Solar Plant Control Using Genetic Fuzzy PID Controller

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Abstract

This paper introduces an optimal fuzzy Proportional-Integral-Derivative (PID) controller for a solar power plant. The fuzzy PID controller is a discrete-time version of the conventional PID controller, which preserves the same linear structure of the proportional, integral, and derivative parts but has constant coefficient, self-tuned control gains. The constant PID control gains and other control parameters are optimized by using the multiobjective Generic Algorithm (GA), thereby yielding an optimal fuzzy PID controller.

1 Introduction

Conventional PID controllers have been well developed and applied for about half a century [1], and are extensively used for industrial automation and process control today. The main reason is due to their simplicity of operation, ease of design, inexpensive maintenance, low cost, and effectiveness for most linear systems. Recently, motivated by the rapidly developed advanced micro-electronics and digital processors, conventional PID controllers have gone through a technological evolution, from pneumatic controllers via analog electronics to micro-processors via digital circuits [1, 5].

However, it has been known that conventional PID controllers generally do not work well for nonlinear systems, higher-order and time-delayed linear systems, and particularly complex and vague systems that have no precise mathematical models. To overcome these difficulties, various types of modified conventional PID controllers such as auto-tuning and adaptive PID controllers were developed lately [5]. Also, a class of non-conventional type of PID controllers employing fuzzy logic have been designed and simulated for this purpose [4, 5, 12].

Stability of these fuzzy PID controllers are analyzed and guaranteed [4, 5, 12]. Many simulation examples have been given to show the superior performance of this class of fuzzy PID controllers. Yet, despite the significant improvement of the fuzzy PID controllers over their classical counterparts, the constant control gains of these controllers are tuned manually; so generally do not achieve their best performance due to the lack of optimization.

This paper aims to design an optimal fuzzy PID controller for a Solar Power Plant of Almería (Spain) [3, 13, 14] by using the Generic Algorithm (GA). The organization of the paper is as follows. The solar plant system is described in the next section. In Sect. 3, a representative fuzzy PI+D controller is introduced, which is used as the controller for the plant. This is followed by a detailed description of the GA approach for the optimization of the fuzzy PI+D controller in Sect. 4. Simulations demonstrating the performance of this optimal controller and conclusions are given in Sect. 5 and 6, respectively.

2 Solar Plant System

The studied plant is a distributed solar collector field ACUREX of the solar plant at Tabernas, in Almería, Spain [2]. The collector field of the plant consists of 480 distributed solar ACUREX collectors arranged in 20 rows forming 10 parallel loops. Each loop is about 172 meters long. The collector uses parabolic mirrors to reflect solar radiation onto a pipe for heating up the oil inside while circulation. A sunlight tracking system is installed to drive the mirrors to revolve around the pipes to achieve a maximum of sun radiation. The cold inlet oil is pumped from the bottom of the storage tank and passes through the field inlet. The heated oil is then transferred to a storage tank for generating the electrical power. The

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system is provided with a three way valve located in the field outlet to allow the oil to be recycled in the field until its outlet temperature is adequately heated for entering into the top of the storage tank. The schematic diagram of the solar plant is shown as Fig. 1.

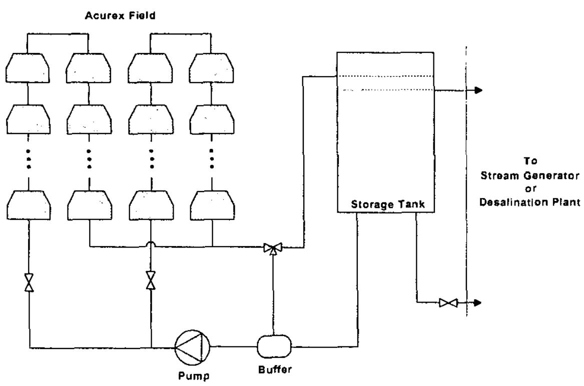

Figure 1: Diagram of the ACUREX distributed solar collector field

The most important objective of the control system is to maintain the outlet oil temperature at a desirable level in spite of disturbances, which may be caused by the changes of solar radiation level, mirror reflectivity and/or inlet oil temperature.

The primary energy of the solar plant is the sun radiation. This is a variable quantity and subjected to the seasonal and daily cyclic variations and atmospheric conditions including cloud coverage, humidity, and air transparency. Since these disturbances lead to significant variation in the dynamic characteristic of the system, it would be difficulties in achieving satisfactory performance with a fixed parameter controller over a wide operation range.

3 The FuzzyPI+D Controller

A digital fuzzy PI+D is adopted for the control of the oil flow in the system for temperature regulation. The block diagram of the overall controller is shown in Fig. 2. It contains a fuzzy PI+D control units arrangement, called the derivative-of-output,which is often desirable if the reference input contains discontinuities [17].

The fuzzy PI controller employs two inputs, the error signal $e_p(nT) = e(nT) = r(nT) - y(nT)$, and the rate of change of the error signal $e_v(nT) = \frac{e(nT)-e(nT-T)}{T}$. Assuming that each input/output has two triangular fuzzy membership functions only, following the derivation in [12], we can have

$$u_{PI}(nT) = u_{PI}(nT-T) + K_{u_{PI}} \Delta u_{PI}(nT) \quad (1)$$

where

$$\Delta u_{PI}(nT) = \begin{cases} \frac{L[K_i e_p(nT)+K_p e_v(nT)]}{2(2L-K_i|e_p(nT)|)} & \text{in IC1, 2, 5, 6} \\ \frac{L[K_i e_p(nT)+K_p e_v(nT)]}{2(2L-K_p|e_v(nT)|)} & \text{in IC3, 4, 7, 8,} \\ \frac{[K_p e_v(nT)+L]}{2} & \text{in IC9, 10,} \\ \frac{[K_i e_p(nT)+L]}{2} & \text{in IC11, 12,} \\ \frac{[K_p e_v(nT)-L]}{2} & \text{in IC13, 14,} \\ \frac{[K_i e_p(nT)-L]}{2} & \text{in IC15, 16,} \\ 0 & \text{in IC18, 20,} \\ L & \text{in IC17,} \\ -L & \text{in IC19.} \end{cases}$$

with the regions IC depicted in Fig. 3 and constants K_p, K_i, L.

The D controller in the control system, as shown in Fig. 2, has two inputs $y_d(nT) = y(nT) - r(nT) = -e(nT)$ and $\Delta y(nT) = \frac{y(nT)-y(nT-T)}{T}$. The output of the D controller is governed by

$$u_D(nT) = -u_D(nT-T) + K_{u_D} \Delta u_D(nT) \quad (2)$$

where

$$\Delta u_D(nT) = \begin{cases} \frac{L[K y_d(nT)-K_d \Delta y(nT)]}{2(2L-|y_d(nT)|)} & \text{in IC1, 2, 5, 6,} \\ \frac{L[K y_d(nT)-K_d \Delta y(nT)]}{2(2L-K_d|\Delta y(nT)|)} & \text{in IC3, 4, 7, 8,} \\ \frac{[-K_d \Delta y(nT)+L]}{2} & \text{in IC9, 10,} \\ \frac{[y_d(nT)-L]}{2} & \text{in IC11, 12,} \\ \frac{[-K_d \Delta y(nT)-L]}{2} & \text{in IC13, 14,} \\ \frac{[y_d(nT)+L]}{2} & \text{in IC15, 16,} \\ 0 & \text{in IC17, 19,} \\ -L & \text{in IC18,} \\ L & \text{in IC20.} \end{cases}$$

with the regions are defined in Fig. 4 and constants K, K_d, L.

Hence, the overall fuzzy PI+D control law is

$$\begin{aligned} u_{PID}(nT) &= u_{PI}(nT-T) + K_{u_{PI}} \Delta u_{PI}(nT) \\ &\quad + u_D(nT-T) - K_{u_D} \Delta u_D(nT) \end{aligned} \quad (3)$$

with constants $K_{u_{PI}}$ and K_{u_D}.

The use of this fuzzy PID controller has the following specific features:

1. It has the same linear structure as the conventional PID controller, but has constant coefficient, self-tuned control gains: the proportional, integral, and derivative gains are nonlinear functions of the input signals.

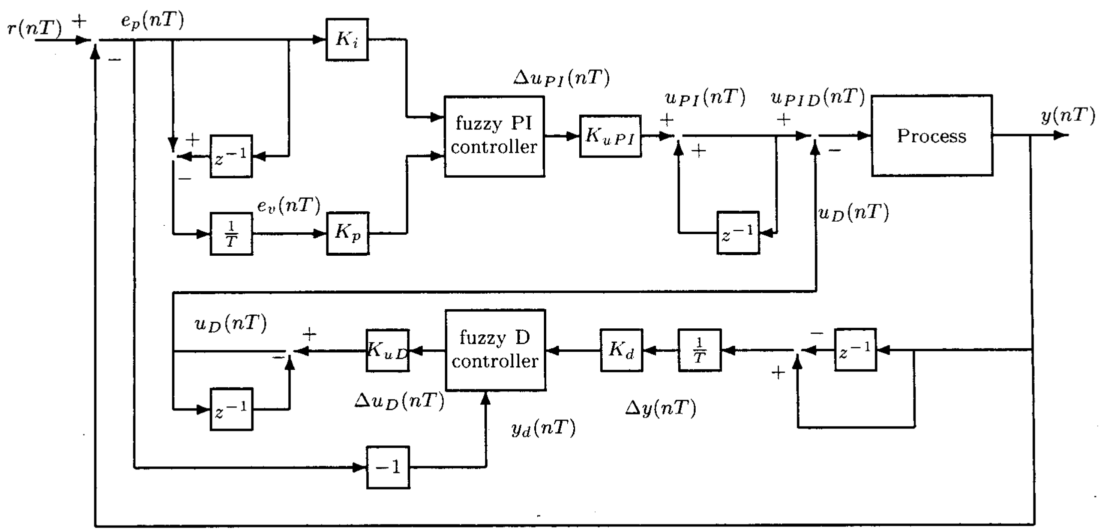

Figure 2: The fuzzy PI+D control system

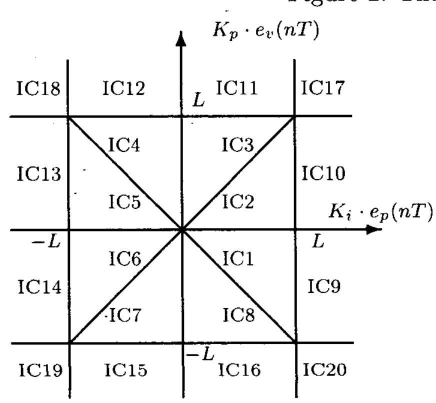

Figure 3: Regions of the fuzzy PI con troller input-combination values

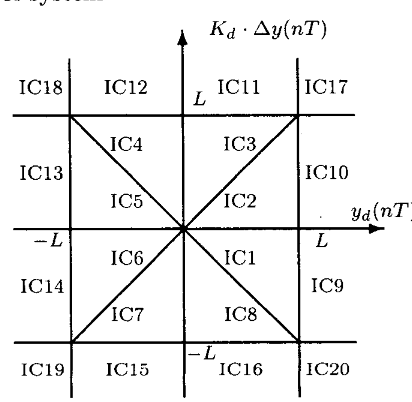

Figure 4: Regions of the fuzzy D controller input-combination values

2. The controller is designed based on the classical discrete PID con troller, from which the fuzzy con trol law is derived. F uzzy logic is emplo yed only for the design; the resulting controller does not need to execute any fuzzy rule base, and is actually a conven tional PID con troller with analytic formulas.

3. Membership functions are simple triangular ones with only four fuzzy logic if-then rules. The fuzzification, control-rule execution, and defuzzification steps are all embedded in the final product of the fuzzy control la w. The resulting control law is an explicit con ven tionaformula, so the controller works just like a conv en tional PID controller, while the fuzzification-rules-defuzzification routine is not needed throughout the entire control process.

4 Optimal Controller Design Using GA

The basic principles of GA were firstly proposed by Holland [9]. Thereafter, a series of literatures [8, 11, 10] and reports [15, 16] hav e become available.

GA is inspired by the mechanism of natural selection where stronger individuals would likely be the winners in a competing environment. Through out genetic evolution, the fitter chromosome has the tendency to yield good quality offspring which means better solution to the problem. An optimal solution is hence finally obtained after generations.

4.1 Chromosome representation

Referring to Eq. (3), there are seven control parameters $a = \{K_p, K_i, K_d, L, K_{uD}, K_{uPI}, K\}$ to be determined for an optimal fuzzy PI+D controller. Hence, the chromosome I is defined as $I = \{K_p, K_i, K_d, L, K_{uD}, K_{uPI}, K\}$ with real number representation.

4.2 Genetic operations

Since the genes are represented in real numbers, the specialized genetic operations developed in GENOCOP [11] are adopted. For crossover, the j-th gene of the offspring I' can be determined by

$$I'_j = \beta I_j^{(x)} + (1-\beta) I_j^{(y)} \tag{4}$$

where $\beta \in [0,1]$ are uniformly distributed random numbers, $I^{(x)}$ and $I^{(y)}$ are selected parents.

Mutation is performed within the confined region of the chromosome by applying gaussian noise to the genes [11].

4.3 Objective functions

The main objective of the control system is to maintain the outlet oil temperature that can follow the desired reference command. The overshoot and the settling time are considered as the objectives (f_1 and f_2) of the problem which can be interpreted as

$$f_1 = \frac{y_{max} - r}{r} \tag{5}$$

where y_{max} and r are the maximum temperature output and the reference temperature, respectively; and

$$f_2 = t_s \tag{6}$$

such that $0.98r \le y(t) \le 1.02r \quad \forall t \ge t_s$.

4.4 Pareto-based fitness assignment

Instead of aggregating them with a weighting function, multi-objective approach [6] is applied.

Definition: For a n-objective minimization problem, u is dominated by v if

$$\begin{aligned} &\forall\, i = 1,\ldots,n, \quad f_i(u) \ge f_i(v) \quad \text{and} \\ &\exists\, j = 1,\ldots,n, \quad \text{s.t.} \quad f_j(u) > f_j(v) \end{aligned} \tag{7}$$

The chromosome I can then be ranked with

$$rank(I) = 1 + p \tag{8}$$

if I is dominated by other p chromosomes in the population. Hence, a pareto-based fitness can be assigned to each chromosome according to its rank in the population.

Figure 5 shows an example of six chromosomes in a minimization problem. Chromosome E is ranked as 3 because it is dominated by chromosomes B and C. Chromosomes A, B, C and D are all ranked as 1 since they are the non-dominated solutions for minimizing O_1 and O_2.

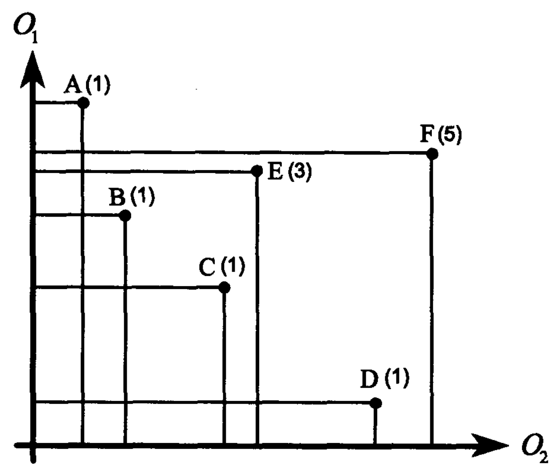

Figure 5: Pareto ranking

Pareto-based ranking can correctly assign all non-dominated chromosomes with same fitness. However, the Pareto set may not be uniformly sampled. Usually, the finite populations will converge to only one or some of these, due to stochastic errors in the selection process. Such phenomenon is known as genetic drift. Therefore, fitness sharing [7] is adopted to prevent the drift and promote the sampling of the whole Pareto set by the population. Individual is penalized due to the presence of other individuals in its neighbourhood. The number of neighbour governed by their mutual distance in objective spaces is counted and the raw fitness value of the individual is then weighted by the this niche count. Eventually, the total fitness in the population is re-distributed favouring those regions with less chromosomes located.

5 Results

The proposed control scheme has been applied to the simulated plant with a testing data simulating the working condition such as the solar radiation and inlet oil temperature etc. of the plant. The rank 1 solution obtained in the last population is depicted in Fig. 6. It can be observed that a well-distributed Pareto set is obtained by the multiobjective approach.

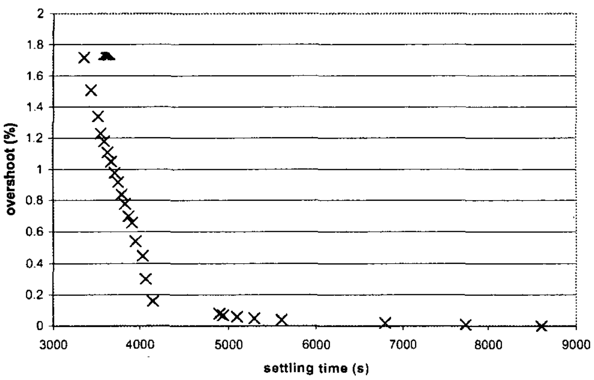

Figure 6: Rank 1 solutions

The following solution set with minimum settling time (denoted as "A") is selected for the the control purpose:

$$K_p = 3.3004, K_i = 2.7463, K_d = 3.1141, K = 0.3077$$
$$L = 185.1126, K_{uPI} = 0.0348, K_{uD} = 1.2086$$

Figure 7 shows the outlet temperature of the controlled plant for a step set point of 180°C. It can be observed that the output is well tracking the reference temperature with fluctuation less than 0.6°C and the overshoot is just about 3°C, even with a large variation on the solar radiation as shown in Fig. 8. The oil flow is also plotted in Fig. 9 for reference.

It should be noticed that the abnormal response in the starting phase of the operation is mainly due to a number of factors:

- the initial temperature profile inside the tubes (including the interconnection tube between the tank and the point in which the inlet oil temperature sensor is placed) is unknown and it causes a wrong results in the numerical integration algorithm in the simulator.

- the oil flow is usually saturated to the minimum value in order to produce the maximum oil heating.

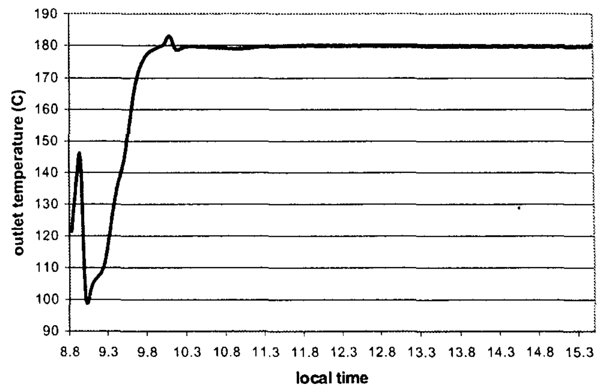

Figure 7: Output response and reference

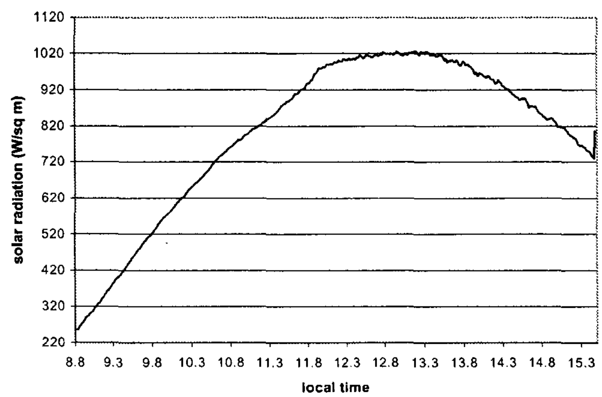

Figure 8: Solar Radiation

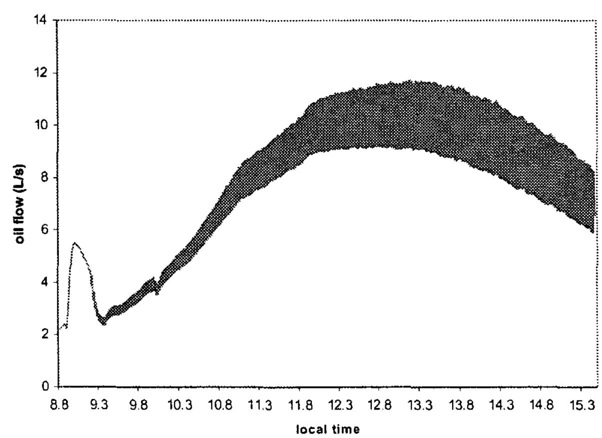

Figure 9: Oil flow

6 Conclusion

This paper describes the design of an optimal fuzzy Proportional-Integral-Derivative (PID) controller for the solar plant at Tabernas, in Almería, Spain. The design parameters of the Fuzzy PID controller are optimized by using Generic Algorithm. With the multiple objective approach adopted, a well distributed Pareto set of solutions is obtained to address the conflicting control design specifications. Finally, the simulation result demonstrated that the controller can provide a well tracking behaviour against the system variations.

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