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Design of PID Controller Using Genetic Multiple Attributed Decision Making for Automatic Voltage Regulator System

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Abstract

Controller design and optimization problems, with more than one objective, are referred as multiple objectives or multiple attributed problems. In this paper, a novel method is proposed for designing optimum PID controller that is called genetic multiple attributed decision making method (GMADM). This method is newer than the previous methods and in this paper some options are considered that have not been considered in previous paper for simplicity. The proposed PID controller is applied on the automatic voltage regulator (AVR).An automatic voltage regulator system is the main part of a generator because this system keeps the output voltage in constant level. The simulation results of automatic voltage regulator system are compared with conventional multiobjective algorithm, known as multiobjective genetic algorithm (MOGA).The simulation results of automatic voltage regulator system show that GMADM method is better than MOGA and number of optimum solutions of the proposed method is greater than the other one.

Keywords: *Genetic multiple attributed decision making, Entropy, TOPSIS, Pareto, Multiobjective genetic, Automatic voltage regulator*

1. Introduction

As a significant goal, input tracking by output is much paid attention in the problem of design controller. Although several control methodology have been developed broadly, the proportional integral derivative (PID) controllers are widely used in process control, motor drives, flight control, and instrumentation. These wide applications are mainly due to simplicity of PID structure which can be easily understood and implemented. Indeed, Industries use these controllers extensively because of their robustness and simplicity [1].

Most optimization problems in control systems have more than one objective function for optimization [2]-[8], which in turn may need a significant computational time to be evaluated [9]. In controller design, maximum overshoot (OS), settling time (t_s), rise time (t_r) and steady state error (e_{ss}) of the step response can be objective functions.

Recently, controllers have been optimally designed by evolutionary algorithms (EAs) such as genetic algorithm (GA) [9]-[10]. GA is good for solving nonlinear problems because of its better robust behavior in nonlinear environments over mixing optimization techniques [11]. There are several EAs based on GA however non-dominated sorting GA (NSGA II) is used widely. A lack of theoretical convergence proof to the Pareto optimal front is considered as the main shortcoming of EAs [12]. Genetic multiple attributed decision making method (GMADM) in comparison with GA can be appropriate in the problems, that solutions of GA are distributed [13].

In multiple attributed optimizations, a matrix is introduced including options and criteria. The optimum solution (best option) is chosen so that the most appropriate criteria are satisfied. In this paper, a PID controller is designed by GMADM.

The designed controller is implemented on an AVR system. Different methods are employed in designing PID for an AVR [14]-[18], amongst, one or more options of the following cases are considered for simplicity:
Linear structure of AVR, single objective solution, solving in frequency space.

In this study, the structure of the AVR is nonlinear and the optimization problem is multiobjective.

2. Multiobjective optimization

In multiobjective optimization problem (MOP), multiple criteria or objectives are optimized so that the optimum solution of the problem is given as a set, called Pareto optimum solution and the objectives are evaluated by Pareto optimum solution called Pareto front.

MOP, without loss of generality, can be represented as following:

$$\min_{\theta \in R^n} J(\theta) = [J_1(\theta), \ldots, J_m(\theta)] \in R^m \tag{1}$$

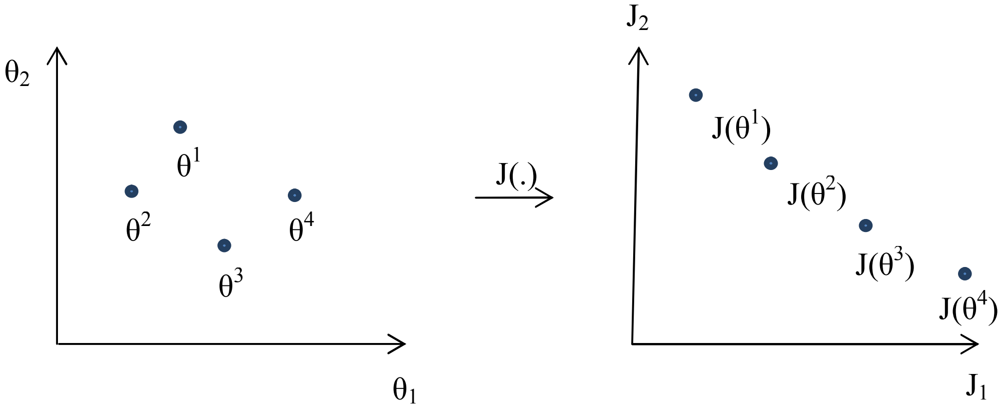


Figure 1. Pareto set (left) and Pareto front (right)

where $\theta \quad R^n$ is defined as the decision vector (Pareto set) and J(θ) as the objective vector (Pareto front), as shown in Figure 1.

Since, there is generally no unique solution for an MOP because none of the solutions are better than the others for all the objectives. Assume θ_P and J_P are respectively defined as the Pareto set and the Pareto front. Each point in the Pareto front represents a non-dominated solution. It is shown in Figure 2.

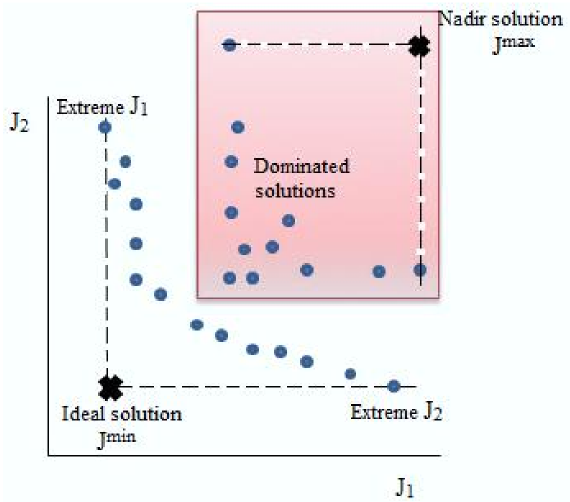


Figure 2. Non-dominated solution

A solution θ^1 with objective vector $J(\theta^1)$ dominates a second solution θ^2 with objective vector $J(\theta^2)$ if and only if:

$$\left\{\forall i \in [1,2,...,m], J_i(\theta^1) \le J_i(\theta^2)\right\} \wedge \left\{\exists q \in [1,2,...,m] : J_q(\theta^1) < J_q(\theta^2)\right\} \tag{2}$$

Which is denoted as $\theta^1 \prec \theta^2$.

The ideal solution J^{min} and the nadir solution J^{max} are defined as follows:

$$J^{ideal} = J^{\min} = \left[\min_{J(\theta)\in J_P^*} J_1(\theta),...., \min_{J(\theta)\in J_P^*} J_m(\theta)\right] \tag{3}$$

$$J^{nadir} = J^{\max} = \left[\max_{J(\theta)\in J_P^*} J_1(\theta),...., \max_{J(\theta)\in J_P^*} J_m(\theta)\right] \tag{4}$$

To determine the Pareto front set, the rank of solutions is calculated. Several algorithms exist to approximate this Pareto front approximation including normal boundary intersection method [19], normal constraint method [20]-[23], and the successive Pareto front optimization [24]. Recently, multiobjective evolutionary algorithms (MOEAs) have been used because of their flexibility in dealing with non-convex and stringently constrained functions [25].

3. Multiobjective genetic algorithm

GA is an optimization method initially introduced by John Holland. It is a stochastic and random search method based on the laws of natural selection, biological evolution, and genetics which operate as a totally different optimization procedure among other optimization methods. Generally, a basic GA consists of three operations: selection, genetic operation, and replacement [26].

Multiobjective genetic algorithm (MOGA) is slightly different with single objective genetic algorithm. In the selection mechanism of MOGA, the rank of any chromosome in the population is equal with number of solutions by which is dominated. All of non-dominated solutions have the same rank. Finally, they have same chances to be selected in the next generation. MOGA uses fitness sharing approach to achieve the solutions that are distributed uniformly in Pareto set and to create appropriate distribution in the solution space.

4. Multiple attributed decision making method

Multi criteria optimization is divided to two parts: multiobjective and multiple attributed optimization.

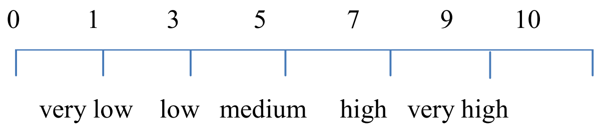
Multiple attributed decision making (MADM) method is used to select the most appropriate option among m options. A multiple attributed problem is shown as a following matrix (decision making matrix (D)):

Option	Criterion			
	x_1	x_2	..	x_n
A_1	r_{11}	r_{12}	..	r_{1n}
A_2	r_{21}	r_{22}	..	r_{2n}
.	.	.	.	.
A_m	r_{n1}	r_{n2}	..	r_{mn}

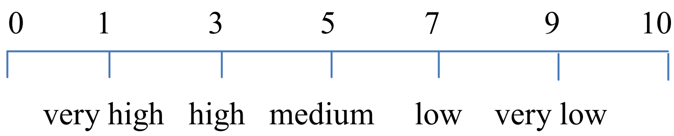
where A_i is i^{th} option, x_j is j^{th} criterion and r_{ij} is worth of j^{th} criterion for i^{th} option. Often, criteria have different scales and are in contradiction with each other. As a result, an option cannot be optimum and obtains ideal point from any criterion [27].

Criteria can be quantitative and qualitative. Quality criteria can be ranked using difference among themselves. A common method is the bipolar distance.

Positive criterion:



Negative criterion:



As quantitative criteria have different scales, they should be dimensionless. The method used in this paper, is Euclidean norm:

$$n_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^2}} \tag{5}$$

where n_{ij} is the dimensionless element, r_{ij} is an element of decision making matrix; and m is the number of row of decision making matrix.

As a first step in MADM, a weight is assigned to each criterion, based on its importance. Then, the most appropriate option is selected by two evaluation models: compensator and non-compensator models. In non-compensator model, there is no trade off among criteria. On the other hand, the weakness of a criterion is not compensated by advantage of another criterion conversely, in compensator model; the adverse effect of a criterion is compensated by changing in other criterion [27].

5. Genetic multiple attributed decision making method

In GA, the selection operation is used to produce the next generation. In this paper, a new method is proposed for selection operation which produces the next generation and the Pareto optimum solutions. In this way, the weights of criteria are calculated. Subsequently, the most appropriate option in each step is chosen by a method of compensator model and some of the chromosomes (each chromosome is an option) are selected for next generation.

5.1 Entropy

There are different methods for allocating weight. The method used for this purpose here is Entropy.

Entropy is a fundamental concept in physical and social sciences and information theory. It is the indicant of unreliability of expected content in a message. In information theory, Entropy is a standard of expressed uncertainty by a discrete probability distribution (P_i). So if values of a criterion change more than other criteria, it is much considered and its weight is more [27].

Given the decision making matrix, the Entropy method is represented as following:
Step 1: Information content is calculated:

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}; \forall i, j \tag{6}$$

Step 2: The uncertainty is computed:

$$E_j = -k \sum_{i=1}^{m} \left[P_{ij} . \ln P_{ij} \right]; k = \frac{1}{\ln m} \tag{7}$$

$$d_j = 1 - E_j; \forall j \tag{8}$$

Step 3: Weight of each criterion is calculated:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}; \forall j \tag{9}$$

where m and n are the number of rows and columns of D, respectively; d_j is the uncertainty (deflection degree); and w_j is the weight of each criterion [27].

5.2 TOPSIS

In MADM, after allocating weights of criteria, the most appropriate option is selected using a compensator or non-compensator model.

Technique for Order-Preference by Similarity to Ideal Solution (TOPSIS) is one of the compensator models that the most appropriate option is chosen according to the minimum difference of the positive ideal solution and the maximum difference of the negative ideal solution. The selection process is presented below:
Step 1: The criteria made dimensionless by Euclidean norm.
Step 2: Given the vector of weights, anew matrix is computed:

$$V = N_D \times W \tag{10}$$

where V is a new matrix. N_D is the dimensionless matrix from D; and W is a matrix in which weights of criteria are placed in the main diagonal and other elements are zero.
Step 3: The positive and negative ideal solution are characterized for each criterion.
Note: The positive ideal solution is the maximum value for the positive criteria and vice versa.
Step 4: The difference between the elements of matrix V and the positive ideal solution (d_i^+) are calculated:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \; ; i = 1, 2, \ldots, m \tag{11}$$

Similarly, d_i^- is computed for the negative ideal solution:

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \; ; i = 1, 2, \ldots, m \tag{12}$$

Step 5: The relative proximity of the A_i (option) to the ideal solution is the following form (cl_i^+):

$$cl_i^+ = \frac{d_i^-}{d_i^- + d_i^+} \; ; 0 \le cl_i^+ \le 1 \tag{13}$$

Step 6: The options are sorted based on cl_i^+.(The cl_i^+ of the most appropriate option is more than the other) [27].

5.3 The novel method

As mentioned earlier, multiple objective decision making (MODM) and multiple attributed decision making (MADM) are two methods in multi-criteria optimization. MODM methods are used to optimize and produce the Pareto optimal solution set. In this study, MADM methods are used for this purpose. It is noted that MADM methods have not been considered in MOEAs.

To use MADM method, first, a population is produced randomly (e.g. the number of chromosomes are fifty in each population); and the objectives are evaluated like MOGA. Next, the chromosomes and value of objectives are placed in the rows and columns of decision matrix, respectively.

After making the decision matrix, weights are allocated for the criteria (value of objectives) by the Entropy method. Then, chromosomes are sorted by the TOPSIS method. The best chromosome which have the maximum value of cl_i^+ would be saved as a Pareto solution in each iteration. Also, the chromosomes which have the better value of cl_i^+ (for example 50% of population) are chosen to produce the next generation. Instead of the eliminated chromosomes, a random population is produced to prevent from creating a local minimum point. Indeed, the Pareto rank of solutions is determined. The crossover and mutation operations are like MOGA. Meanwhile, the probability of crossover and mutation is changed based on the difference between maximum and minimum of cl_i^+ in each iteration (e.g. different of $cl_i^+{}_{max}$ and $cl_i^+{}_{min}$ is less than 0.2 probability of crossover is 0.8).The name of algorithm is genetic multiple attributed decision making (GMADM).

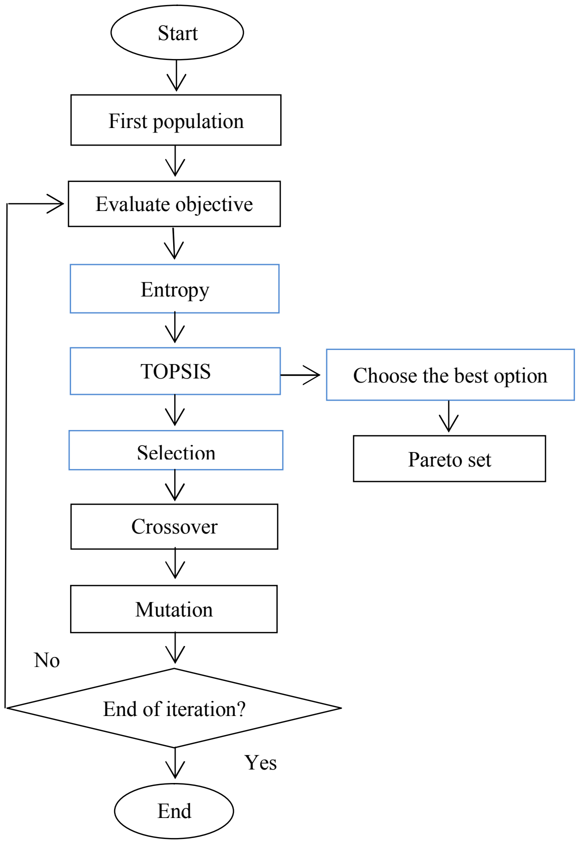


Chart of new method

By having the maximum value of cl_i^+ in all of iterations, the solutions are finally the Pareto optimum solution set and their corresponding value of objectives from Pareto front. In the online systems, GMADM does not act well, because it is an offline method and spends several hours. The chart of the proposed method is shown as following:

6. Automatic Voltage Regulator

In a generator, the output voltage amplitude must be a constant value. There are many disturbances in a power system, like, temperature rise, speed change, load change and power factor change, which all affect the voltage level of the generator [28]. So, it is necessary to keep the voltage level constant. In response to active power changes, the input fuel to the turbine (steam, water) must be increased to match the demanded power, or the frequency of the network decreases. This can be done automatically by a system called automatic generation control (AGC). In addition to this, variation in reactive power may change the voltage level. So, the exciter should be regulated in order to match the voltage drop (or rise). There must be a voltage regulator device in order to adjust the voltage according to the new conditions. Voltage regulator can be controlled automatically or manually by tap-changing witches, a variable auto transformer and also an induction regulator [29]. When controlling manually, an operator reads the voltage by a voltmeter and decides what to do, but it is not always possible, especially in modern large networks. AVR system is designed for this purpose. Generally, three important tasks exist for an AVR system:
1) Better regulation of voltage,
2) Increasing the stability,
3) Reducing over-voltage on loss of load [28].

A simple AVR system is shown in Figure 3. The AVR system consists of four parts: amplifier, exciter, generator and sensor.

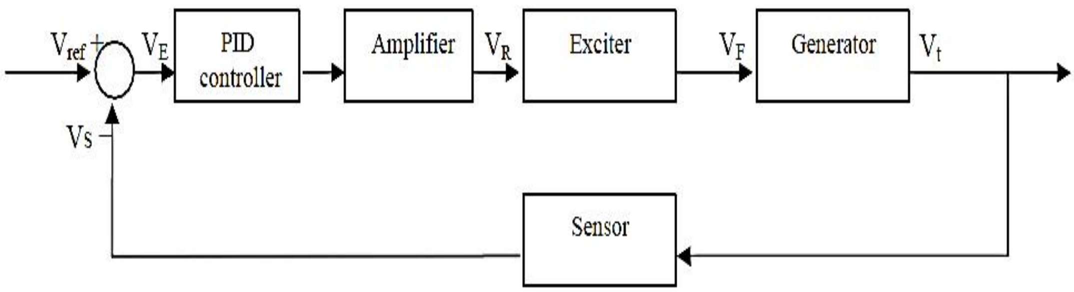


Figure 3. AVR system

Amplifier model:

The transfer function of amplifier is represented by a gain K_A and a time constant τ_A;

$$\frac{V_R}{V_E} = \frac{K_A}{1+\tau_A S} \tag{14}$$

The range of K_A is from 10 to 400, and the range of τ_A is from 0.02 to 0.1 s.

Exciter model:

The transfer function of exciter is represented by a gain K_E and a time constant τ_E;

$$\frac{V_F}{V_R} = \frac{K_E}{1+\tau_E S} \tag{15}$$

The range of K_E is from 10 to 400 and the range of τ_E is from 0.5 to 1.0 s.

<u>Generator model:</u>

The transfer function of generator represented by a gain K_G and a time constant τ_G;

$$\frac{V_t}{V_F} = \frac{K_G}{1+\tau_G S} \tag{16}$$

The range of K_G is between 0.7 and 1, and the range of τ_G is between 1 and 2 s.

<u>Sensor model:</u>

The sensor is modeled by a simple first-order transfer function that consists of K_R and τ_R;

$$\frac{V_S}{V_t} = \frac{K_R}{1+\tau_R S} \tag{17}$$

The time constant τ_R is very small, changing from 0.001 to 0.06 s [1].

Exciter system is the main part of AVR loop and supplies the energy of the generator's field. In old power houses, the exciter system consists of a generator that was rotated by the shaft of main generator. This system required loops and sliding brushes to transfer DC power to generator's field. Nowadays, the exciter has no brush.

6.1 Modeling an exciter system of synchronization generators

In this paper, the exciter system model of the synchronization generator is ST-Static. This exciter system is of type IEEE-ST1A, as shown in Figure 4. Also, The parameter values are in Table 1.

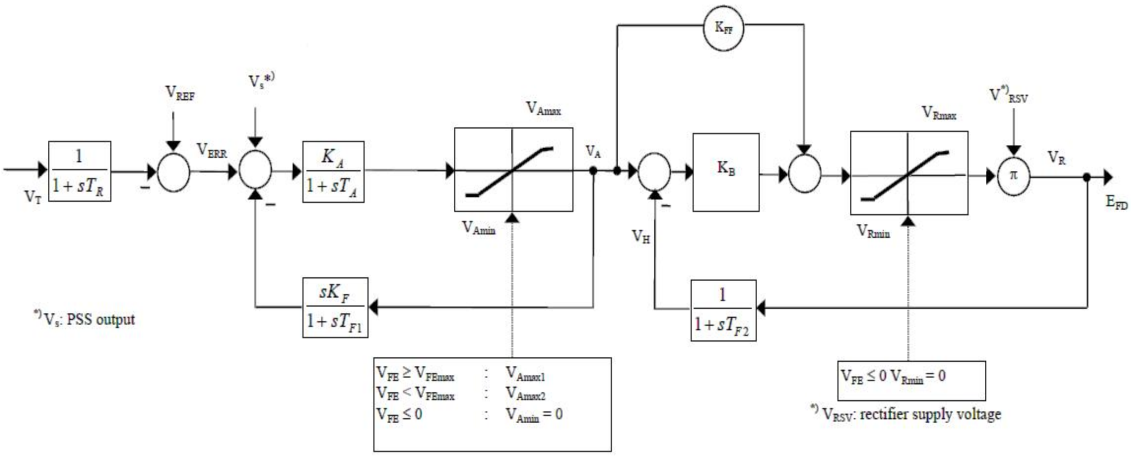


Figure 4. The IEEE-ST1A exciter

7. Simulations

In this paper, a PID controller is designed by GMADM method for an AVR system with an exciter of the IEEE-ST1A type. The Chromosomes are PID parameters (K_d, K_p and K_i). The range of PID parameters is shown in Table 2.

Table 1. Parameter of exciter

Parameter	**Value**
T_A	1 ms
T_{F1}	400 ms
T_{F2}	100 ms
T_R	12 ms
K_A	4000
K_F	400ms
K_{FF}	1
K_B	1
E_{FDmax}	6.38 p.u.
V_{FEmax}	4.399 p.u.
V_{Amax2}	6.38 p.u.
V_{Amax1}	3.506 p.u.
V_{Rmax}	6.38 p.u.
V_{Rmin}	- 5.101 p.u.

Table 2. The range of PID parameters

	Low	Up
K_p	10	50
K_i	0	1
K_d	0.0001	1

The objectives are introduced as following:

$$\begin{cases} f_1 = \exp(OS) \\ f_2 = t_s \\ f_3 = 1 + e_{ss} \end{cases} \tag{18}$$

In GMADM, the PID controller parameters are optimized to minimize the performance indexes. The results of this method are compared with the MOGA (NSGA II). The Pareto front solution (OS, e_{ss} and t_s) of GMADM and MOGA are shown in Figures 5 and 6. As shown in Figure 5, the objectives have been minimized by GMADM well, but the MOGA has not been capable to minimize the objectives well. It is noted the values of OS and e_{ss} of GMADM are similar to MOGA. Furthermore, the values of t_s are approximately 14 seconds in MOGA method and very much better in GMADM. GMADM in comparison with MOGA is appropriate, that solutions of MOGA are distributed.

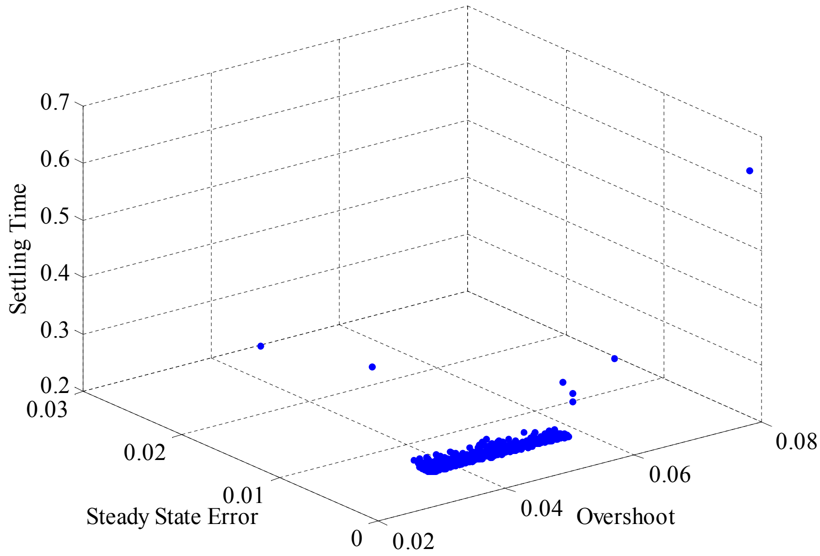


Figure 5. GMADM Pareto front

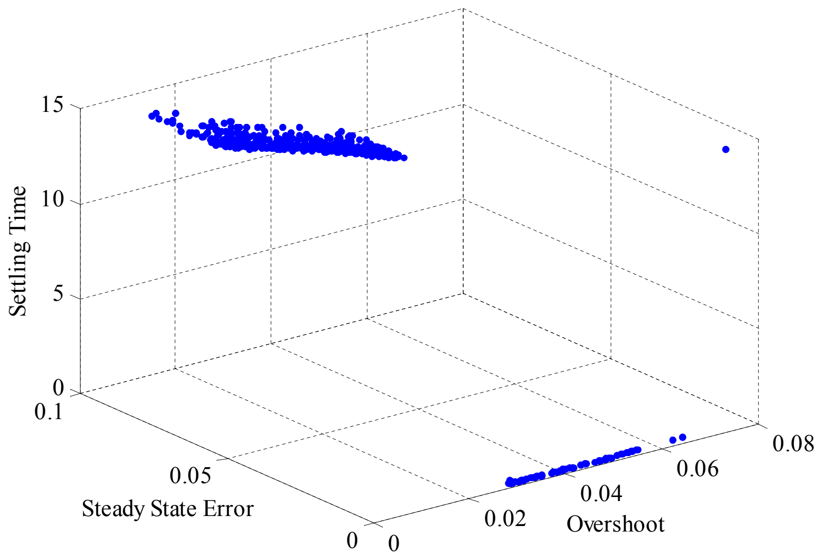


Figure 6. MOGA Pareto front

The best solution of Pareto set of two methods is shown in Figure 7.

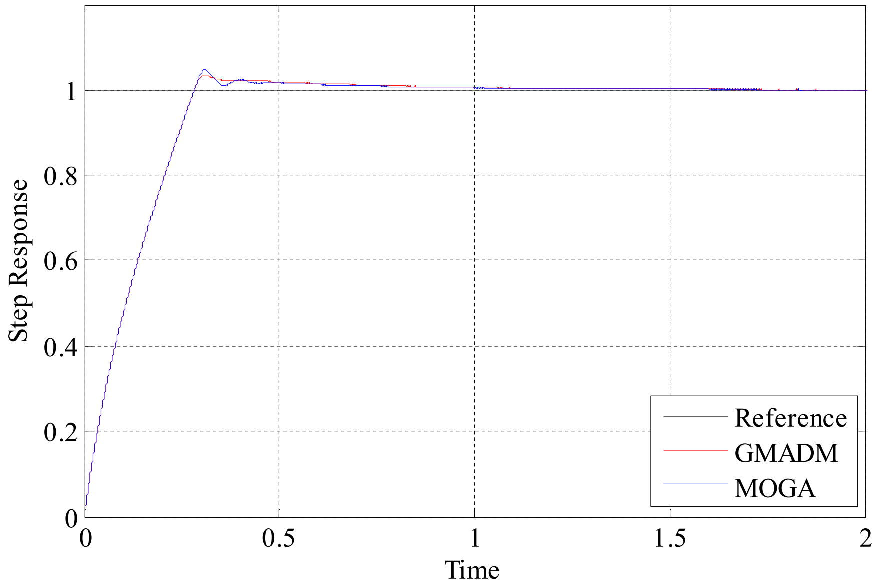


Figure 7. The best solution of Pareto set

It is seen that both methods approximately have same response, but the OS of the step response of GMADM is slightly less than the other method. The control signal of the best solution of GMADM is shown Figure 8. It is shown that the control signal can achieve to zero.

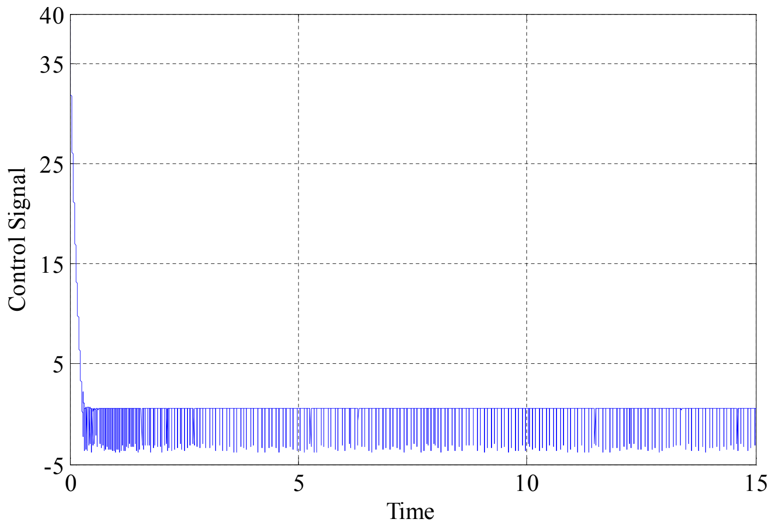


Figure8. Control signal

The worst solution of Pareto set of two methods is shown in Figure 9.

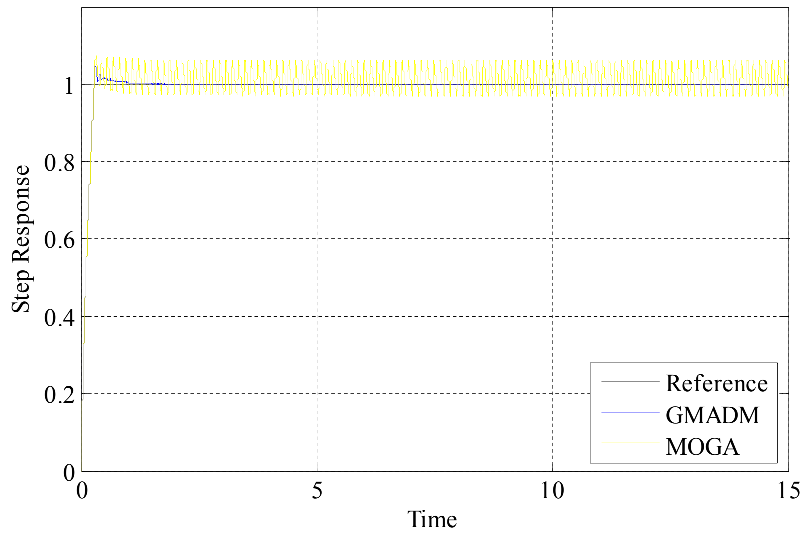


Figure 9. The worst solution of Pareto set

Therefore, the step response of GMADM is much better than the MOGA. The steady state error of GMADM is zero, but the step response of MOGA oscillates around final point. Also, steady state error is not zero. The control signal of the worst solution of GMADM is shown in Figure 10. It is shown that the control signal can achieve to zero.

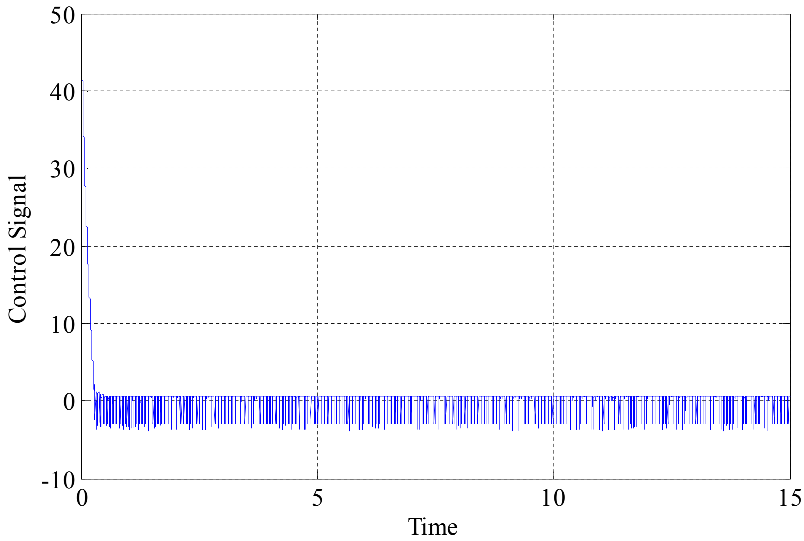


Figure 10. Control signal

To test disturbance rejection of designed PID, a step disturbance is applied (the size of step is considered as 0.5). Figure 11 shows the disturbance rejection of the best solution of GMADM. The disturbance is rejected in 0.7 s.

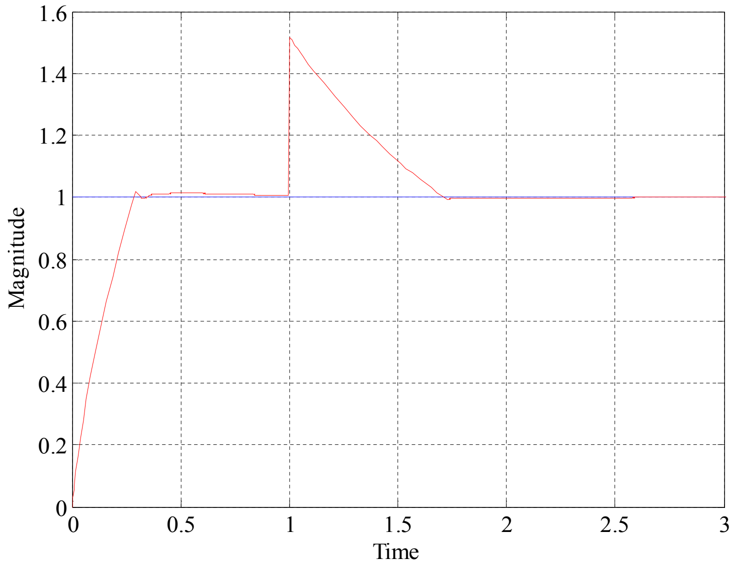


Figure 11. Disturbance rejection

To show the designed PID controller operates, the input is changed. The result is shown in Figure 12.

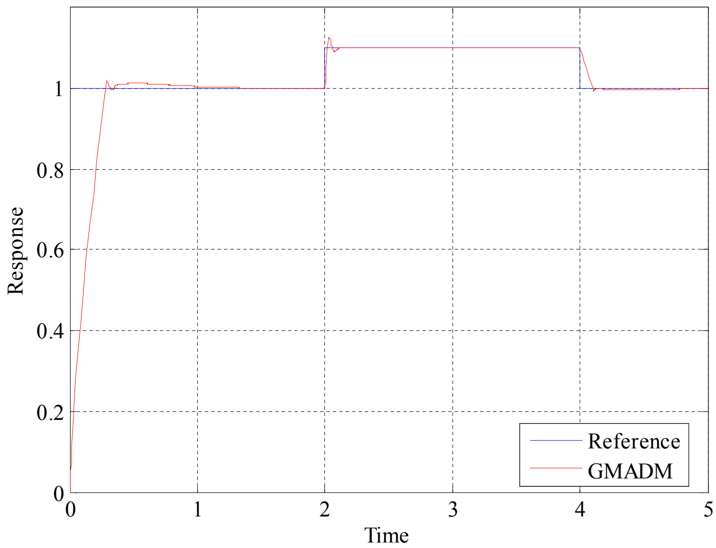


Figure 12. Response to input variations

It is seen that output of system could track reference and PID controller has act well. The results of simulations are presented in Table 3.

Table 3. Results of simulations

Method	Results						
	Type	OS	t_s (5%)	e_{ss}	K_p	K_i	K_d
GMADM	Best	0.033	0.2628	0	39.375	0.0001	0.109375
	Mean	0.0412	0.2628	0	45	0.00166	0.275781
	Worst	0.0494	0.2628	0	48.125	0.0001	0.453125
MOGA	Best	0.0471	0.2628	0	45.3597	0.0669	0.397939
	Mean	0.0547	1.03524	0	40.4503	0.09645	0.499809
	Worst	0.0731	14.9512	0	42.5769	0.1376	0.87308

8. Conclusions

In this study, a novel method was proposed for designing PID controller. This method is based on multiple criteria optimization method. In this method, a matrix is defined that options (chromosomes) and criteria (objectives) are placed in its rows and columns, respectively. The criteria that are the maximum of overshoot, settling time and steady state error, have been weighted based on their importance by Entropy. The optimum solution (the best controller) was chosen by TOPSIS, to be as near as possible to the positive ideal solution and as far as possible from the negative ideal solution. The designed controller was implemented on an AVR system. The simulations show that GMADM performs better than MOGA and number of optimum solutions of the proposed method is greater than the other one. Furthermore, in order to show the appropriate performance of designed PID, a disturbance is applied and the input is changed. In the first case, the disturbance is rejected. In the second case, the output of system tracks the reference. Finally, it can be said that the performance of new method is Efficient.

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