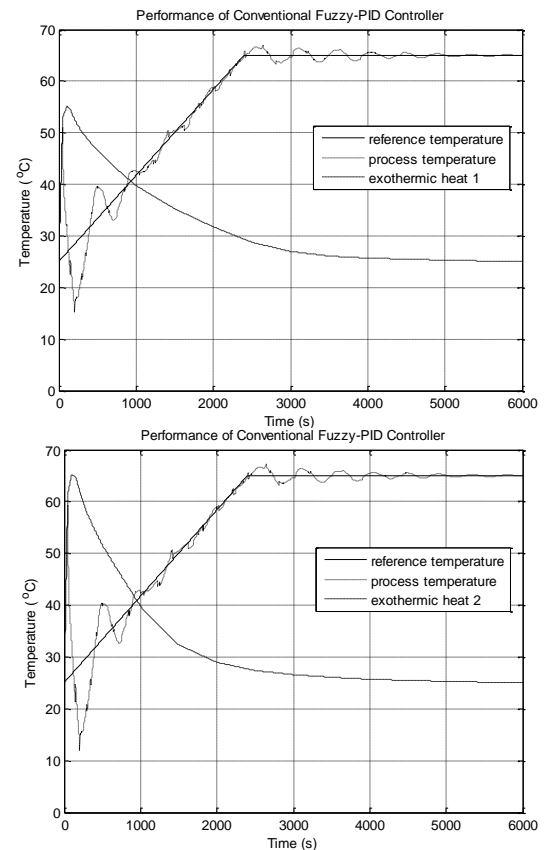


Fig.9. Performance of Conventional Fuzzy-PID Controller

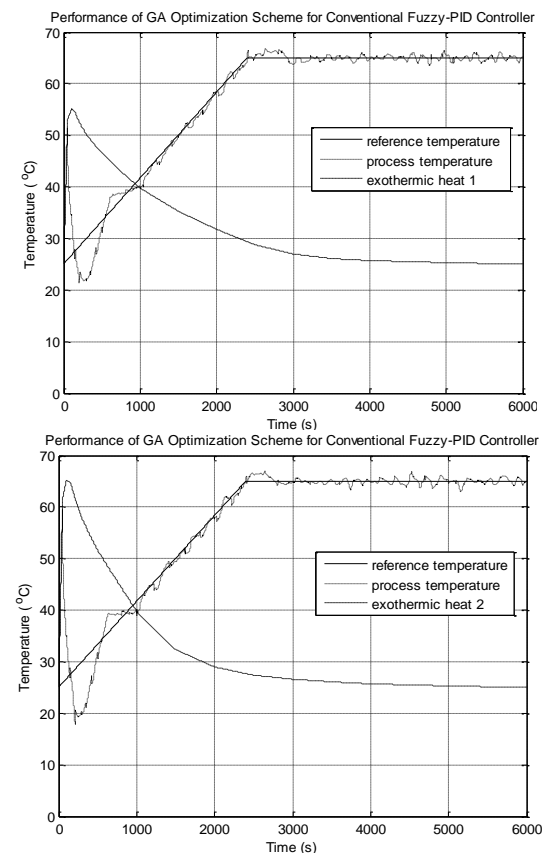


Fig.10. Performance of GA Optimization Scheme Fuzzy-PID Controller

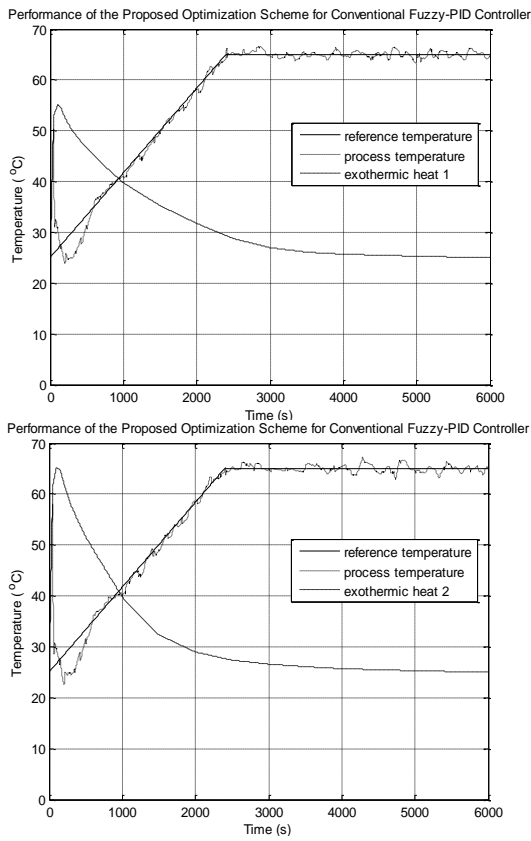


Fig.11. Performance of the Proposed Optimization Scheme Fuzzy-PID Controller

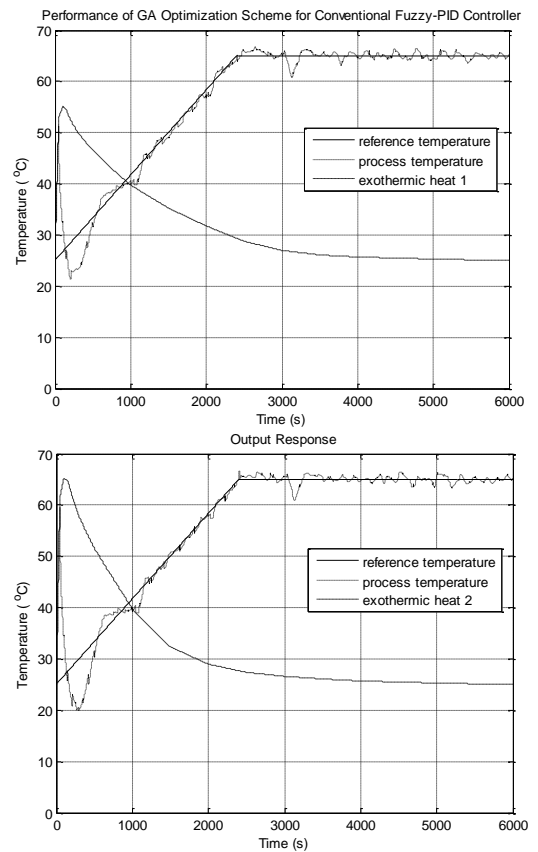


Fig.13. Performance of GA Optimization Scheme Fuzzy-PID Controller under Disturbances

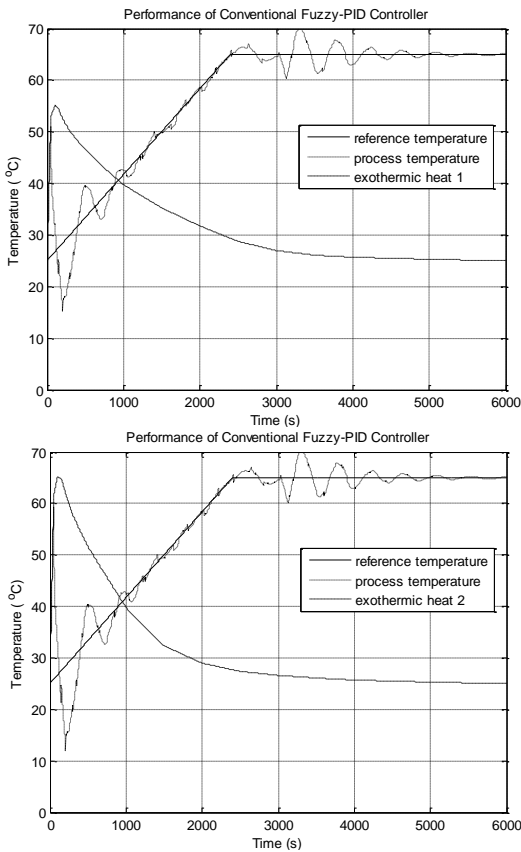


Fig.12. Performance of Conventional Fuzzy-PID Controller under Disturbances

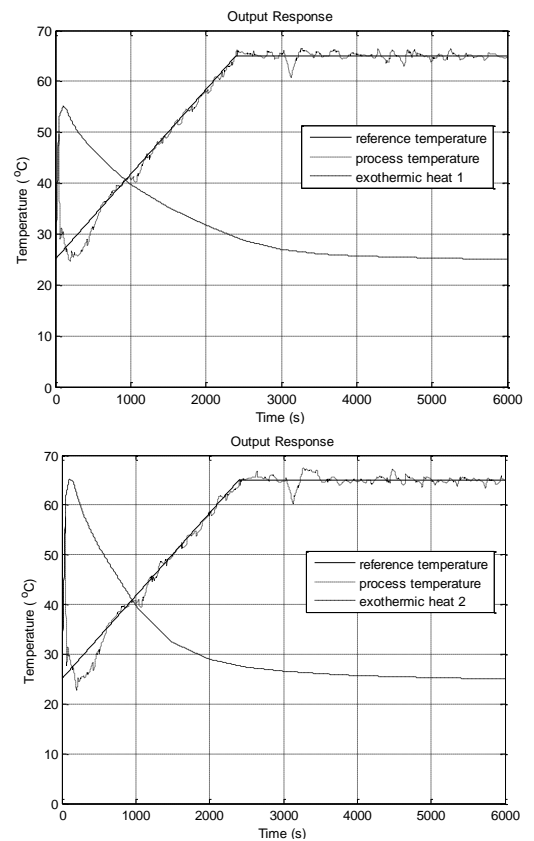


Fig.14. Performance of the Proposed Optimization Scheme Fuzzy-PID Controller under Disturbances

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