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# 자기부상시스템을 위한 교수-학습 최적화 알고리즘 기반의 퍼지 PID 제어기 설계

## Design of TLBO-based Optimal Fuzzy PID Controller for Magnetic Levitation System

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(Jae-Hoon Cho · Yong Tae Kim)

**Abstract** - This paper proposes an optimum design method using Teaching-Learning-based optimization for the fuzzy PID controller of Magnetic levitation rail-guided vehicle. Since an attraction-type levitation system is intrinsically unstable, it is difficult to completely satisfy the desired performance through the conventional control methods. In the paper, a fuzzy PID controller with fixed parameters is applied and then the optimum parameters of fuzzy PID controller are selected by Teaching-Learning optimization. For the fitness function of Teaching-Learning optimization, the performance index of PID controller is used. To verify the performances of the proposed method, we use a Maglev model and compare the proposed method with the performance of PID controller. The simulation results show that the proposed method is more effective than conventional PID controller.

**Key Words** : Teaching-learning-based optimization, Fuzzy PID controller, Magnetic levitation, Rail-guided vehicle

## 1. 서 론

Up to now, many kinds of Magnetic levitation(Maglev) systems have been developed and reported. Generally, three types of levitation technologies are applied to magnetic levitation systems: electromagnetic suspension (EMS) based on attraction force, electrodynamic suspension (EDS) based on repulsive force, and electromagnet-permanent magnet (EM-PM) hybrid electromagnetic suspension with various advantages such as increasing levitation air gap length and decreasing total weight of the system[1-2]. Although EMS Maglev system was developed almost 30 years ago, many countries still has been exploring EMS system because EMS-type Maglev system is more cost-effective than EDS and EM-PM type systems[3]. EMS Maglev system is a complex, nonlinear and inherently unstable system. Because the stability of suspension control directly affects the safety of an EMS Maglev, various kinds of control algorithm have been studied[4-5]. To obtain a stable controller of EMS Maglev system, many control methods such as PID control, state feedback, optimal control, robust control, feedback linearization have been introduced. However, some control methods show the poor performance of suspension control [6-10].

In recent years, fuzzy logic controller and fuzzy PID controller have been widely used for industrial processes owing to their heuristic nature associated with simplicity and effectiveness. In fact, for single-input single-output systems, fuzzy logic controllers are essentially fuzzy PD type, fuzzy PI type or fuzzy PID type associated with nonlinear gains. Because of the nonlinear property of control gains, fuzzy PID controllers possess the potential to improve and achieve better system performance over the conventional PID controller if the nonlinearity can be suitably utilized.

On the other hand, due to the existence of nonlinearity, it is usually difficult to conduct theoretical analysis to explain why fuzzy PID can achieve better performance. From the theoretical and practical points of view, it is important to explore the essential nonlinear control properties of fuzzy PID and find out appropriate design methods which will assist the control engineers to confidently utilize the nonlinearity of the fuzzy PID controllers to improve the closed-loop performance. There are many design factors determining its structure in a fuzzy logic controller such as membership functions, input space partition of fuzzy rules, various types of fuzzy inference mechanisms, defuzzification schemes, etc. They may appear either highly nonlinear or approximately linear. Nevertheless, to perform proportional, integral and derivative control modes,

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the structure of a fuzzy logic controller has to be analogous to a normal PID controller in some way. Although various types of fuzzy PI, PD and PID controllers have been proposed, they can be classified into two major categories according to the way of construction. The fuzzy PID controller is composed of the conventional PID control system in conjunction with a set of fuzzy rules and a fuzzy reasoning mechanism. The main difficulty in using fuzzy PID controller is that the analysis task is relatively tough, as it is hard to acquire the equivalent nonlinearity of the fuzzy knowledge base. Besides, associating three PID gains adaptively with the system responses requires expertise which may not be so straightforward for a user or designer to extract [11-13].

In the paper, a fuzzy PID controller with fixed parameters is applied and then the optimum gains of fuzzy PID controller are selected by Teaching-Learning-based Optimization (TLBO) method. For the fitness function of TLBO, the performance index of PID controller is used. To verify the performance of the proposed method, we use a model of Maglev vehicle and compare the performance of the proposed method with conventional PID controller through the simulation results.

## 2. Design of electromagnet for EMS-type Maglev system

Many studies dealing with Maglev system are based on linearization model using a Taylor series. In this paper, we use the linearized Maglev model based on a Taylor series of the actual nonlinear dynamic model and force distribution at nominal operating points. Fig. 1 shows the simplified EMS-type Maglev system and Table 1 shows the parameters

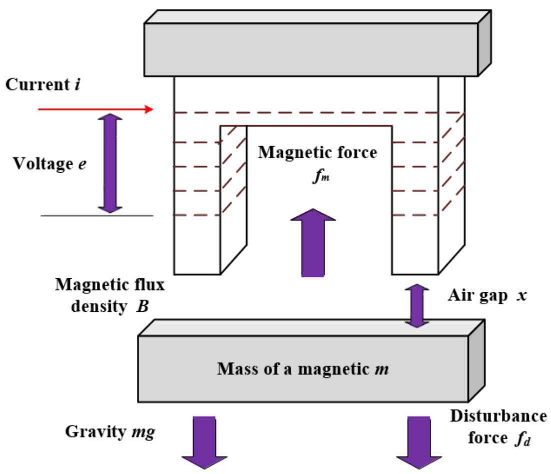



Fig. 1 Structure of the EMS-type Maglev system

Table 1 System parameters of the Maglev transportation system

| | Parameters | Nominal value |
|---|---|---|
| $Q\,[Hm]$ | Speed electromotive force | $13.1812\times10^{-4}$ |
| $k\,[Hm]$ | Force coefficient | $6.5906\times10^{-4}$ |
| $L\,[H]$ | Nominal inductance | 0.1097 |
| $R\,[\Omega]$ | Coil resistance | 31.1 |
| $X_1\,[m]$ | $X+X_0$ | 0.01 |
| $m\,[kg]$ | Magnet mass | 0.01058 |
| $I\,[A]$ | Nominal current | 0.125 |

of Maglev system used in this paper. The dynamic equation of a Maglev system is as follow[14]:

$$m\frac{d^2x}{dt^2}=mg-f_m+f_d=mg-k\left(\frac{i}{x+X_0}\right)^2+f_d \tag{1}$$

where $k=(N^2\mu_0 S)/4$, N is the number of winding turns of the electromagnet; $\mu_0$ is the permeability of free space; S is the pole face area of the electromagnet; and $x$, $f_m$ and $f_d(t)$ denote the air gap, magnetic force and disturbance force input, respectively. If R is the total resistance of the circuit, then an instantaneous voltage e can be described by

$$e=\frac{d}{dt}(L\,i)+R\,i\;=-\frac{Q}{(x+X_0)^2}\,iv+L\frac{di}{dt}+R\,i \tag{2}$$

$$X_0=\frac{l_m}{2\mu_s},\; Q=\frac{\mu_0 N^2 S}{2} \tag{3}$$

where $l_m$ is the magnet length of the guideway and iron core along the magnetization direction.

In nominal equilibrium point, The transfer function of system is obtained by using Laplace transform and the parameters shown in Table 1.

$$G(s)=\frac{-1419.60}{s^3+283.50s^2+392.38s-551880} \tag{4}$$

## 3. Fuzzy PID controller with parallel structure

### 3.1 The structure of a fuzzy PID controller

In the paper, a fuzzy PID controller with parallel structure is used. The block diagram of the fuzzy PID controller is described by Fig. 2. Although most of fuzzy controller

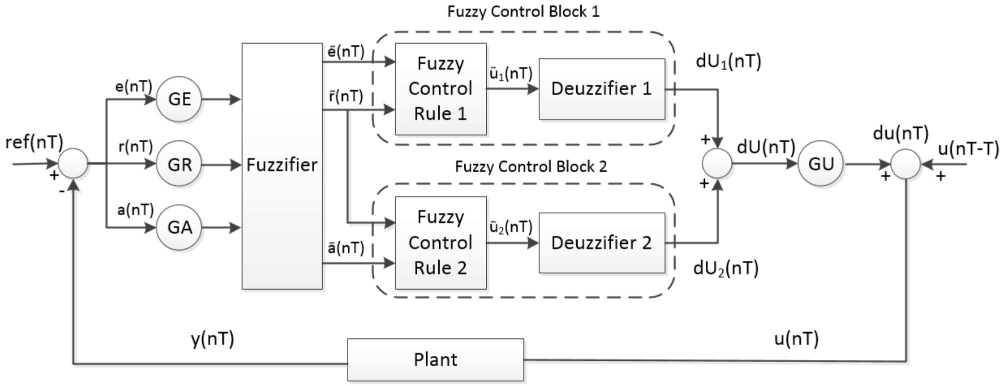



Fig. 2 Structure of a fuzzy PID control system with fixed parameters

employs two inputs such as error and rate of change of error(rate for short) about a set-point, an additional input named as accelerated rate of change(acc for short) of error is used for the fuzzy PID controller. The fuzzy PID controllers with these three inputs can be composed of two independent parallel fuzzy controllers which contain fuzzy control rules and defuzzier, respectively.

The incremental output of the fuzzy PID controller is formed by algebraically adding the two outputs of fuzzy control blocks. In this paper, we employ the following notations:

$$e(nT) = ref(nT) - y(nT) \tag{5}$$

$$e^{*} = GE \times e(nT) \tag{6}$$

$$r(nT) = [e(nT) - e(nT-T)]/T \tag{7}$$

$$r^{*} = GR \times r(nT) \tag{8}$$

$$\begin{aligned} a(nT) &= [r(nT) - r(nT-T)]/T \\ &= [e(nT) - 2e(nT-T) + e(nT-2T)]/T^2 \end{aligned} \tag{9}$$

$$a^{*} = GA \times a(nT) \tag{10}$$

$$dU(nT) = dU_1(nT) + dU_2(nT) \tag{11}$$

$$du(nT) = GU \times dU(nT) \tag{12}$$

$$u(nT) = du(nT) + u(nT-T) \tag{13}$$

where $n$ is positive integer, $T$ is sampling period, $y(nT)$, $e(nT)$, $r(nT)$ and $a(nT)$ denote process output, *error*, *rate* and *acc* at sampling time $nT$, respectively. $GE$ is the input scale value for error, $GR$ is the input scale value for rate, $GA$ is the input scale value for *acc* and $GU$ is the output scale value for the fuzzy PID controller at sampling time $nT$. The $dU$ denotes the incremental output of the fuzzy PID controller, the $dU_1$ is the output of fuzzy control block 1, $dU_2$ is the output of fuzzy control block 2 in the Fig. 2 and

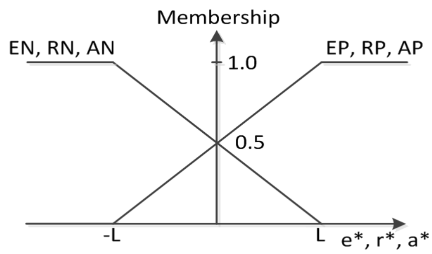
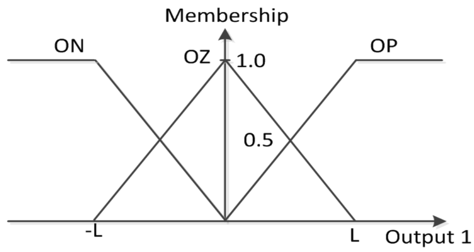
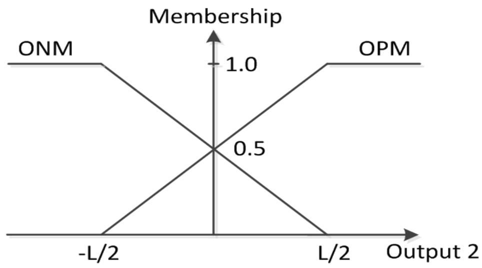



Fig. 3 Membership functions for input variables




(a) $dU_1$




(a) $dU_2$

Fig. 4 Membership functions for output variables

u is the control input. The membership functions for input variable are shown in Fig. 3. The fuzzy set for the error has two membership expressed as $EP$ and $EN$, the fuzzy set for the rate has two membership expressed as *RP* and *RN* and the fuzzy set for *acc* has two membership expressed three membership function shown as Fig. 4(a) and the as *AP* and *AN*.

The output of the control block 1 has output of control block 2 has two membership function shown as Fig. 4(b).

### 3.2 Fuzzy control rules

The fuzzy control rules were made based on expert experiences and control engineering knowledge, and each control rule sets are composed of four fuzzy control rules for each fuzzy control block.

For fuzzy control block 1, four liner fuzzy control rules are given as

R1-1 : if error=EP and rate=RP, then output=OP
R1-2 : if error=EP and rate=RN, then output=OZ
R1-3 : if error=EN and rate=RP, then output=OZ
R1-4 : if error=EN and rate=RN, then output=ON

Also, for fuzzy control block 2, four liner fuzzy control rules are given as

R2-1 : if rate=RP and acc=AP, then output=OPM
R2-2 : if rate=RP and acc=AN, then output=ONM
R2-3 : if rate=RN and acc=AP, then output=OPM
R2-4 : if rate=RN and acc=AN, then output=ONM

### 3.3 Defuzzication method and gains of fuzzy PID controller

In the paper, the center of area method is used as the defuzzification method, which amounts to a normalization of the grades of membership of the members of the fuzzy set being defuzzified to a sum of one. The defuzzified output of a fuzzy set is defined as the following Eq. (14).

$$dU = \frac{\sum_{i=0}^{n} \mu_{output}(w_i) \times w_i}{\sum_{i=0}^{n} \mu_{output}(w_i)} \tag{14}$$

where n is the number of rule, $\omega_i$ is the membership value and $\mu_{output}(\omega_i)$ is the degrees of membership. The incremental output of the fuzzy control block 1 within the interval $L$ can be described by the following equations.

$$\begin{aligned} &IF\ GR\times|r(nT)| \le GE\times|e(nT)| \le L, \\ &dU_1(nT) = \frac{0.5\times L}{2L - GE\times|e(nT)|} \\ &\qquad \times[GE\times e(nT) + GR\times r(nT)] \end{aligned} \tag{15}$$

$$\begin{aligned} &IF\ GE\times|e(nT)| \le GR\times|r(nT)| \le L, \\ &dU_1(nT) = \frac{0.5\times L}{2L - GE\times|r(nT)|} \\ &\qquad \times[GE\times e(nT) + GR\times r(nT)] \end{aligned} \tag{16}$$

Also, the incremental output of the fuzzy control block 2 is given by the following equations.

$$\begin{aligned} &IF\ GA\times|a(nT)| \le GR\times|r(nT)| \le L, \\ &dU_2(nT) = \frac{0.25\times L}{2L - GR\times|r(nT)|} \\ &\qquad \times[GA\times a(nT)] \end{aligned} \tag{17}$$

$$\begin{aligned} &IF\ GR\times|r(nT)| \le GA\times|a(nT)| \le L, \\ &dU_2(nT) = \frac{0.25\times L}{2L - GA\times|a(nT)|} \\ &\qquad \times[GA\times a(nT)] \end{aligned} \tag{18}$$

The total incremental output of the fuzzy PID controller, $dU(nT)$ can be obtained by the summation of the incremental output of the control block 1 and block 2. Then the crisp value of incremental output $du(nT)$ can be obtained via multiplying $dU(nT)$ by output scale $GU$.

$$dU(nT) = dU_1(nT) + dU_2(nT) \tag{19}$$

$$du(nT) = GU\times dU(nT) \tag{20}$$

The incremental output of fuzzy PID controller can be divided into four different rules according to the input range and Eq. (12) can be rewritten as the following Eq. (21) through the previous equations.

$$du(nT) = K_i e(nT) + K_p r(nT) + K_d a(nT) \tag{21}$$

where $K_i$, $K_p$ ,and $K_d$ are as follows:

$$K_i = \frac{0.5\times L\times GU\times GE}{2L - GE\times|e(nT)|} \tag{22}$$

$$K_p = \frac{0.5\times L\times GU\times GR}{2L - GE\times|e(nT)|} \tag{23}$$

$$K_d = \frac{0.25\times L\times GU\times GA}{2L - GR\times|r(nT)|} \tag{24}$$

The fuzzy PID controller described by Eq. (21) has same structure of conventional PID controller. From Eq. (22) to Eq. (24), the gains of conventional PID controller are fixed, but the gains of fuzzy PID controller are changed by the values of *error*, *rate* and *acc*. If *error*, *rate* and *acc* converge to zero, the gains of fuzzy PID controller can be obtained by following equation.

$$K_p^* = \frac{GU \times GR}{4}, \quad K_i^* = \frac{GU \times GE}{4}, \quad K_d^* = \frac{GU \times GA}{8} \tag{25}$$

## 4. Optimization algorithm for parameter selection of the fuzzy PID controller

TLBO algorithm has been recently developed by Rao et al[15], which is population-based optimization method. This method is based on the mechanism of teaching and learning process. The method is inspired by the influence of a teacher on the output of students (learners) in the class. The output is considered in terms of grades and marks. Usually, the teacher is supposed to be a highly learned person who shares knowledge with the students. Naturally the quality of teacher affects the outcome of students. Learning is accomplished using two ways for learner (i) through teacher known as Teacher Phase, (ii) interaction between learners known as Learner Phase. In this algorithm an optimization problem is to optimize considering tuning variables as different subjects (grades/marks) and assuming different learners as population.

An initial population is randomly generated, which resembles many evolutionary algorithms. An individual $X_i$ within the population represents a single possible solution to a particular optimization problem. $X_i$ is a real-valued vector with $D$ elements, where $D$ is the dimension of the problem and is used to represent the number of subjects within the TLBO context. Then, the algorithm attempts to improve certain individuals by changing these individuals during the Teacher and Learner Phases, where an individual is only replaced if the new solution is superior to the previous solution. The algorithm repeat until it reaches the maximum number of generations[14]. During the Teacher Phase, the teaching role is to assign the best individual ($X_{teacher}$).

The algorithm attempts to improve other individuals ($X_i$) by moving their positions towards the position of the $X_{teacher}$ by considering the current mean value of the individual ($X_{mean}$). This is constructed using the mean values for each parameter within the problem space and represents the qualities of all the students from the current generation. Eq. (26) simulates how the improvement of a student may be influenced by the difference between the knowledge of the teacher and the qualities of the entire student. For stochastic purposes, two randomly generated parameters are applied within the equation: $r$ ranges between zero and one and $T_f$ is a teaching factor which can be either one or two, emphasizing the importance of the student quality.

$$X_{new} = X_i + r\{X_{teacher} - T_f\ X_{mean}\} \tag{26}$$

During the Learner Phase, a student Xi attempts to improve the knowledge by peer learning from an arbitrary student $X_{ii}$, where Teacher Phase is not equal to Learner Phase. In the case, when $X_{ii}$ is superior to $X_i$, $X_i$ is moved towards $X_{ii}$ as indicated in Eq. (27). Otherwise, it is moved away from $X_{ii}$ as in Eq. (28). If student $X_{new}$ performs better by following Eq. (27) or Eq. (28), it will be accepted into the population. The algorithm will continue its iterations until reaching the maximum number of generations.

$$X_{new} = X_i + r\{X_{ii} - X_i\} \tag{27}$$

$$X_{new} = X_i + r\{X_i - X_{ii}\} \tag{28}$$

Fig. 5 shows the flowchart of Teaching-Learning Based Optimization. The implementation steps of the TLBO are summarized as follows:

**Step 1** : Define the optimization problem and the parameters

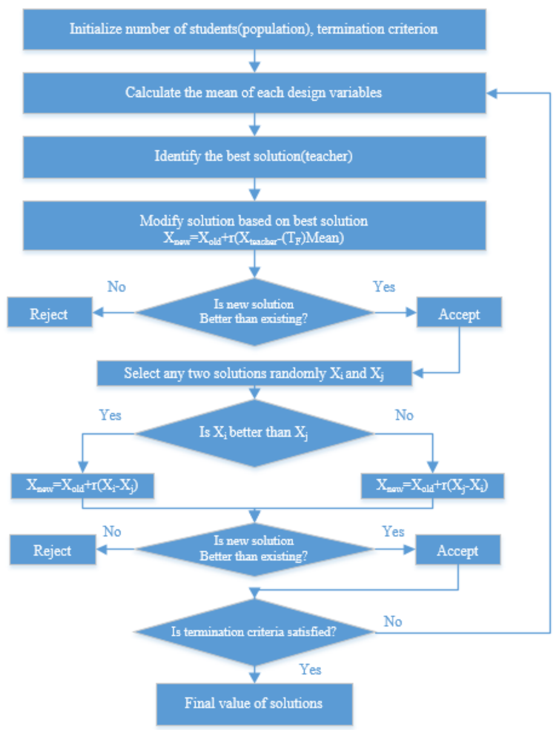



**Fig. 5** Overall flowchart of Teaching-Learning based optimization

Define the population size ($P_n$), number of generations ($G_n$), number of design variables ($D_n$) and the optimization problem as : Minimize $f(X)$ subject to $X_i \in x_i = 1,2,\cdots,D_n$ where $f(X)$ is the objective function and $X$ is a vector for design variables.

**Step 2**: Initialize the population

Generate a random population and design variables of the optimization problem with random generation and evaluate them. In the procedure of TLBO, the population size and the number of learners are same. The population is expressed as

$$X_{population} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \vdots & & \vdots & \vdots \\ x_{p_n,1} & x_{p_n,2} & \cdots & x_{p_n,D} \end{bmatrix} \tag{29}$$

**Step 3**: Teacher phase

Substep 3-1: The mean result of the population column-wise ($X_{mean}$)

Substep 3-2: Calculate the objective function for each learner and select the best learner as teacher ($X_{teacher}$).

Substep 3-3: The current solution($X_i$) is updated by Eq. (26).

Substep 3-4: Calculate the objective function of the new solution ($X_{new}$) and accept $X_{new}$ if it gives better than $X_i$.

**Step 4**: Learner phase

Learners increase their knowledge by utilizing the knowledge of some other learner according to the Eq. (27) and the Eq. (28)

**Step 5**: Stop if the maximum iteration umber is achieved. Otherwise, repeat from step 3.

## 5. Simulation

To verify the proposed control method, a Maglev model was established by using MATLAB/Simulink and global optimization toolbox for simulation of gentic algorithm(GA) and particle swarm optimization(PSO). Table 2 shows initial parameters for the proposed algorithm and GA. Eq. (30) is used as objective function which is in the range from 0 to 1. In Eq. (30), we use integral of time-weighted absolute error (ITAE) as the performance index. The four parameters (GE, GCE, GCU and CU) described in Section 3 are selected as design variables. We use two step input (0.3mm and 0.5mm) as reference set-point. The simulation results for the PID control and fuzzy PID control using each algorithm are summarized in Table 3 and Table 4.

From the simulation results, we obtain the values of performance indices such as overshoot, rise time and settling time for the first step input. We can find that the rise time and settling time performances obtained by TLBO are inferior to others. However, TLBO is able to find the best reliable solution for the ITAE objective function because TLBO does not require any algorithm parameters to be tuned. In the results of simulation, ITAE values for the GA, PSO and the proposed method are 0.0087, 0.0059 and 0.0057, respectively. Fig. 6 shows the step responses of Maglev system using the PID parameters selected by each algorithms and Fig. 7 shows the ITAE performance according to the algorithms. From the simulation results, we can see that the proposed TLBO-based fuzzy PID controller obtain the better performance than conventional PID controller.

$$J = f(GE, GCE, GCU, CU) \tag{30}$$

**Table 2** Parameters for the simulation

| Parameters | Nominal value |
|---|---|
| Population size of GA, particle, Class size of TLBO | 100 |
| Probability of crossover of GA | 0.65 |
| Probability of mutation | 0.05 |
| Inertia weight $w$ | 1 |
| $c_1$ and $c_2$ | 2, 2 |
| Iteration for the proposed algorithm and GA | 100 |

**Table 3** Simulation result for the PID control method

| Parameters | $K_p$ | $K_i$ | $K_d$ | Overshoot (%) | Rise time (sec) | Settling time (sec) | ITAE |
|---|---|---|---|---|---|---|---|
| Result | 987.4 | 3971.5 | 30.4 | 81.7 | 0.00861 | 0.173 | 0.012 |

**Table 4** Simulation results for the fuzzy PID control method

| Parameters | GE | GCE | GCU | CU | Overshoot (%) | Rise time (sec) | Settling time (sec) | ITAE |
|---|---|---|---|---|---|---|---|---|
| GA | 69.9 | 0.91 | 340.91 | 68.02 | 27.7791 | 0.0155 | 0.3701 | 0.0087 |
| PSO | 100 | 0.62 | 400 | 51.57 | 39.5284 | 0.0219 | 0.2419 | 0.0059 |
| TLBO | 100 | 0.7259 | 400 | 50.19 | 37.0203 | 0.0212 | 0.2482 | 0.0057 |

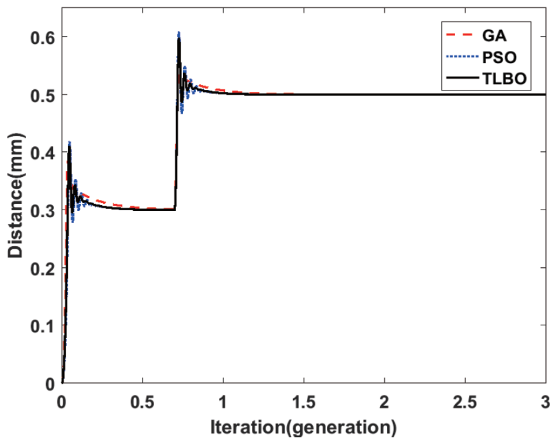



Fig. 6 Step response of Maglev system

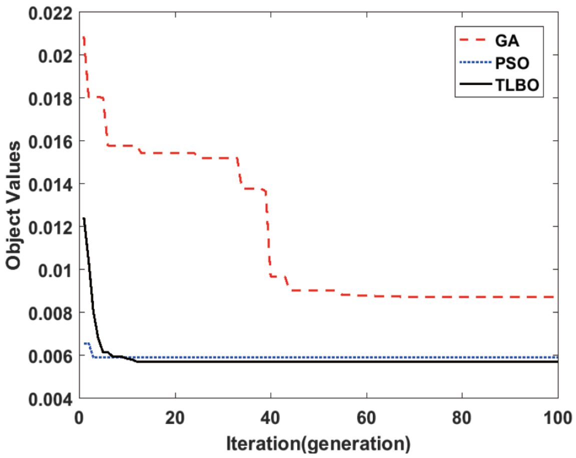



Fig. 7 ITAE performance indices according to GA, PSO and TLBO

## 6. Conclusions

In the paper, a fuzzy PID controller is proposed for the Maglev system and optimum gains of fuzzy PID controller are selected by TLBO algorithm. The fuzzy PID controller with the four scaling parameters carries out the control of Maglev system and the optimal parameters of the fuzzy PID controller are selected by TLBO. For the object function of TLBO, the performance index of ITAE is employed. To verify the proposed design method, a simple Maglev system is established. For the set-point references, the proposed method is better than others. Also, we show that the proposed method is more effective than the fuzzy PID controller using GA and PSO methods.

감사의 글

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## References

[1] Lee, Hyung-Woo, Ki-Chan Kim, and Ju Lee, "Review of maglev train technologies," IEEE transactions on magnetics, vol. 42, No. 7, pp. 1917-1925, 2006.

[2] Cho HW, Han HS, Lee JM, Kim BS, Sung SY, "Design considerations of EM-PM hybrid levitation and propulsion device for magnetically levitated vehicle," IEEE Transactions on Magnetics, vol. 45 No. 10, pp. 4632-4635, 2009.

[3] Cho HW, Kim CH, Han HS, Lee JM, Kim BS, Kim DS, Lee YS, "Design and Characteristic Analysis of Hybrid-Type Levitation and Propulsion Device for High-Speed Maglev Vehicle," The Transactions of Korean Institute of Electrical Engineers, vol. 59, No. 4, pp. 715-721, 2010.

[4] Tozoni OV, "Amlev-a self-regulating version of maglev," IEEE transactions on magnetics, vol. 37 No. 6, pp. 3925-3933, 2001.

[5] Danfeng Z, Jie L, "Analysis of the low-frequency vibration of ems maglev vehicles," Control and Automation, 2007. ICCA 2007, pp 3157-3161, 2007.

[6] Paddison JE, Ohsaki H, Masada E, "Control strategies for maglev electromagnetic suspension bogies," Decision and Control, 1996., Proceedings of the 35th IEEE Conference on, IEEE, vol. 3, pp. 2796-2797, 1996.

[7] Taghirad H, Abrishamchian M, Ghabcheloo R, Toosi K, "Electromagnetic levitation system: An experimental approach," Proceedings of the 7th international Conference on Electrical Engineering, Power System Vol, pp. 19-26, 1998.

[8] Chen H, Hao A, Long Z, "The controller design and performance index analysis of maglev train's suspension system," Intelligent Control and Automation, 2004. WCICA 2004. Fifth World Congress on, IEEE, vol. 1, pp 596-599, 2004.

[9] Hurley WG, Hynes M, Wole WH, "Pwm control of a magnetic suspension system," IEEE Transactions on education, vol. 47, No. 2, pp. 165-173, 2004.

[10] Zhang X, Liu H, Li Y, "Adaptive current-loop design for an electromagnetic suspension system," Intelligent

Computation Technology and Automation (ICICTA), 2011 International Conference on, IEEE, vol. 1, pp. 341-344, 2011.
[11] Lee BK, Kim IH, Kim JH, “Stability analysis and proposal of the simplified form of a fuzzy pid controller with fixed parameters,” Journal of Korean Institute of Intelligent Systems, vol. 14, No. 7, pp. 807-815, 2004.
[12] Xu JX, Hang CC, Liu C, “Parallel structure and tuning of a fuzzy pid controller,” Automatica, vol. 36, No. 5, pp. 673-684, 2000.
[13] Kim JH, “A suggestion of nonlinear fuzzy pid controller to improve transient responses of nonlinear or uncertain systems,” Journal of Korean Institute of Intelligent Systems, vol. 5, No. 4, pp. 87-100, 1995.
[14] Cho JH, Kim YT, “Design of pid controller for magnetic levitation RGV using genetic algorithm based on clonal selection,” Journal of Korean Institute of Intelligent Systems, vol. 22, No. 2, pp. 239-245, 2012.
[15] Rao RV, Savsani VJ, Vakharia D, “Teaching learning-based optimization: a novel method for constrained mechanical design optimization problems,” Computer-Aided Design, vol. 43, No. 3 pp. 303-315, 2011.

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