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Stability Control of EMS Maglev Train using New Lambda (λ) Tuning Approach of Single Input Fuzzy Logic using Gradient Descent Algorithm and Particle Swarm Optimization

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Abstract: Magnetically Levitated (Maglev) trains to change from traditional trains in that they are regenerated, oriented, and driven along a guided path using a variable magnetic field. This paper introduces a new approach to the development of SIFLC and GDA and PSO for the implementation of EMS Maglev Train displacement control. The Maglev train was modeled using the Mathematical modeling technique to mimic the displacement control system. The PID controller is modeled as the default controller. SIFLC was then modeled in three heuristic tuning methods. The real-time system model has been simulated using MATLAB and rise time (Tr), percentage overshoot (OS), and settling time (Ts) for the Maglev displacement and stability control have been compared and analyzed. The result shows that the SIFLC GDA output has an excellent effect on the specifications of 0.1021% (OS), 2.1332s (Tr), and 17.9790s (Ts).
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Introduction

Magnetic levitation is a technology that allows trains to float above their track, guiding themselves and speeding along silently. It's similar to a maglev train, but it doesn't use a form of superconductivity. Magnetic levitation is inspired by the way magnets' natural repulsion causes them to push away from each other when they are brought close together. [1]

Maglev trains have set many records of speed and Maglev trains can raise and decrease tons faster than traditional trains; the most sensible difficulty is the safety and comfort of the passengers. The desired power output is now no longer a large percentage of the standard power supply of the high-voltage magnets. [2] Overcoming gravity, which makes all land transfers with greater force at a better speed, absorbs more energy. Maglev buildings are less expensive to assemble than traditional buildings, although the production of maglev cars is less expensive to manufacture and repair.

The Maglev train can be registered from 1934 when Hermann Kemper of Germany was granted a patent. In the last few decades since then, the development of the Maglev train passed through the early 1960s, 1970s-1980s, and the 1990s inspection period, eventually ending the 2003 public service in Shanghai, China. With the Maglev train looking like a promising solution for the near future, many researchers have developed technologies such as modeling and analysis of precise electrical equipment, power efficiency, high power, and so on. [3]

Because there is no contact between the rail and the wheels on the Maglev train, the tow truck should not only provide movement but should also hold the brakes with direct electron and metal contact. Second, more weight, more power is needed to support the catch, and they are not suitable for the transport of goods. Third, due to the structure of the train, closing or closing a branch is currently difficult. Fourth, it cannot be overlooked that magnetic fields are composed of powerful electrons that propel a passenger's power into space. [4] Without proper magnetic protection, the magnetic field in the passenger compartment will reach 0.09 T at the lowest level and 0.04 T at the lowest level. Such camps may not be dangerous for humans, but they may cause some disruption. Passenger protection can be done in many ways such as adding iron to them, using a Halbach magnet array with a protective element, and so on. [5]

Shanghai Maglev teaches, also known as Shanghai Trans fast has a top velocity of 425 km / h. The line is the fastest working high-velocity maglev educate, designed to connect Shanghai International Airport and suburbs in central Pudong, Shanghai. It covers a distance of 30 km in just over eight minutes. For the given time, the release produced the best of public entertainment and media attention, raising awareness of the process. [3] In addition to more than a hundred studies and developments, maglev shipbuilding facilities currently operate in only 3 countries (Japan, South Korea, and China). The growing blessings of the maglev era have always been considered difficult to justify money and risk, especially when there is a modern high-speed or proposed teaching line with passenger space, such as the high-speed European train, the UK's High Speed 2, and Shinkansen in Japan.

A magnetic levitation machine is a heavy machine that is not in a mechatronic line where electrical pressure is required to stop something in the air and requires an over-the-counter control to control current with large magnets. [4]

The study aims to develop ways to improve transportation efficiency. Other technologies are used that may be used in other systems, from satellite-based communications to magnetic probes.

Mathematical Models

Electromagnetic pressure f (i, z), operates on a train, which can be demonstrated as the following dynamic system in the upward direction in line with Newton's law

$$m\frac{d^2z(t)}{dt^2} = mg - f(i,z)$$

Where m is the mass of the train and g is the gravitational force.

The electromagnetic force induced is

$$f(i,z) = -\frac{i^2(t)}{2}\frac{dL(z)}{dz}\Big|_{i=constant\ for\ linear\ system}$$

The current-voltage relationship for the train coil is given as

$$V(t) = Ri(t) + L(z)\frac{di(t)}{dt}$$

The vertical displacement of the train is measured by a sensor image-detector that is the output displacement and calculated as:

$$Y = V_z(z) = \beta z$$

Where

β is the gain of the sensor

The transfer function between the coil voltage input V(s) and the sensor voltage output Vz(s) is given as

$$G(s) = \frac{V_z(s)}{V(s)} = -\frac{K_I\beta}{(R+sL_1)(ms^2-K_z)}$$

Two approaches can be used to control the train.

2.2 Outward approach:

Is it a composition that starts from the inside out? First, the open-loop transfer function is formed by controlling the poles and zeros, adding the right configuration of the system, so that the normal transfer function is achieved.

2.3 Inward approach:

It is an external deviation which is, First select the function to transfer the closed-loop, and then adjust the required control.

2.4 Stability approach of the maglev train system

The magnetic levitation train system model can be represented by the given transfer function G(s).

$$G(s) = \frac{Y(s)}{U(s)} = \frac{-280}{(s+29)(s+56)(s-56)} \qquad (1)$$

The systems zeros are found at s = -29 and the poles are found at s = −56, and s = 56. The observation shows that the system has a pole on the right-hand side of the s-plane and this makes the system unstable.

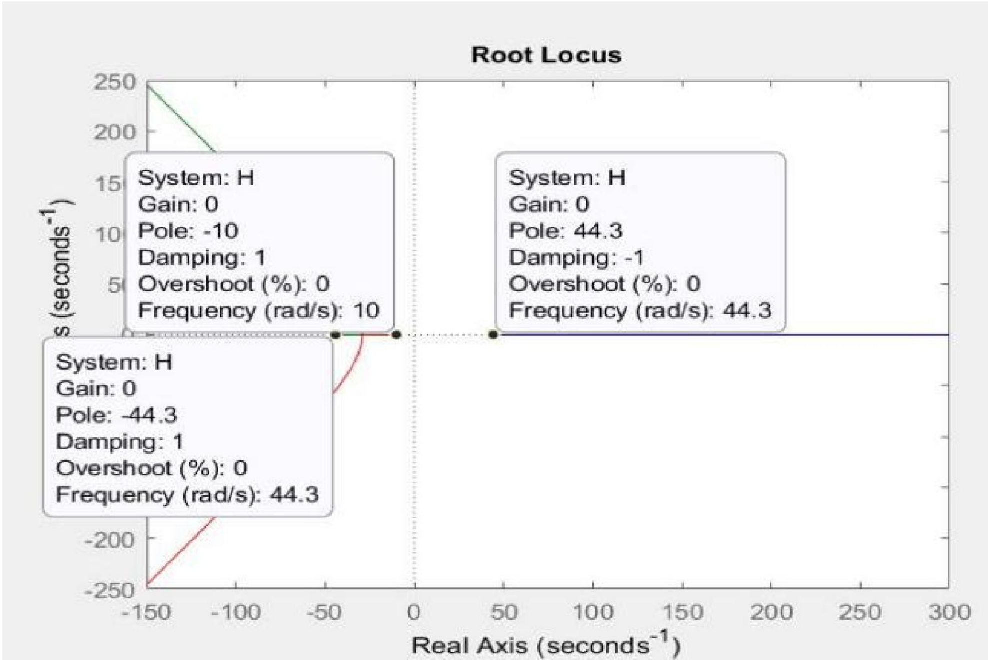

Figure 1. Root locus stability of maglev train system

Proposed Controller Design

In this paper, the PID controller is designed to use the default tuning provided by MATLAB Simulink. The SIFLC controller is designed and configured using heuristic, GDA, and PSO. PID has been used as a basic control that can be compared to the default control of SIFLC.

PID Controller

As mentioned earlier, a PID controller is a basic controller used in the ROV system. Blocks of P, I, and D are placed parallel to the front of the system control system. P fights direct error; I show complete errors in the system while D shows how fast errors occur. The P controller will make the response faster but aims to generate overshoots. The controller I tend to remove SSE while controller D is extremely low. The PID is tuned using the automatic tuning in MATLAB Simulink [11].

SIFLC controller

The SIFLC controller is designed according to the standard FLC configured. Standard FLC table; Table 1, is used in the form of a range of symbols (SDM) which has reduced the rules table to a list of other sizes [9]. From the table, it can be seen that there is a consistent pattern in the decision-making process of extracting FLC.

Table 1: 7 X 7 FLC table

Err vs du/dt or 1/s	**PL**	**PM**	**PS**	**Z**	**NS**	**NM**	**NL**
NL	Z	NS	NM	NL	NL	NL	NL
NM	PS	Z	NS	NM	NL	NL	NL
NS	PM	PS	Z	NS	NM	NL	NL
Z	PL	PM	PS	Z	NS	NM	NL
PS	PL	PL	PM	PS	Z	NS	NM
PM	PL	PL	PL	PM	PS	Z	NS
PL	PL	PL	PL	PL	PM	PS	Z

B

A

From table 1, two separate lines are formed named A and B. 'D' is the distance between A and B given by the equation. Figure 2 shows the derivation of d, which is the distance between point, Q, and point, P.

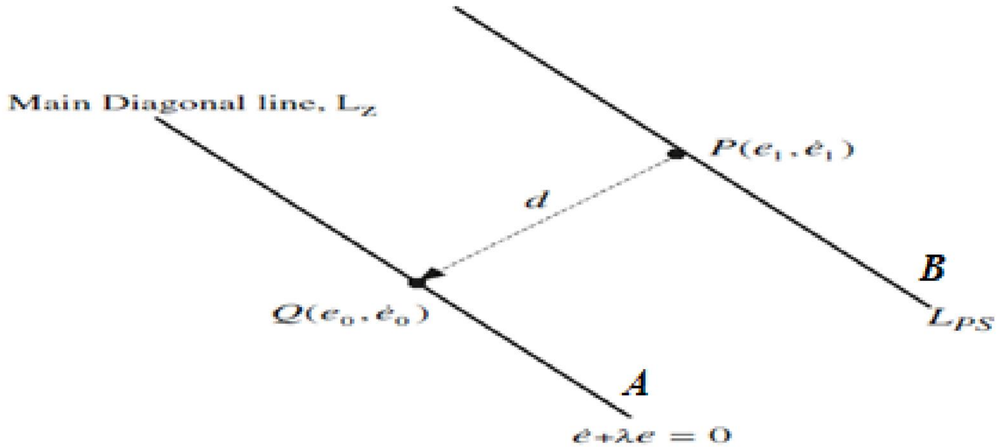

Figure 2: Derivation of d, the distance between point Q and P[40]

$$d = \frac{w+Z_e\lambda}{\sqrt{1+\lambda^2}} = \frac{w}{\sqrt{1+\lambda^2}} + \frac{Z_e\lambda}{\sqrt{1+\lambda^2}} \qquad (2)$$

$$\dot{e} + \lambda e = 0 \qquad (3)$$

$$\therefore \lambda = -\frac{\dot{e}}{e} \qquad (4)$$

The standard FLC table has now been reduced to Table 2 where the dragline represents LNL, LNM, LNS, LZ, LPS, LPM, and LPL while NL, NM, NS, Z, PS, PM, and PL represent the output of straight parallel lines.

Table 2: Reduced FLC table using SDM

d	**LNL**	**LNM**	**LNS**	**LZ**	**LPS**	**LPM**	**LPL**
output	NL	NM	NS	Z	PS	PM	PL

These SIFLC entries can be changed with the viewing table. SIFLC is then prepared using the cleaning method of lambda (λ) proposed. The value of (λ) varies up and down to get the best output result. (Λ) connected to FLC via FLC input. The extent of the error and the combined error is determined on the graph shown in Figure 3.

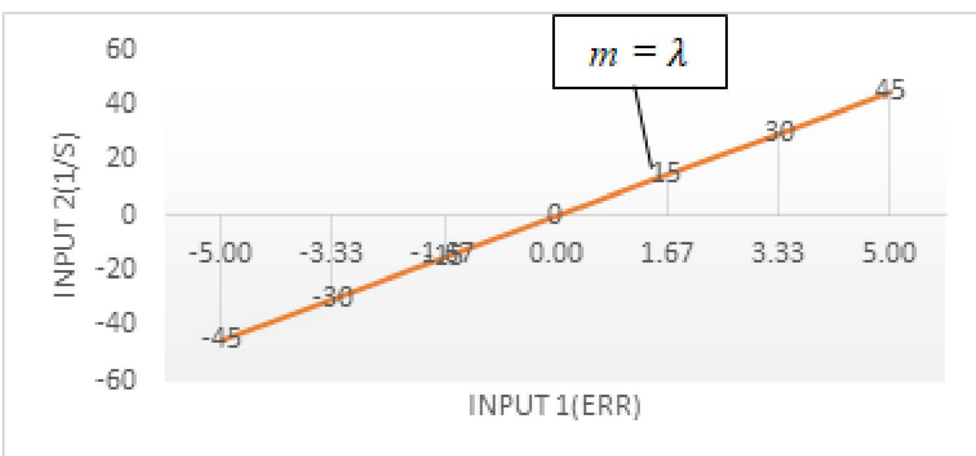

Figure 3: Graph of the second input versus the first input FLC.

SIFLC Heuristic Tuning Method

The line gradient is lambda (λ). The various effects (λ) of SIFLC were then analyzed, and the best result was selected. The variation of the lambda (λ) up and down in an attempt is called the heuristic method. Figure 4 shows the flow diagram of the heuristic tuning process.

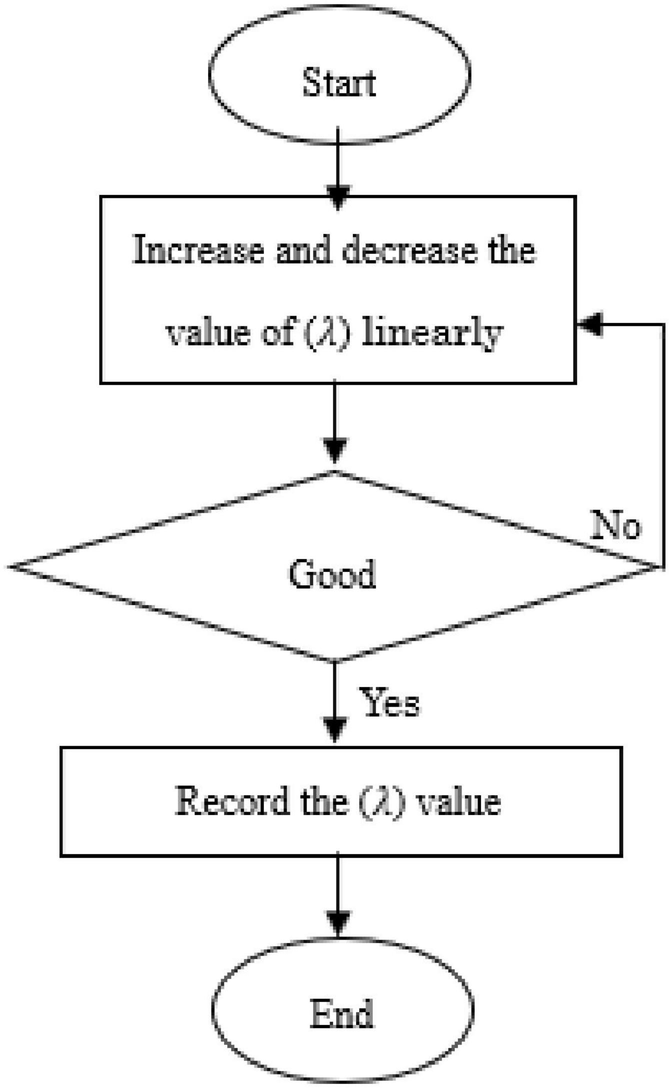

Figure 4: Flow chart for SIFLC heuristic tuning

As shown in Figure 8, a value difference (λ) or gradient is made until a positive result is obtained. It takes a lot of time and knowledge of the controller to be tested.

SIFLC GDA Tuning Method

The GDA is an over-the-top algorithm that can detect minimum activity. GDA is used to replace the heuristic lambda (λ) tuning of SIFLC. The objective function is based on predicted output compared to a given input. It is a simple mathematical method based on the division of arithmetic where the output of the first point is the target output by calculating the errors. Two (2) important parameters require a directional guide and step size to be used. Movement direction is defined by the tangential point of the first point. The sharpness of the tangent line also indicates how close the point is to the lowest point and how to determine the level of reading to be chosen. Figure 5 shows the flow diagram of the gradient descent algorithm [10]. From Figure 9, the GDA will continue to operate until a favorable condition is obtained or its acquisition is achieved.

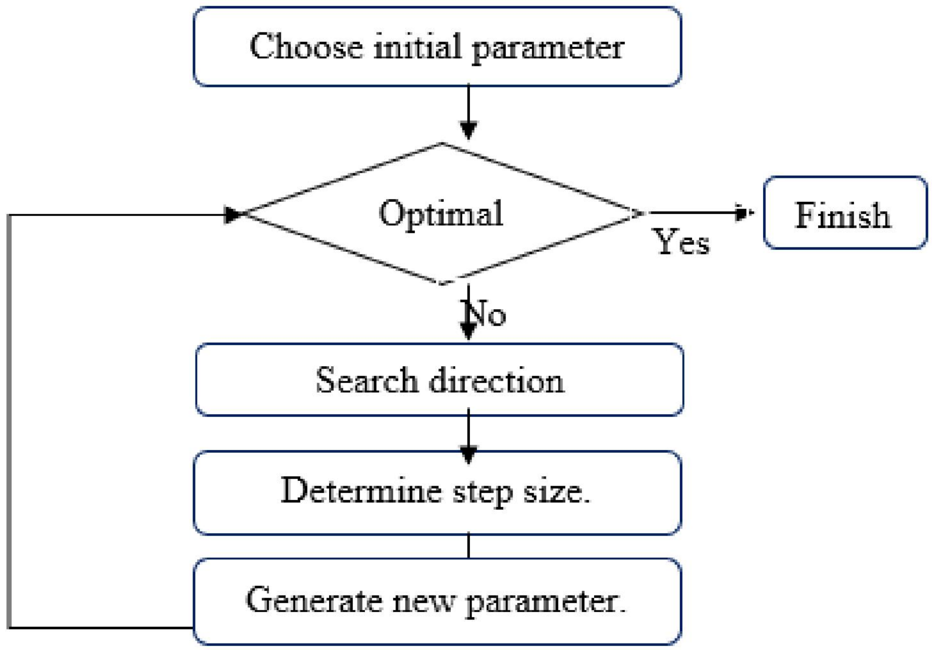

Figure 5: Flow diagram of gradient descent algorithm

SIFLC PSO Tuning Method

The PSO was proposed by [11] in 1995. It is inspired by the practice of studying fish and the migration of birds in search of food at a certain speed and position. Similarities are observed between particles and swarm elements [12]. The movement of the particles is divided into two components: its current position x and velocity v, respectively. It has been very effective in a variety of use problems. The particle swarm optimization algorithm is analyzed using general results from a robust theory [13]. The PSO algorithm starts by randomly launching the stimulus in the search space. Two consecutive repetitions, t and t + 1 correspond to the x state of each particle changed during processing by adding a new velocity. The new velocity is measured by summarizing the increase in the value of the previous velocity. Climbing is the work of two things that represent cognitive and social knowledge [14]. The understanding of each particle is included by examining the difference between the current state x and its best position, PBEST. The social information of each particle is categorized by the difference between its current state x and the best global position achieved, GBEST. The cognitive and social aspects are repeated with randomly generated words produced ϕ1 and ϕ2, respectively [15]. Equation (5) shows the position vector while equation 6 shows the velocity vector. P in the equation is PBEST while G is

$$\text{GBEST}.\overrightarrow{X_i^{t+1}} = \overrightarrow{X_i^t} + \overrightarrow{V_i^{t+1}} \quad (5)$$

$$\overrightarrow{V_i^{t+1}} = w\overrightarrow{V_i^t} + c_1 r_1 \left(\overrightarrow{P_i^t} - \overrightarrow{X_i^t}\right) + c_2 r_2 \left(\overrightarrow{G^t} - \overrightarrow{X_i^t}\right) \quad (6)$$

Result and Discussion

All of the designed controls were combined into a single block diagram to compare the result. There are 6 updated features which are installation steps, open loop, close loop, PID, SIFLC heuristic, SIFLC GDA, and SIFLC PSO. Figure 6 shows a block diagram of 6 investigated symbols.

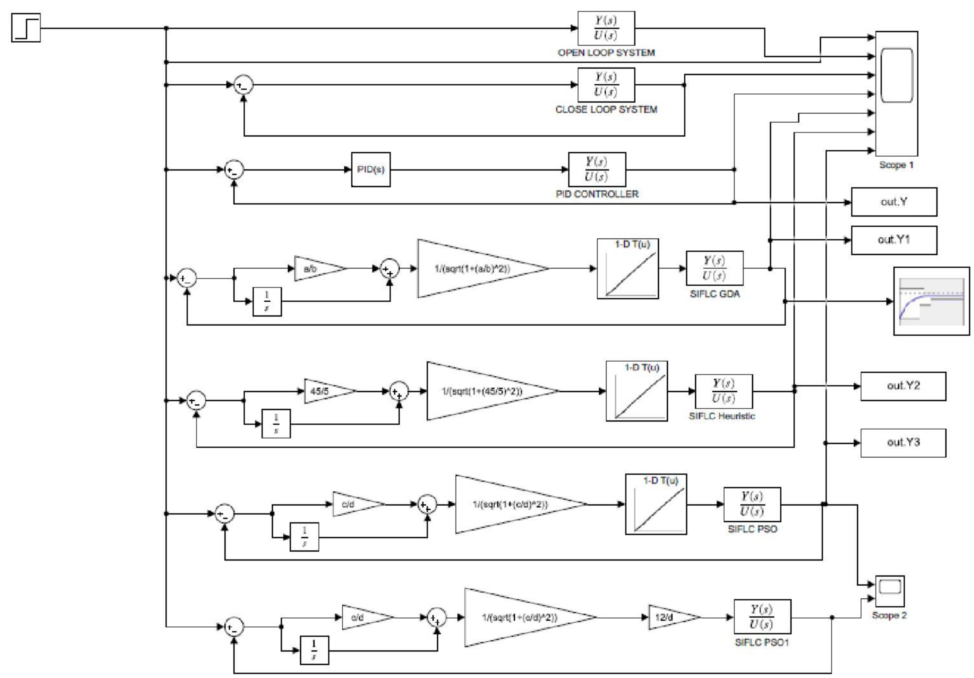

Figure 6: Block diagram for the 6 signals investigated.

From the block diagram, Scope 1 shows six signals while Scope 2 is used to compare between the PSO of the measurement results (SIFLC PSO) and the Simulink monitoring table (SIFLC PSO1). This subtraction shows the same effect (Figure 7). Figure 8 shows the effect of the release of Scope 1.

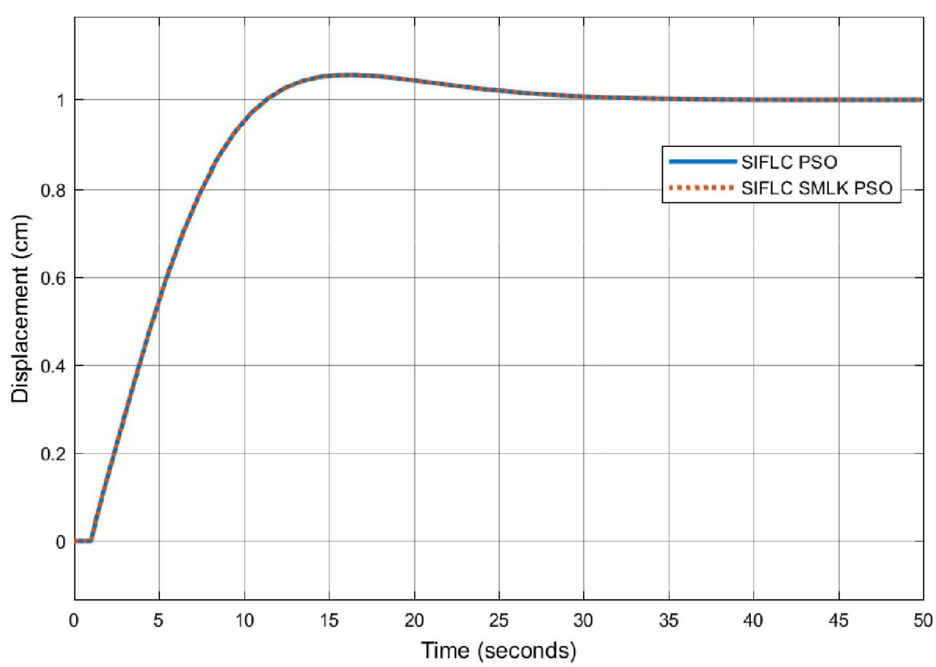

Figure 7: Comparison result between PSO result using command windows (SIFLC PSO) and Simulink (SIFLC PSO1).

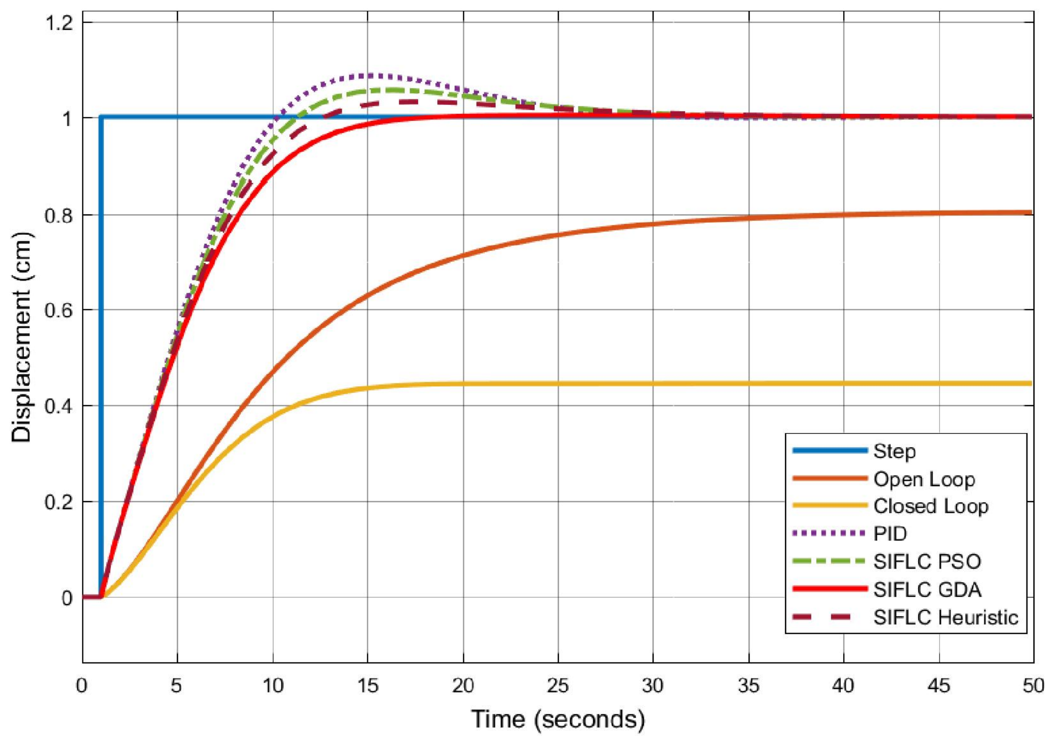

Figure 8: The output result of Scope 1

In Figure 8, SIFLC GDA shows the almost identical result to the step input given. It is then followed by the SIFLC heuristic. The SIFLC PSO shows improvement in the Tr but a bit of steady-state error. The PID shows a bit of overshoot but no steady-state error. The output result is tabulated in Table 3 below.

Table 3: Output result of the controller's implementation to the Maglev system

	PID	SIFLC Heuristic	SIFLC GDA	SIFLC PSO
Tr (s)	2.3746	2.3686	2.1332	2.3686
Ts (s)	28.6687	25.1023	17.9790	26.2348
%OS	11.3613	9.7988	0.1021	10.2368

From Table 3, it is clear that the SIFLC GDA shows good results and balance as it can detect the lowest error parameters. For Tr (s), the SIFLC GDA shows 2.1332s results. Next to it are SIFLC PSO (2.3686s), PID (2.3746s), and SIFLC Heuristic (2.3686s). For Ts (s), next to the SIFLC GDA (17.9790s) there are SIFLC Heuristic (25.1023s), SIFLC PSO (26.2348s), and PID (28.6687s). With the last parameter (overshoot), the SIFLC GDA shows 0.1021% positive results. This was followed by the SIFLC heuristic (9.7988%), PID (11.3613%), and SIFLC PSO (10.2368%).

Conclusion

Two differential adjustment controls were used in the Maglev position control system. A new way to tune the SIFLC lambda controller (λ) is suggested and compared to the basic PID controller. SIFLC GDA shows good results and balance as it has the lowest errors in all investigated parameters. The SIFLC PSO is facing a rapid and stable state error. The basic PID controller can be removed but has a fixed time and long-term decision, Ts. With SIFLC Heuristic, the result can also be extracted as it has a better effect compared to the PID controller in Ts and % OS. The problem with the SIFLC controller experience is necessary and it takes a lot of time to tune it. The SIFLC GDA gets good results because it has implemented a specific type of objective work based on all parameters. The SIFLC PSO received a higher error compared to the SIFLC GDA because the target used was a completely mean error number. In all results, it has been proven that the SIFLC lambda (λ) modification method has successfully produced a positive output effect. With the implementation of a method such as GDA and PSO, a better output effect can be obtained. Objective work is selected from the performance of the method and plays important role in achieving a positive outcome. In future practice exercises, a variety of goal-oriented activities can be learned and promoted in the program.

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