FIREFLY ALGORITHM BASED POSITION CONTROL OF MAGLEV SYSTEM

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by

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2K22/C&I/08

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I, Vedika Kapoor, Roll No – 2k22/C&I/08 student of M.Tech (Control & Instrumentation), hereby declare that the project Dissertation titled "**FIREFLY ALGORITHM BASED POSITION CONTROL OF MAGLEV SYSTEM**" which is submitted by me to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associate-ship,Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "**FIREFLY ALGORITHM BASED POSITION CONTROL OF MAGLEV SYSTEM**" which is submitted by Vedika Kapoor, whose Roll No. is 2k22/C&I/08, Electrical Engineering Department, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or fullfor any Degree or Diploma to this University or elsewhere.

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ABSTRACT

This research work aims to control and stabilize the Magnetic Levitation (Maglev) system, which levitates a magnetic ball in space being under the influence of a magnetic field only. Different controllers' feedback is used to stabilize the highly unstable nature of the MagLev system. The transfer function is constructed through dynamic model analysis, which is then applied to a more straightforward mathematical model. Different controllers used are PD and PID. Also, the gain values of the controllers are found out after applying optimization algorithms. The applied algorithms for optimization are Genetic Algorithm, Particle Swarm Optimization, and Firefly Algorithm. The applied algorithms are found to be helpful in reaching a steady state at a faster rate with less steady state error, integral square error and integral time absolute error.

May, 2024 Vedika Kapoor

Delhi (India) (2K22/C&I/08)

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ACRONYMS

PID	Proportional Integral Derivative
MagLev	Magnetic Levitation
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
FFA	Firefly Algorithm
SSE	Steady State Error
SS	Static State
DS	Dynamic Stability
EC	Eddy Current
MF	Magnetic Fields
TS	Transient Response
CARIMA	Controlled Auto-Regressive Integrated Moving-Average

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The Maglev system, in which a ball is suspended in space without the need of physical support other than a MF uses the principle of MagLev. MagLev system is a single input single output with high instability and non-linearityin nature. The system is made to be linear and stable in order to be applied to real world applications [1].

1.2 OVERVIEW

MagLev is a process of suspending an object in the space only by the force of MF. Magnetic force is utilized to offset the gravitational force imposed on an object. There are two prominent issues which need to be resolved in maglev system. One is the issue of **lifting forces** i.e.providing an upward force sufficient to counter the effect of gravity and the other issue is **stability** i.e. ensuring the system doesn't flip or slide and remain stable throughout.

Maglev uses the electromagnetic force to suspend the object in air, which effectively reduces the friction induced by mechanical vibrations and the wearing losses which are caused by contact operations. The parameters are related to permanent geometry of magnet, mass of the object and the distance of its suspension.

Earns haw's theorem states that if only paramagnetic materials are used, it is not possible for system to stabilize statically opposite to gravity [2]. **SS** is definedin the way that any little displacement which is away from the stable equilibrium can cause a force which pushes it back in the equilibrium. In addition, **DS,** isdefined in which the system is able to damp out any vibrations. MFs are forces which are conservative in nature and they have no in-built damping mechanism which can permit vibrations to exist eventually make them leave the stable region [3].

Damping can be done in the following ways:

a) External mechanical damping like dashpots and air drag.

b) Tuned mass dampers

c) ECs damping

In maglev system, ECs are shown to stabilize the levitated object. ECs produce MF which in turn opposes the levitated object's motion as per Lenz's law.

1.3 BASICS OF MF

The MF can be found out at any point using the equation given by Biot Savart's law.

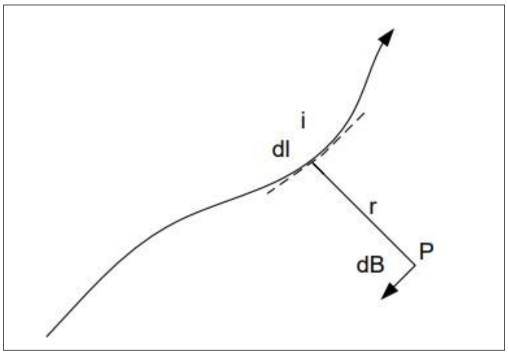

Figure 1.1 Current carrying wire exerts MF at P

The above said law states that an element *'dl'* which is carrying current *'i'* contributes to a MF *'B'* at any point '*p*' which lies perpendicular to plane of *'dl'* with vector *'r'* that is given by

$$dB = \frac{\mu_0 i \sin\theta dl}{4\pi r^2} \tag{1.1}$$

Where, μ_o is free space permeability constant

i is current in element

B is MF

dl is section of the wire that carries current

r is vector distance from the element to the point ‘P’

Electromagnetic coil is used in producing the MF. Maglev is a concept involving electromagnetic coupling [4]. The coil, which has an electrical component that attracts magnetizable objects, creates the MF. is generated by the coil wherein electrical part attracts the magnetizable object. The coil’s current drops when the object begins to move away from the magnet and vice versa. Repulsion and attraction can cause MagLev.

1.4 APPLICATIONS

Maglev provides friction less movement and isolation with environment. A few of the applications for the same are stated below:

a) MagLev Train

The train must go along the guide way under the influence of MF that assists the train in propelling and levitating. The first commercial implementation of maglev train was Shanghai’s Trans rapid system which used German model

b) Magnetic bearings

For levitation and rotation, rotor with stator mounted electromagnets interacting with magnetic flux. These are utilized in flywheels as energy storage device since there is no friction, drag and or component wear and strain.

c) Launching Rocket

It entails creating a track that levitates the rocket and give it a necessary initial velocity to escape from Earth. This project aims to make transportation less expensive.

d) Maglev wind turbine

Magnetically levitated wind turbine can be 20% more efficient as compared to traditionalwind turbines. Because efficiency is higher, the area required to create same power, substantially smaller than typical turbine.

1.5 LITERATURE REVIEW

The metallic ball's position has been tracked and controlled at a specific height using traditional PID controllers. The derivative component of the controllers enhances the TR and lessens ripples and overshoots, the integral part improves the SS response, and decreases SS error, and proportional part assists to improve the TR more quickly. Several techniques are employed to determine the controller's gain values, including hit, trial, and Cohen-Coon.

For the MagLev system, the concept of linear and non-linear state space controllers was put forth in 1996. The feedback was linearized to create the linear controller [5]. The system is linearized by means of the Refinement of a nonlinear state space using transformation state feedback. The oscillations of the system have a position tracking inaccuracy of approximately ± 0.45 mm.

The initial step involves linearizing the system prior to deploying controllers for stabilization purposes. Various algorithms are employed to implement these controllers effectively. Optimal PID controllers are also specifically tailored for MagLev system, accommodating both fractional and integer orders within the linearized model [6]

In their study of stabilizing and controlling a single-axis MagLev system, Dan Cho and team compared sliding mode controllers to classical controllers [7]. They observed that sliding mode controllers offer greater damping compared to classical ones. Additionally, they implemented a second-order sliding mode controller to stabilize the system and mitigate noise and disturbances within it [8]. To regulate the current influencing the magnetic force, a sliding mode controller was utilized.

For a Maglev system with a time delay, Sirsendu S. M., et al. developed a PID controller based on the Coefficient Diagram Method [9]. CMD-PID controller parameters are changed via algebraic methods. The TR anderror indices have improved as a result of the proposed controller.

Sum of Squares (SoS) technique was used by Bhawna T to access the stability of a MagLev system employing a non-linear controller [10]. Applying SoS to the Maglev System must necessitate a nonlinear controller. Rosalia H. Subrata to stabilize floating items in Maglev systems created a PID controller [11]. It is important to consider the unstable non-linear dynamics of the maglev system. The controller plays a crucial role in stabilizing the system by taking into account its nonlinear dynamics. A model-based feed-forward PI-PD controller for position tracking of the Maglev system was developed by A. S. C. Roong. However, this controller requires both a sensor and a model to address every disturbance [12].

R. E. Precup proposed an evolving Takagi-Sugeno (T-S) fuzzy model to depict the nonlinear dynamics observed in the positioning of Maglev systems [13]. Prior to using a linearization strategy to stabilise the nonlinear process at specific operating points, a state feedback control structure must be designed. An adaptive control algorithm was put forth by B. Singh for the MRAC technique-based location tracking of a real-time Maglev system [14]. Finding the fine tuning so that astable system reduces the error to 0 is a crucial issue with the MRAC system. In the MRAC technique, the PID controller's parameters are automatically updated.

K. H. Su proposed fuzzy and supervisory fuzzy models using a gradient descent technique for the MagLev system [15]. This approach involves replacing the mathematical model of the Maglev system with a fuzzy model to enhance tracking accuracy, reduce chattering, and improve TR. Subsequently, Ahmed El Hajjaji developed a nonlinear model for the MagLev system, followed by the creation and real-time application of a nonlinear control rule based on differential geometry.

An indirect technique for self-adjusting a PID controller's gains in a digital excitation system was given by Kim K [17]. The PID controller settings are modified using this approach by utilizing the RLS (Recursive Least Squares) estimate method. The loop gain is assessed in the suggested method when the closed loop is under PI controller control and in a steady state. The time constants for the generator and tuner are then found using RLS. Furthermore, an adaptive finite impulse response (FIR) controller was created by M. Shafiq et al. to track an iron ball under magnetic force [18]. This controller, alongside the PID controller, incorporates an adaptive FIR filter to enhance stability. Stability is maintained because adaptive FIR filters possess inherent stability properties.

For an active magnetic bearing system, Chang, Wu created a straightforward implicit generalized Predictive self-tuning control involves the application of (CARIMA) model [19]. The suggested control technique is an innovative approach to remote predictive control that ensures the stabilityof an open loop unstable system by fusing the benefits of several algorithms collectively.

The CDM-PID controller's settings are adjusted using algebraic techniques. S. Sgaverdea introduced a feed-back controller, also MPCs (model predictive controllers) for regulating sphere location in MagLev systems. Initially, state feedback control is created to uphold system stability. To address any potential issues with state-space control, a secondary controller based on MPC was devised for the outer control loop.

M. Ahsan devised various nonlinear controllers to tackle position tracking in a magnetic suspension system amidst uncertainties in parameters and external disturbances. A. Rawat employed Lyapunov's stability analysis and feedback linearization techniques to craft an adaptive linear and neural controller for the Maglev System. Stability of the closed-loop system is achieved through a combination of an adaptive rule and a feedback linearizing control law. Additionally, I. Mizumoto developed an adaptive PID controller for a MagLev system, integrating an almost strictly positive real (ASPR)-based parallel feedforward compensator (PFC). However, the static PFC exhibits windup phenomena and loses control performance when the input saturates.

C. S. Chin engineered a prototype microprocessor-controlled hybrid MagLev and propulsion system (MCLEVS) designed for transportation purposes, comprising a linear synchronous motor and a hybrid electro MagLev setup. Meanwhile, C. S. Teodorescu delved into analytical solutions, systematically addressing feasibility, stability, and optimality concerns in Maglev systems, underscoring the significance of understanding dynamic system behavior. Additionally, J. H. Yang introduced modeling equipment for Maglev systems and an automated algorithm for generating a 2D lookup table from experimentally obtained data. This apparatus measures parameters such as the levitation object's magnetic force, the electromagnet's coil current, and the separation between the levitation object and the electromagnet.

An analog controller suspension model has been integrated alongside the PID controller. Additionally, a Grey Wolf Optimization algorithm has been employed to fine-tune the PID gain values. Utilizing teaching learning-based optimization methods, improvements in time domain and frequency domain parameters can be achieved by minimizing the objective function. Furthermore, an LQR-PID controller has been utilized for maglev system control. Nevertheless, selecting the weight matrices R and Q in the LQR controller implementation necessitates a comprehensive understanding of the mathematical aspects involved also been implemented for the maglev system [32].

A PSO-PID control strategy was developed to enable a maglev system's accurate positioning and balancing. Furthermore, a LQG-based controller was utilized to regulate the ball's location by adjusting the electromagnet's current in order to push the ball to a stable state with the least amount of error. PID settings were adjusted using the extremum seeking (ES) approach, which improved steady-state responsiveness with less oscillations. Moreover, to stabilize the maglev architecture, a cuckoo search fractional order PID (CSFOPID) controller was created.

In a controlled environment, an analog controller has been employed to model the system, utilizing the pole-assigned method to integrate a PID controller. Moreover, predictive fuzzy PID, coupled with PSO, has been introduced to address issues of poor robustness. Additionally, stabilization of the controller has been achieved through the implementation of sliding mode surface, time delay compensation, and a double-layer neural network alongside adaptive laws

FSMC(Fuzzy Sliding Mode Controller) application facilitates the system in achieving asymptotic stability, offering a valuable solution without necessitating detailed information. Furthermore, NFSMC (Novel Fuzzy Sliding-Mode Control) has been utilized to analyze the comparative effects of uncertainty in ball mass across SMC, FSMC, and NFSMC, providing insights into their respective performance

Moreover, adaptive neural controllers featuring input delay compensation have been developed leveraging machine learning techniques. This implementation incorporates an optimization method with controlled parameters. Furthermore, a Projection Recurrent Neural Network-based adaptive backstepping control approach has been deployed to stabilize the system and fine-tune the position of the ball.

The Manta Ray Foraging Optimization (MRFO) technique has been augmented by integrating an opposition-based learning approach and the Nelder-

Mead (NM) algorithm, resulting in the development of a new and innovative algorithm termed the Novel Improved Manta Ray Foraging Optimization.

1.6 SCOPE OF WORK

Significant contributions of this study are:

- Proposing that the firefly algorithm be used to find the PID's controllers gain settings.
- A To evaluate the effectiveness of the suggested techniques, reference signals such as square wave, sine wave and step signal were employed.
- To assess the performance of Firefly Algorithm (FFA) compared to GA and PSO for finding optimal gainvalues of the controllers for the MagLev System

1.7 THESIS ORGANIZATION

The thesis is divided into six chapters:

- Chapter I INTRODUCTION
- Chapter II MODELLING OF MAGLEV SYSTEM
- Chapter III DESIGINING OF CONTROLLERS FOR MAGLEV
- Chapter IV OPTIMIZING ALGORITHMS
- Chapter V SIMULATION AND RESULTS
- Chapter VI CONCLUSION AND FUTURE SCOPE

Chapter I - Includes the introduction about maglev system and overview about MagLev system. Basics of MF has been discussed along with its applications.A detailed literature review has been written which records the types of researches done yet on maglev system.

Chapter II - This chapter gives an insight about the hardware system of the maglev and its mathematical modelling along with its block diagram.

Chapter III - This chapter includes the various types of controllers used in feedback to stabilize the maglev system

Chapter IV - This chapter includes the various types of optimizing methods to be used in finding the gain values of the controllers. It discusses methods like PSO, GA, FFA.

Chapter V - This chapter includes the simulations and results.

Chapter VI - This includes the conclusion about the research work and future scope further.

CHAPTER 2

MODELLING OF MAGLEV SYSTEM

2.1 INTRODUCTION TO MAGLEV MODEL

In this section, an electrical-mechanical model and the control aspect of the maglev model will be discussed. A project starts with the modelling of the plant and the electrical-mechanical model is shown in the figure 2.1 [43].

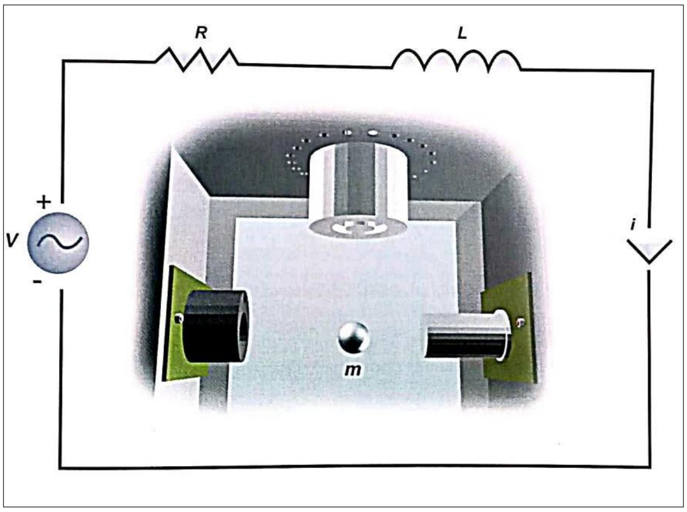

Figure 2.1 Electro-mechanical model of Maglev System

Usually, the models are non-linear in nature. At least one of the states (i- current or x- ball position) is an argument for the function which is nonlinear. Thus, the model needsto be linearized in order to be presented as a transfer function. The linearization has beendiscussed in details later on.

2.2 HARDWARE SETUP OF MAGLEV

MagLev setup comprises of these main parts

a) **Electromagnetic coil:** It generates magnetic filed when current flows through them. The magnetic object interacts with the generated field, producing the necessary lifting.

b) **Infrared light Sensor:** The IR sensor is composed of two elements. One is an IRlight transmitter, while the other is an IR light receiver. When an object is suspended, parts of the lights are obstructed, which causes a proportional increasein voltage. The quantity of voltage generated reveals the object's position.

c) **Metallic Object:** Here, a metallic hollow ball is regarded as an object. The ball is about 20 grams in weight.

d) **Digital and Analogue interface:** Since a computer operates in the digital domainwhile a maglev plant operates in continuous time, the two devices are connected via analogue and digital interfaces. Therefore, an interface is required to couple the two.

e) **Controller:** The open loop stability of the maglev plant. So a controller is requiredin order to perform levitation. Advantech PCI1711 card is used to connect the required controller to the Maglev system. The controller is designed in MATLABor 14 Simulink. The limit for the control output is between +5V and -5V. [44].

Figure 2.2 Maglev System

2.3 MATHEMATICAL MODELLING OF MAGLEV

The dynamics of metallic ball under the electro MF is determined by the non-linear Maglev system, which is represented as:

$$m\ddot{x} = mg - f_e \tag{2.1}$$

Where f_e is magnetic force and given by:

$$f_e = k_1 \frac{i^2}{x^2} \tag{2.2}$$

Substituting value, we get:

$$m\ddot{x} = m\overline{g} - k(\frac{i^2}{x^2}) \tag{2.3}$$

$$i = k_2 u \tag{2.4}$$

Where, k_1= constant depending on the coil

k_2 = input conductance

x = ball position

u = controlling voltage m = mass of metallic ball

g = Earth's gravitational force

The non-linear model can be linearized as follows:

$$\ddot{x} = \frac{-2ki_0}{mx_0^2}\delta x + \frac{2kx_0^2}{mx_0^3}\delta x \tag{2.5}$$

Equilibrium points are calculated, at $\ddot{x} = 0$,

$$\ddot{x} = 0 \tag{2.6}$$

$$g = \frac{mi_0}{mx_2^0} \tag{2.7}$$

Substituting values from equation (6) in equation (4), obtained equation :

(2.8)

$$\ddot{x} = \frac{-2g}{i_0}\delta i + \frac{2g}{x_0}\delta x$$

Take ,

$$k_i = \frac{2g}{i_0} \tag{2.9}$$

$$k_x = \frac{-2g}{x_0} \tag{2.10}$$

After applying Laplace Transform, we get

$$\frac{\delta x}{\delta i} = \frac{-k_i}{s^2 - k_x} \tag{2.11}$$

Equation 13 is obtained by taking the equilibrium points xo= -1.5V (0.009m) and io= 0.8A, determining ki and kx, and then plugging these values into equation 11.

$$V = 143.48x - 2.8 \tag{2.12}$$

$$G(s) = \frac{-24.525}{s^2 - 2180} \tag{2.13}$$

The relationship between voltage and current are:

$$i = 1.05 * v \tag{2.14}$$

Measured output sensor is calculated as:

$$x_v = 143.48x_m - 2.8 \tag{2.15}$$

2.4 BLOCK DIAGRAM OF MAGLEV SYSTEM

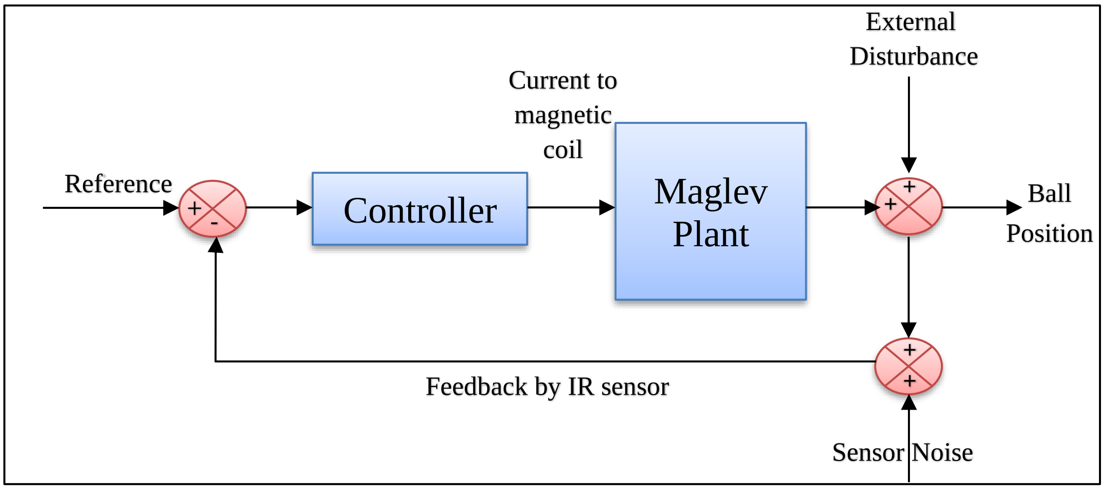

Figure 2.3 Block Diagram for Maglev

With a feedback controller in the system to minimize the error between the reference signal and the output. The output is a function of the x i.e. ball position which in turn is converted to voltage internally and which is again compared with the referencesignal i.e. we define as error. The error here is Integral Square Error which is fed in the controller to be minimized.

CHAPTER 3

OPTIMIZING ALGORITHMS

3.1 GENETIC ALGORITHM

Genetic algorithms, drawing inspiration from natural selection, are adept at tackling various optimization challenges, be they bounded or unbounded. In this iterative process, a population's individuals undergo modifications, serving as parents to generate the subsequent generation of offspring in each step of the genetic algorithm.

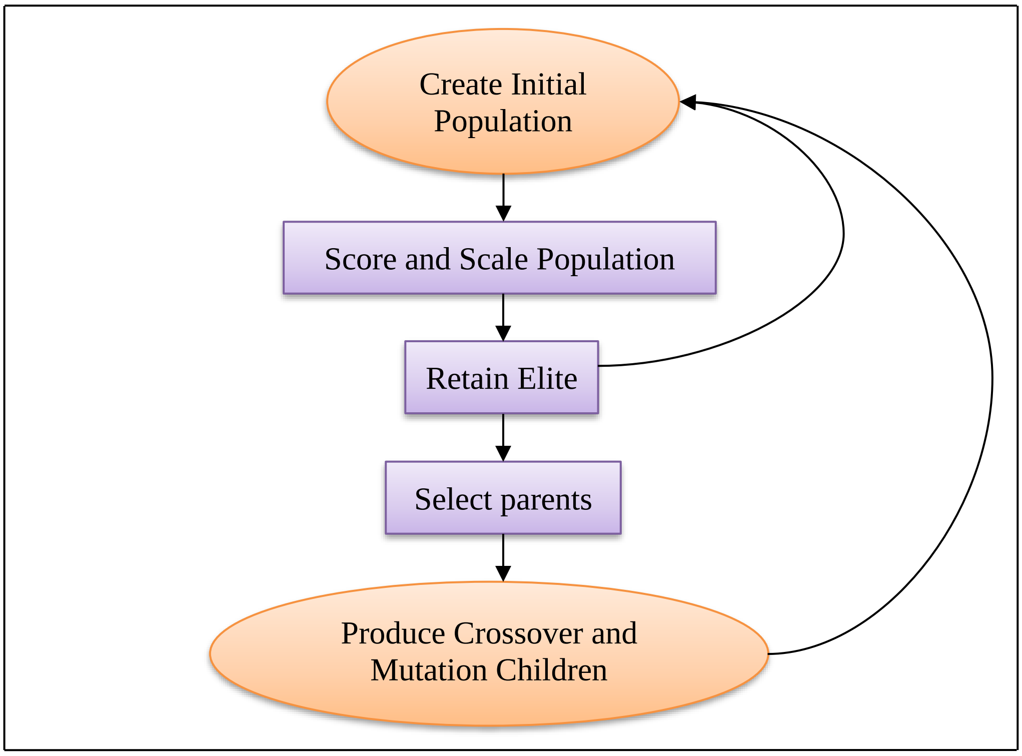

Figure 3.1 Genetic Algorithm Flowchart

The following overview summarizes how the genetic algorithm works.

1. The algorithm creates a random initial population.
2. The algorithm creates a set of new populations after step 1. At every step, the algorithm uses the current generation of individuals to create the next

population.The algorithm performs the following steps to create a new population.

2.1 Calculate the fitness score and score each member of the current population.These values are called raw fitness values.

2.2 Scale the raw fitness values into a more usable range of values. These scaledvalues are called expected values.

2.3 Based on your expectations, select a member called Parent.

2.4 Some individuals with low fitness in the current population are selected as elites. These elite individuals are carried over to the next population.

2.5 Give birth to a child from a parent. Children are created by random alterationsto a single parent (mutation) or by combining vector entries of paired parents(crossover).

2.6 Replace the current population with children to form the next generation.

3. The algorithm stops when one of the stopping criteria is met.
4. The algorithm performs modified steps for linear and integer constraints.
5. This algorithm is further modified for nonlinear constraints.
6. GA toolbox provided has been used to find out gain values of the controllers.

3.2 PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is one of the biologically-inspired algorithms thatcan easily find the best solution in the solution space. It differs from other optimization algorithms in that it only requires an objective function and does not depend on the gradient or differential form of the objective function. It also has few hyper parameters.

Particle Swarm Optimization was proposed by Kennedy and Eberhart in 1995. As mentioned in the original paper, sociobiologists believe a school of fish or a flock of birdsthat moves in a group "can profit from the experience of all other members”. In other words, while a bird flying and searching randomly for food, for instance, all birds in theflock can share their discovery and help the entire flock get the best hunt [50].

We can simulate the movement of a flock of birds, but each bird is designed to help find the best solution in a high-dimensional solution space, and the best solution found by the flock is the You can also imagine that it is the best solution. This is a heuristic solution. Because it cannot be proved that a real global optimum is found, and usually not. However, the solution found by PSO is often very close to the global optimum [51].

All PSO algorithms are pretty much the same as above. In the example above, we setthe PSO to run with a fixed number of iterations. It's easy to set the number of iterations to run dynamically based on progress. There is also a proposal to create a cognitive coefficient while the social coefficient is decreasing. Gradually brings more exploration at the beginning and more exploitation at the end [52].

In particle swarm optimization

$$v_i^{t+1} = v_i^t + \varphi_1 U_1^t (pb_i^t - x_i^t) + \varphi_2 U_2^t (gb^t - x_i^t) \quad (3.1)$$

In Modified particle swarm optimization

$$v_i^{t+1} = wv_i^t + \varphi_1 U_1^t (pb_i^t - x_i^t) + \varphi_2 U_2^t (gb^t - x_i^t) \quad (3.2)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3.3)$$

While going through iteration process the value of inertia weight updating

$$W = W_{max} + [\frac{W_{max} - W_{min}}{iter_{max}}] \times iter \quad (3.4)$$

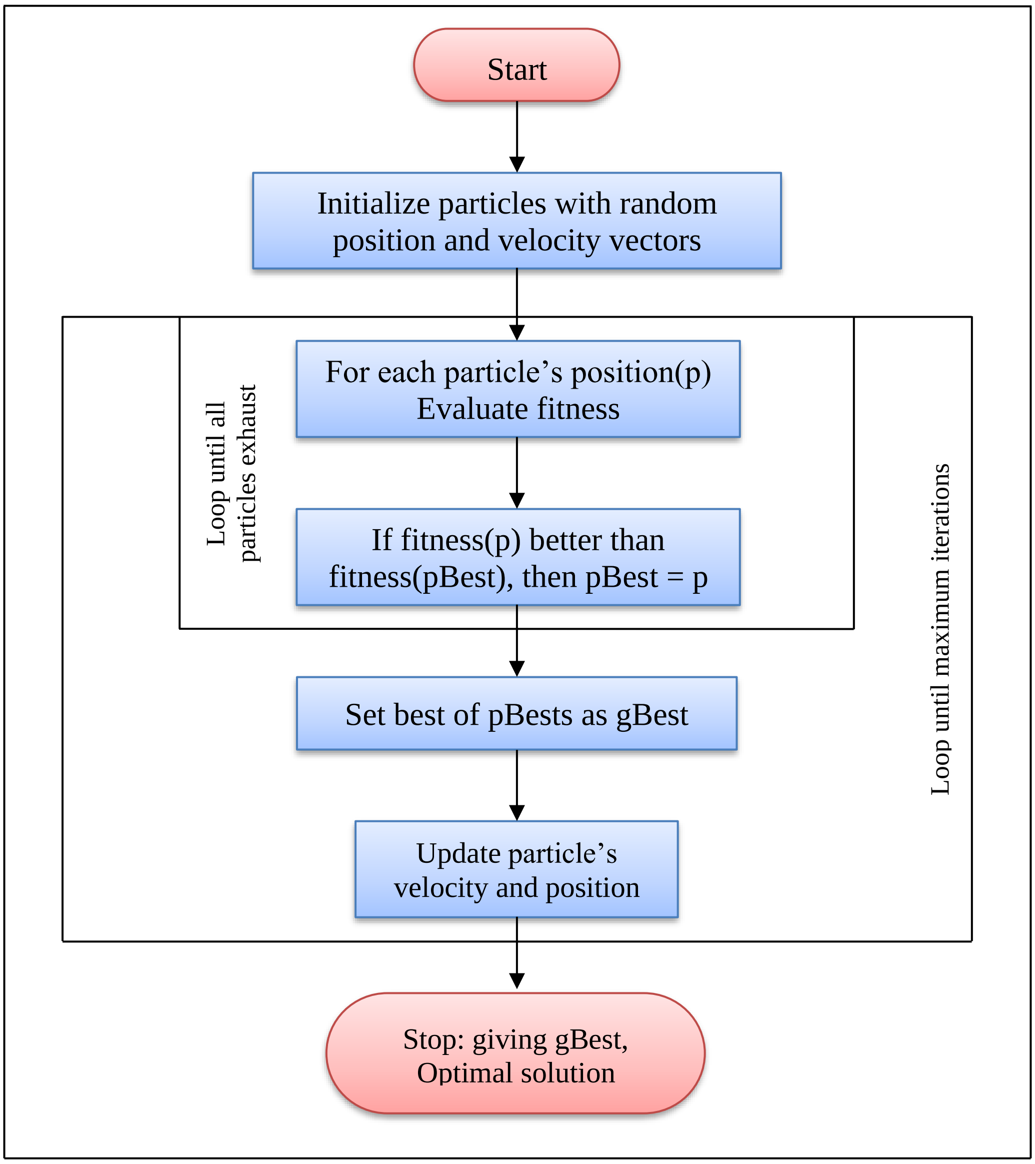

Figure 3.2 PSO Flowchart

3.3FIREFLY ALGORITHM

Bio-inspired algorithms, also known as nature-inspired or evolutionary algorithms, are computational techniques that mimic the behaviors and processes observed in the natural world. These algorithms draw inspiration from biological systems, evolutionary processes, and ecological interactions to solve complex optimization and decision-making problems. By emulating the mechanisms found in nature, bio-inspired algorithms offer innovative solutions to a wide range of real-world challenges.

- All fireflies are unisex, so one firefly will be attracted to other fireflies regardless of their sex.
- Attractiveness is proportional to a firefly's brightness. Thus for any two flashing fireflies, the less brighter one will move toward the brighter one. The attractiveness is proportional to the brightness, both of which decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly.
- The brightness of a firefly is affected or determined by the landscape of the objective function.

Light Intensity and Attractiveness - The attractiveness of a firefly is determined by its brightness, which in turn is associated with the encoded objective function. In maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as I(x) ∝ f(x). The attractiveness β will vary with the distance r(i, j) between firefly i and firefly j.

Light intensity is given as follows where I0 is the light intensity at the source, r is the distance between 2 fireflies, and γ is the light absorption constant for a given medium.

$$\boldsymbol{I(r) = I_0\, e^{-\gamma r^2}} \tag{4.1}$$

Light Intensity

The attractiveness between 2 fireflies is given as follows where β0 is the attractiveness a r=0.

$$\boldsymbol{\beta = \frac{\beta_0}{1+\gamma r^2}} \tag{4.2}$$

Attractiveness

Distance Between Fireflies and Movement - In a simpler case , the distance between 2 fireflies can be given by a Cartesian distance, where x(i,k) is the kth component of the spatial coordinate xi of ith firefly.

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}\left(x_{i,k} - x_{j,k}\right)^2} \qquad (4.3)$$

Cartesian distance

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (4.4)$$

2D Cartesian distance

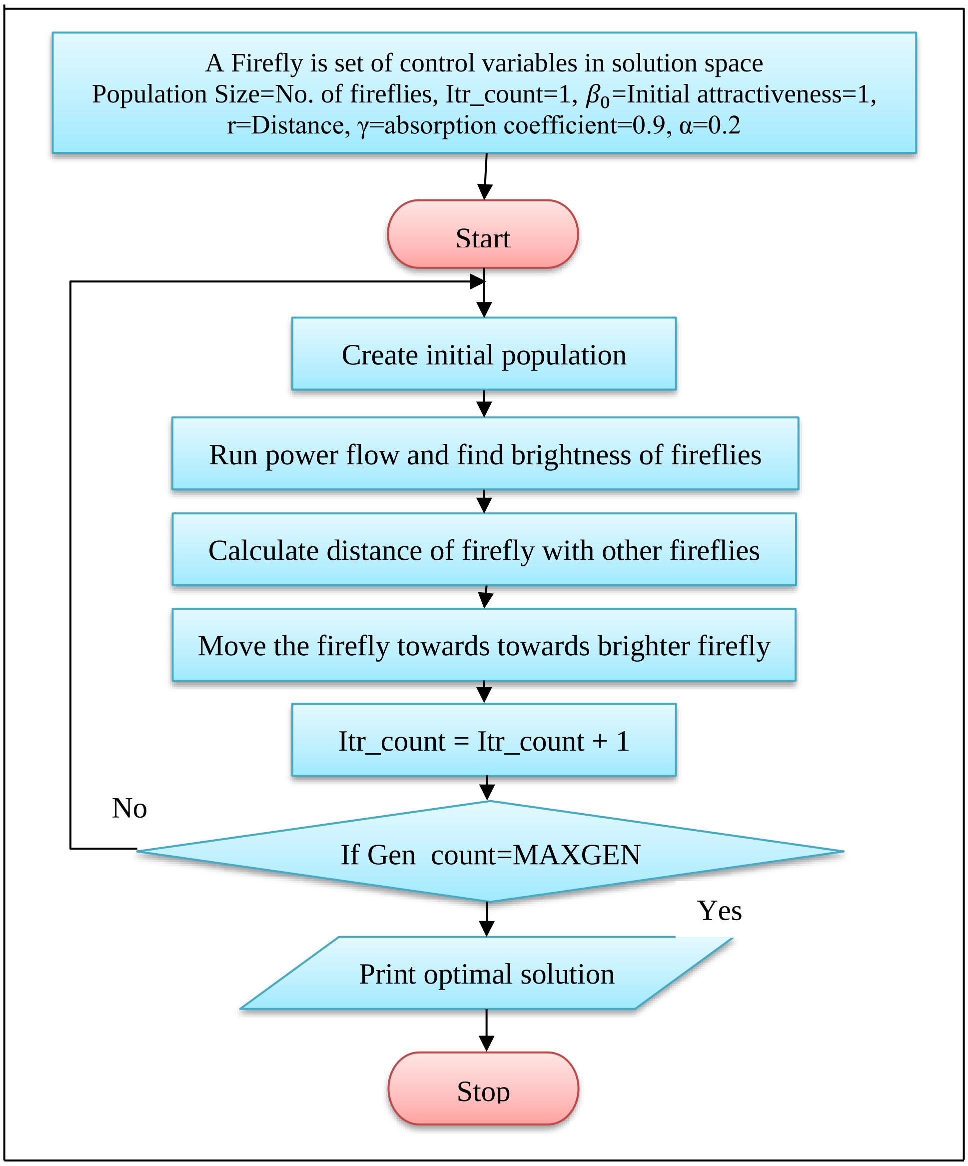

Figure 4.2 Firefly algorithm Flowchart

CHAPTER 4

DESIGINING OF CONTROLLERS FOR MAGLEV SYSTEM

4.1 FEEDBACK CONTROLLERS

A feedback controller gauges the process's output before adjusting the input as necessary to move the process variable closer to the intended setpoint. A controller responds to both operator-initiated setpoint adjustments and erratic process variable disturbances brought on by outside sources. This cycle of measuring, deciding, and actingis repeated until the process variable reaches the setpoint.

Designing a controller to periodically improve one of these exhibition gauges involves numerical models of interactions, individualized recovery programs, and replicated experiments. The designer repeats this trial-and-error process, either manually or under computer control, until the degradation of performance measurements is no longer imminent. The final set of tuning parameters can then be loaded into the actual controller to bring the actual process variables closer to their setpoints under realoperating conditions [45].

4.2 PD CONTROLLER

This type of controller in a control system whose output varies proportionally to both the error signal and the derivative of the error signal, is known as a proportional derivative controller. This type of controller offers the combined effect of both proportional and derivative control actions [46].

In this case, the control signal is proportional to both the error signal and the integral of the error signal. The mathematical expressions for proportional and integral controllers are given by Equation (3.2)

$$c(t) = k_p e(t) + k_d \frac{\mathrm{d}e(t)}{\mathrm{d}t} \tag{3.2}$$

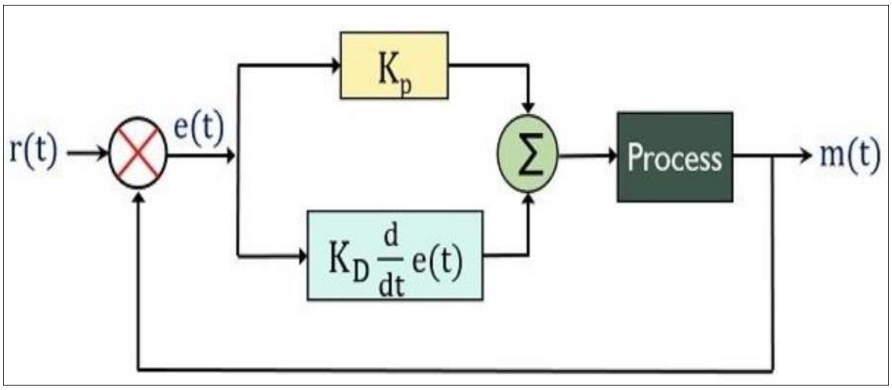

Figure 4.1 PD Controller

The control effect of the differential controller was used separately in the controlsystem. However, merging the proportional controller with the derivative controller yields a more efficient system. Here, proportional controllers eliminate the drawbacks associated with differential controllers.

The presence of a derivative control action with a proportional controller increasessensitivity. This helps generate an early corrective response even with small values of theerror signal, increasing system stability. However, we are also aware of the fact that the derivative controller increases the SS error. On the other hand, proportional controllers reduce SS errors.

4.3 PID CONTROLLER

A type of controller in which the output of the controller varies proportionally to the error signal, the integral of the error signal, and the derivative of the error signal is known as a proportional-integral-derivative controller. PID is an acronym for this type ofcontroller [47]. Combining all three types of control actions improves the overall performance ofthe control system and provides the desired output in an efficient manner.

We already know that in PI controllers, the combined action of proportional and integral controllers reduces the SS error and thus acts as a beneficial factor for the overall control system. Therefore, the SS operation of the whole system is improved. However, in this case, the stability of the system remains unchanged, as no improvement is observed.

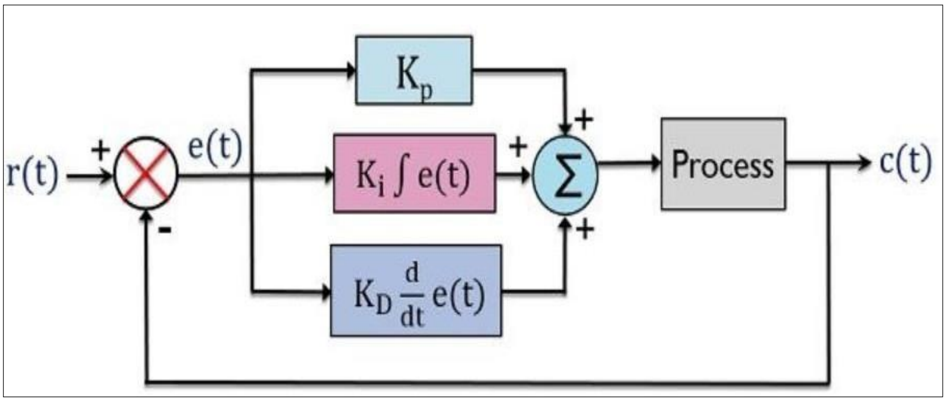

Figure 4.2 PID Controller

The output of the PID controller is specified as Equation (3.3).

$$c(t) = k_p e(t) + k_i \int e(t) + k_d \frac{\mathrm{d}e(t)}{\mathrm{d}t} \tag{3.3}$$

In this way, an early corrective response of the system is generated, thereby improving the overall system stability. However, a notable feature of PD controllers is that the SS error is unaffected. More simply, we can say that a derivative controller leads to a SS error. Stability errors occur with integrated controllers. PID controllers are used to overcome the respective drawbacks of both controller types. Therefore, PID controllers create systems with improved stability and reduced steady- state error.

4.4 GA BASED CONTROL

Genetic Algorithm (GA) based PID control is a sophisticated optimization technique aimed at fine-tuning the parameters of a Proportional-Integral-Derivative (PID) controller for optimal performance in controlling dynamic systems. At its core, this method leverages principles inspired by natural selection and genetic inheritance to iteratively refine PID parameters.

The process starts with the creation of an initial population of PID parameter sets, typically represented as chromosomes, each encoding values for Kp, Ki, and Kd. These chromosomes undergo a rigorous evaluation where their fitness is assessed through simulations of the control system, measuring metrics like overshoot, settling time, or integral of absolute error. Subsequently, a selection process based on fitness determines which chromosomes are chosen for reproduction through crossover and mutation. During crossover, genetic material from selected parent chromosomes is exchanged to generate offspring with potentially improved characteristics. Mutation introduces random changes to maintain genetic diversity and prevent premature convergence. The new offspring and a portion of the original population are then used to form the next generation. This cycle of evaluation, selection, crossover, and mutation iterates until a termination criterion, such as convergence to a satisfactory solution, is met.

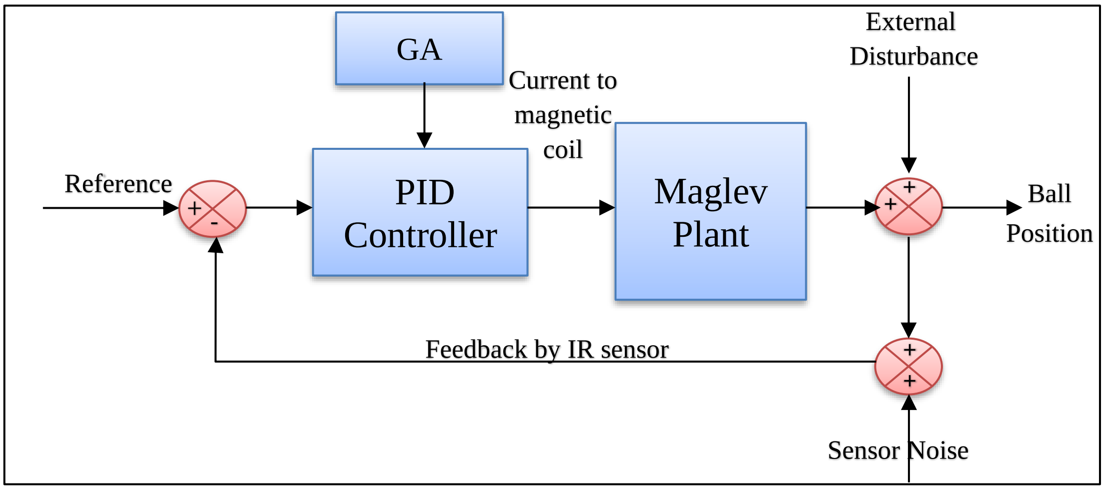

Figure 4.3 Ball position control of Maglev using GA

The final result is a set of PID parameters that offer optimal control performance based on the defined criteria.

4.5PSO BASED CONTROL

Particle Swarm Optimization (PSO) based PID control is an intelligent optimization technique designed to enhance the performance of Proportional-Integral-Derivative (PID) controllers by iteratively adjusting their parameters. Inspired by the social behavior of birds flocking or fish schooling, PSO simulates a population of candidate solutions, called particles, moving through a multidimensional search space to find the optimal solution.

In the context of PID control, each particle represents a set of PID parameters (Kp, Ki, Kd). The process begins with the initialization of a swarm of particles, each assigned random positions and velocities in the parameter space.

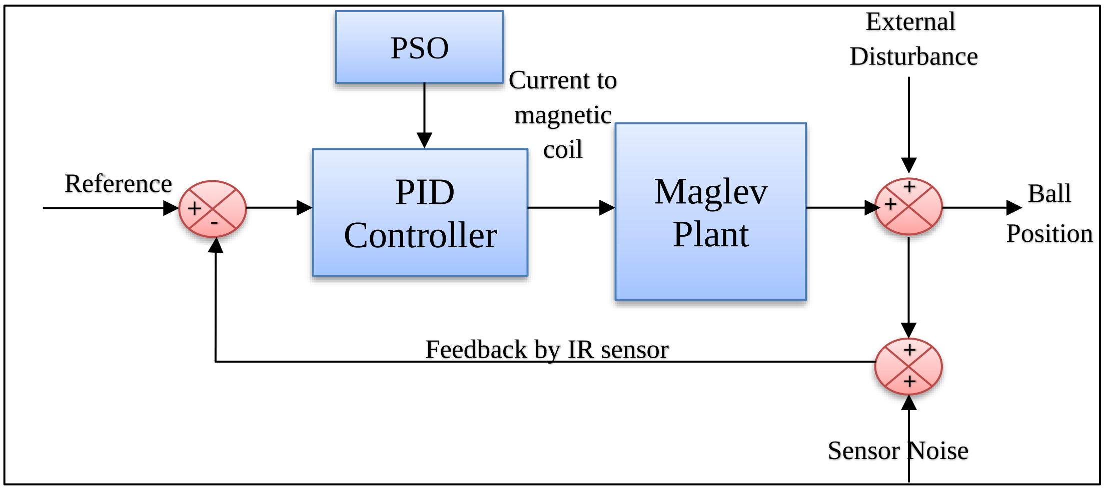

Figure 4.4 Ball position control of Maglev using PSO

The fitness of each particle is then evaluated by simulating the control system with its corresponding PID parameters and measuring performance metrics such as overshoot, settling time, or integral of absolute error. Throughout the optimization process, particles adjust their positions and velocities based on their own best-known position (pBest) and the overall best-known position in the swarm (gBest).

Particle movement is guided by two main factors: personal experience (exploitation) and social interaction (exploration). Exploitation occurs when particles adjust their positions towards their own best-known solution, exploiting local improvements. Exploration, on the other hand, involves particles exploring new areas of the search space by moving towards the global best-known solution found by any particle in the swarm.

PSO-based PID control offers several advantages, including simplicity of implementation, efficiency in finding near-optimal solutions, and the ability to handle complex, nonlinear systems. However, like any optimization method, proper parameter tuning and selection of performance metrics are crucial for achieving desirable results. Additionally, the computational cost of running simulations and the choice of termination criteria should be carefully considered to balance optimization effectiveness with computational resources.

4.6FFA BASED CONTROL

The Firefly Algorithm (FA) is a nature-inspired optimization algorithm based on the flashing behavior of fireflies. It's used for solving optimization problems and has been applied in various fields, including control systems. When integrating FA with PID control, the goal is typically to optimize the parameters of the PID controller to achieve better system performance.

It's important to note that while the Firefly Algorithm can help optimize PID parameters, it might require fine-tuning of algorithm parameters (e.g., attractiveness coefficient, light absorption coefficient) and careful selection of objective functions to ensure effective performance.

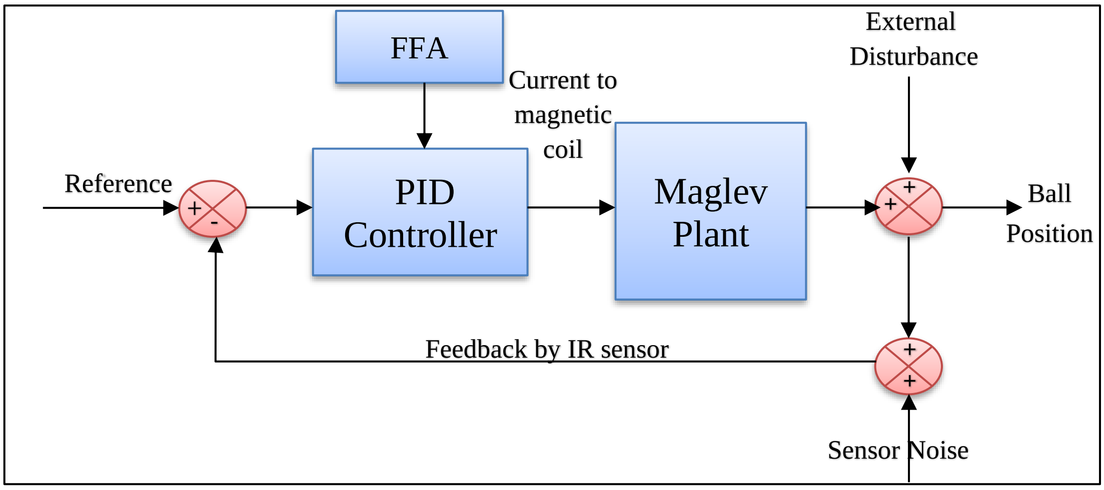

Figure 4.5 Ball position control of Maglev using FFA

CHAPTER 5

SIMULATION RESULTS AND DISCUSSION

This research utilized three optimization algorithms, namely the FireFly Algorithm (FFA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), to optimize the gain values of a PID controller for the Maglev system. Figure4.2 demonstrates the sequential procedure of the HBA algorithm in this context. To achieve a finely-tuned PID controller for the Maglev system, each optimization method was employed with a population size of 50 and a maximum of 10 iterations. These iterations were carried out to ascertain the most optimal values for the proportional, integral, and derivative gains (Kp, Ki, and Kd).

5.1 PD CONTROLLER

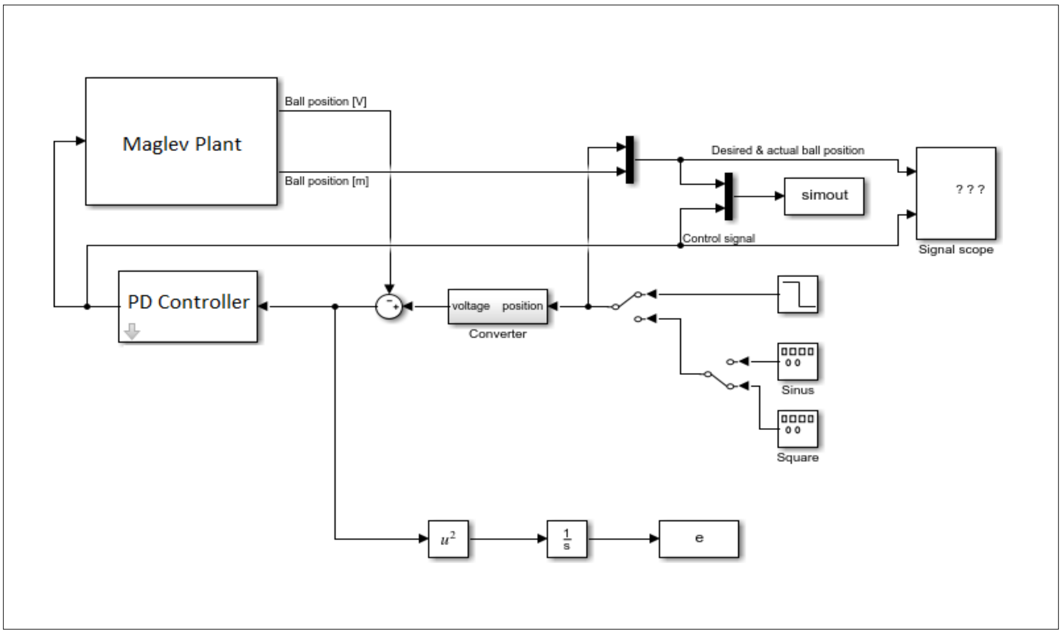

Figure 5.1 Simulink model for PD controller

A Simulink model of a PD (Proportional-Derivative) controller is a visual representation of a control system that uses both proportional and derivative terms to regulate the output of a DS.

Table 5.1 PD Gain Values

Controller Type	K_P	K_D
GA	8.01	1.71
PSO	8.1432	1.821
FFA	9.001	0.75

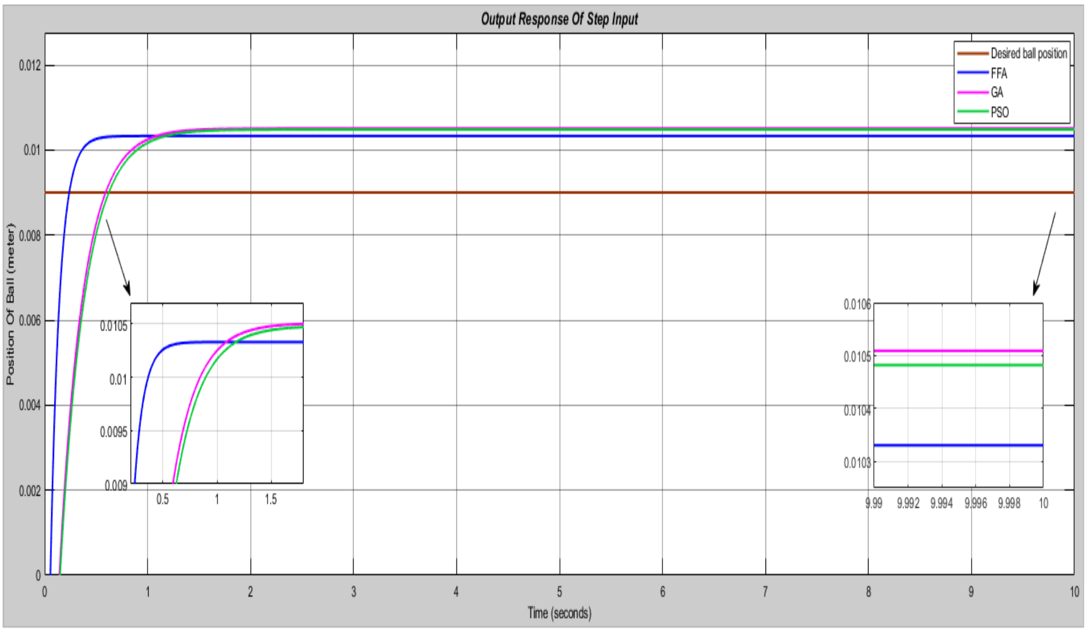

Figure 5.2 Step response of FFA, PSO and GA

In output response of PD controller, SSE from FFA is minimum that is 14.78%.

TABLE 5.2 STEP RESPONSE PARAMETERS

Controller	***Maximum Overshoot***	***Rise Time***	***Steady State Error***	***ISE***	***ITAE***
GA	16.77%	0.4791	16.77%	1.0955	10.816
PSO	15.90%	0.5037	16.47%	1.1108	10.625
FFA	14.44%	0.1915	14.78%	0.6156	9.5460

By using different algorithms, better values of SSE, ISE and ITAE are obtained. This decrement of errors is from 16.77% to 14.78% for SSE, 1.0955 to 0.6156 for ISE, 10.816 to 9.5460 for ITAE.

This implies, improvement in Transient and SS response with less settling time.

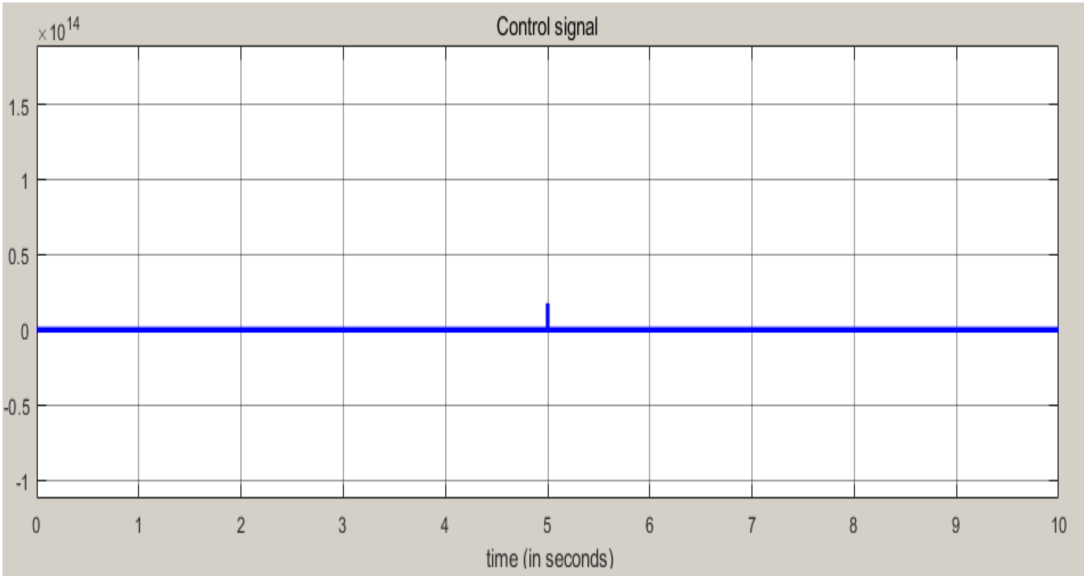

Figure 5.3 Control signal for step input (PD)

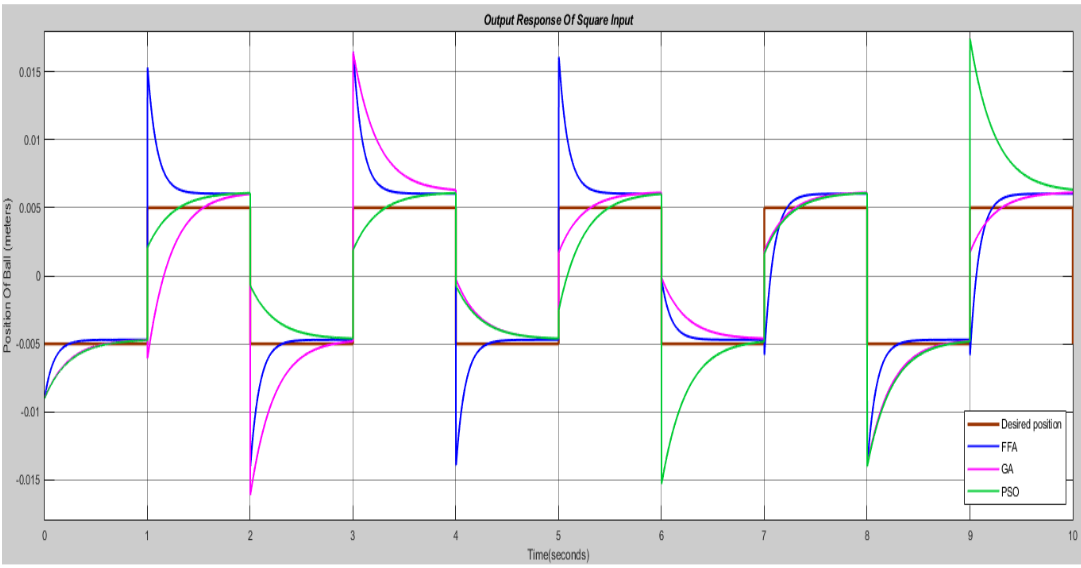

Figure 5.4 Square response of FFA, PSO and GA

Deviation from desired value that is from -0.005 to +0.005, is minimum in case of FFA response.

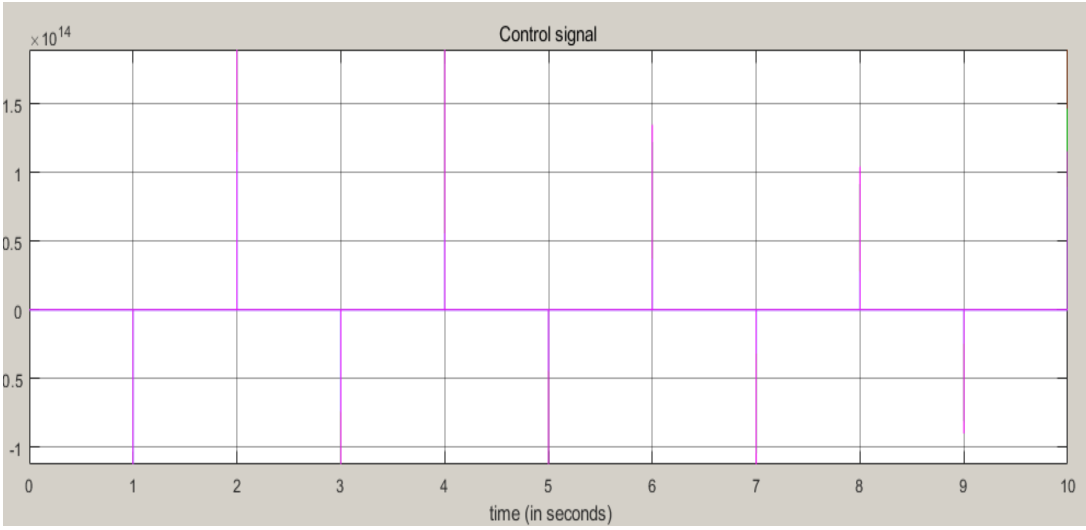

Figure 5.5 Control signal for square input (PD)

The voltage applied in a MagLev system with a single levitating ball is instrumental in creating the magnetic fields necessary to levitate, stabilize, and control the position and movement of the ball in mid-air, allowing for captivating and visually stunning demonstrations of magnetic levitation principles.

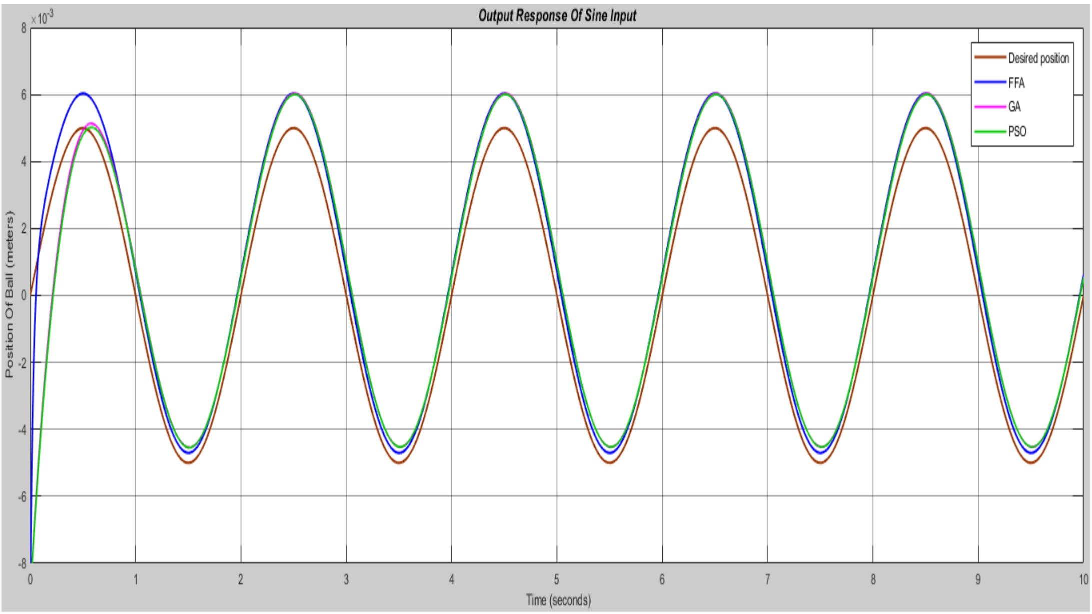

Figure 5.6 Sine response of FFA, PSO and GA

5.2 PID CONTROLLER

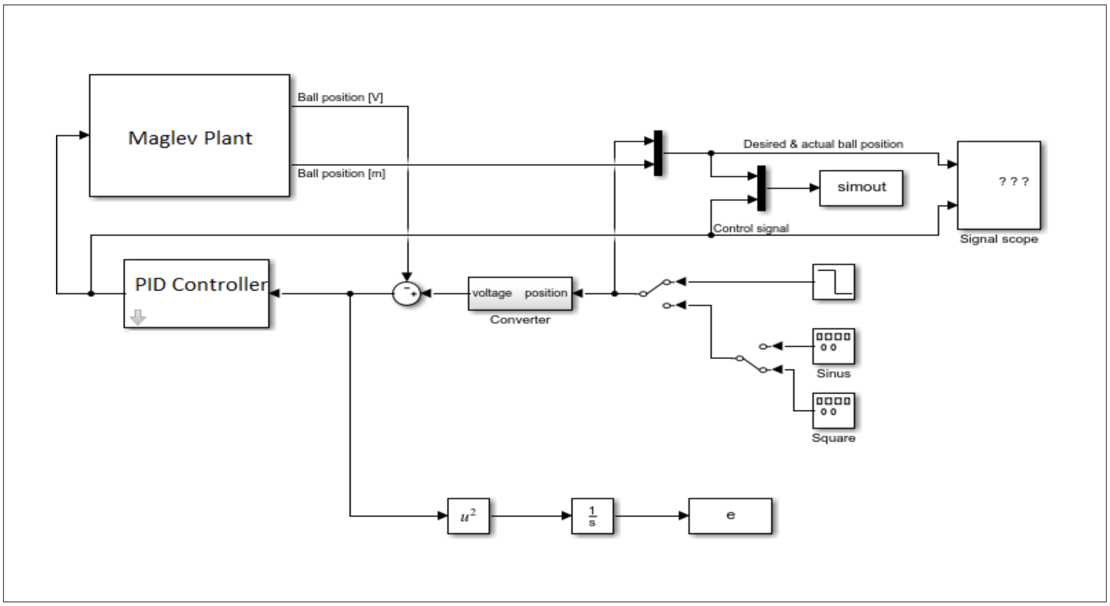

Figure 5.7 Simulink model for PID controller

A Simulink model of a PD (Proportional-Derivative) controller is a visual representation of a control system that uses both proportional and derivative terms to regulate the output of a DS.

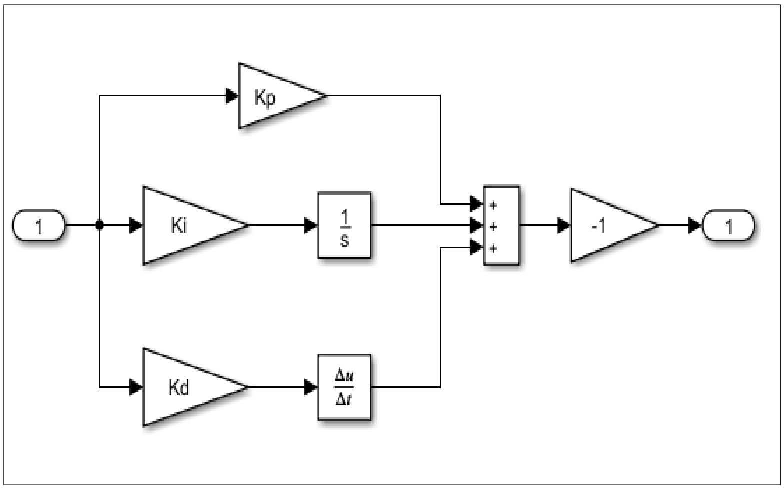

Figure 5.8 PID controller

A type of controller in which the output of the controller varies proportionally to the error signal, the integral of the error signal, and the derivative of the error signal is known as a proportional-integral-derivative controller.

TABLE 5.3 PID GAIN VALUES

Controller Type	K_P	K_I	K_D
GA	14.736	6.01	0.228
PSO	15	5.7392	0.0873
FFA	15	9.967	0.1

By using MatLab code for GA, PSO and FF algorithm, different values of controller gains are obtained.

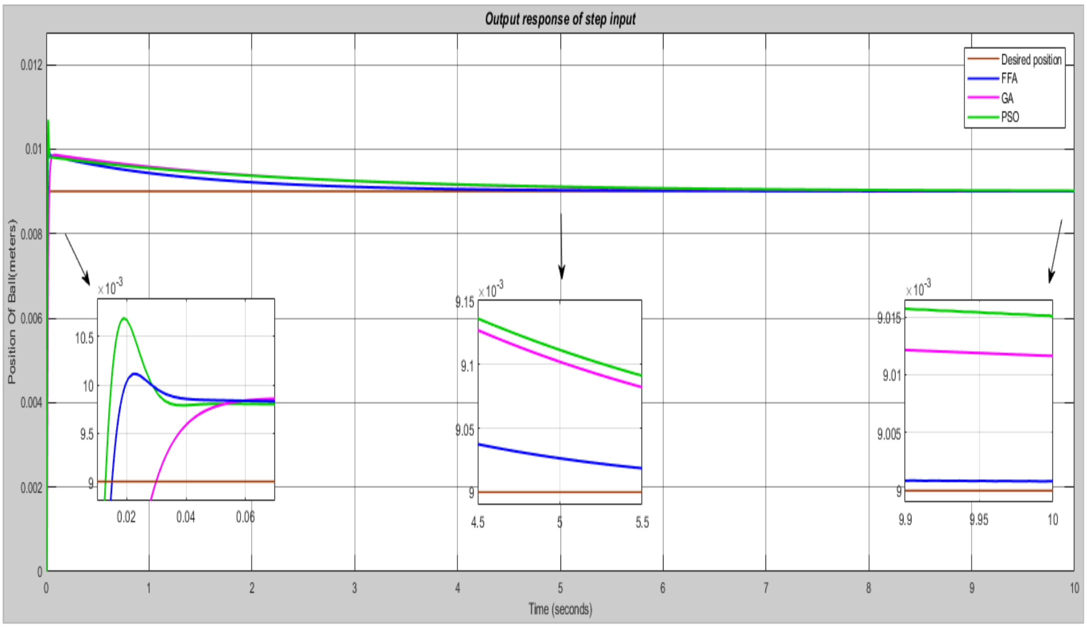

Figure 5.9 Step response of FFA, PSO and GA

In output response of PD controller, SSE from FFA is minimum that is 14.78%, with maximum overshoot of 12.38% and settling time 2.2616s, which shows increase in SS response. As mentioned, green is PSO, pink is GA and blue is output from FFA.

Also, here this simulation is for 0 to 10 seconds, in which response settling happened before 5 seconds. Minimum settling time is from FFA – 2.2616s.

TABLE 5.4 Output response parameters

Controller	***Maximum Overshoot***	***Rise time***	***Settling Time***	***Steady State Error***	***ISE***	***ITAE***
GA	10%	0.0372	3.8285	0.14%	0.0737	0.6725
PSO	14%	0.0048	4.5633	0.17%	0.0474	0.6708
FFA	12.38%	0.0131	2.2616	0.012%	0.0423	0.2545

By using different algorithms, better values of SSE, ISE and ITAE are obtained. This decrement of errors is from 0.14% to 0.012%% for SSE, 0.0737 to 0.0474 for ISE, 0.6725 to 0.2545 for ITAE.

This implies, improvement in Transient and SS response with less settling time.

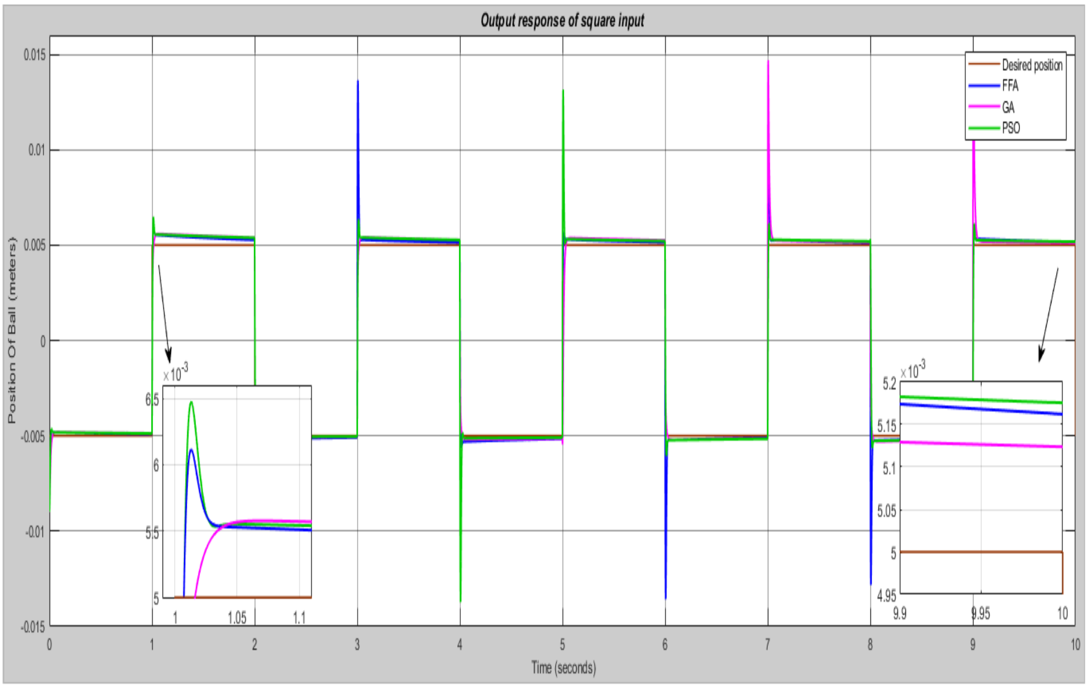

Figure 5.10 Square response of FFA, PSO and GA

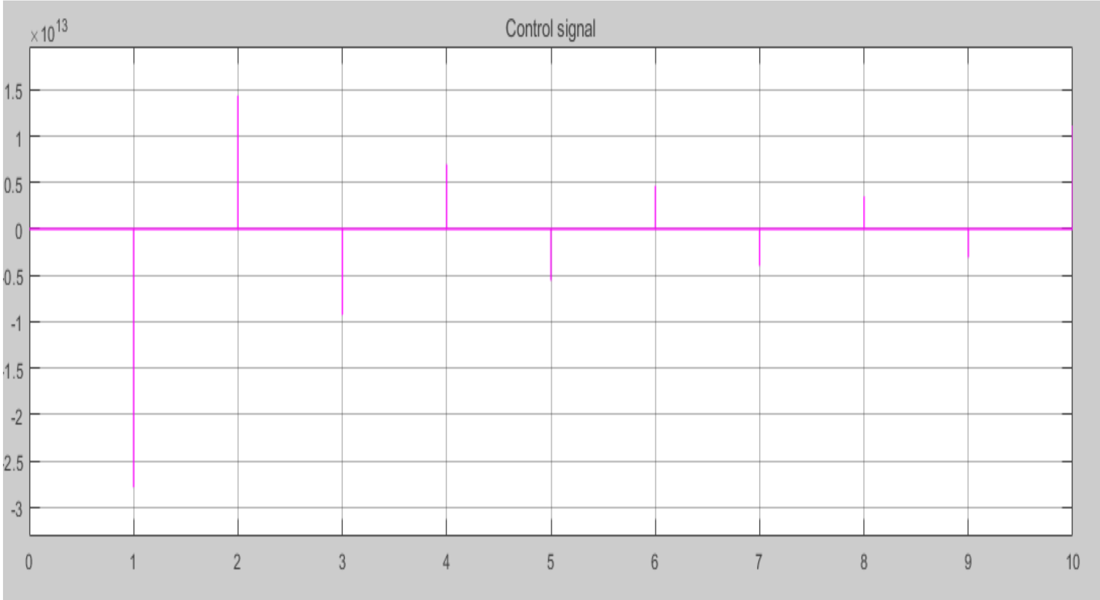

Figure 5.11 Control signal for square input (PID)

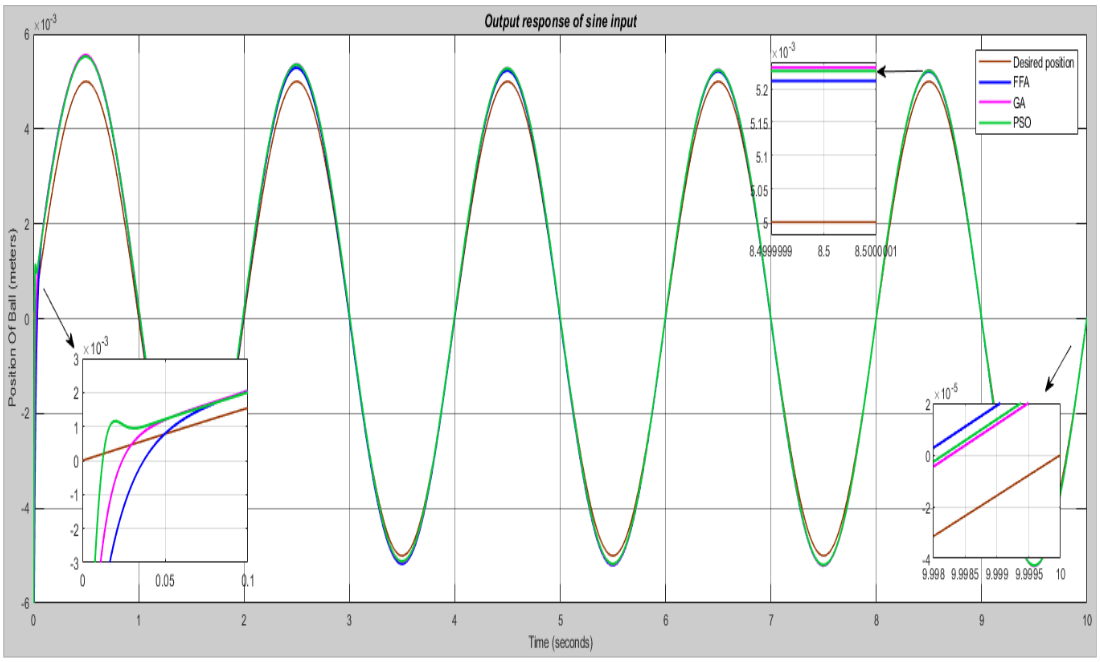

Figure 5.12 Sine response of FFA, PSO and GA

In Figure 5.12, the output response to a sine wave input is depicted, revealing a closely followed trajectory, particularly noticeable in the case of the Firefly Algorithm (FFA).

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

In this study, the FireFly Algorithm (FFA) was employed to determine the optimal gain values for a PD controller and PID controller, aiming to minimize the error between the reference input and the system's output response. The simulation results underscored the effectiveness of FFAs in controlling complex search space systems, demonstrating superior convergence speed.

With the application of various controllers, it is also found that with the additions of more gain values and blocks, a better TR and stability are observed. With the implementation of PD controller in the feedback, we observe an improvement in TR but a decent amount of SSE is observed. With the introduction of PID controller in feedback, improvement in TR aswell as SS is observed. Different controllers can be applied to observe more closely followed trajectoryof the reference signal.

Various algorithms have been helpful in getting an almost following trajectory. Newly developed algorithms like FFA have proved to be useful in finding thegains of the controller for the best results.

Following the development of a mathematical model, a linear model was derived. Subsequently, three algorithms—FFA, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA)—were applied. It was noted that while there was a slight increase in maximum overshoot (12.38%) when using FFA, all other parameters, including Settling Time, Rise Time, steady-state error (SSE), and Integrated Squared Error (ISE), Integrated Time Absolute Error (ITAE) were significantly reduced to 2.2616s, 0.0131s, 0.012%, 0.0423 and 0.2545, respectively.

The study concluded that FFA proved highly effective in diminishing SSE and reducing the settling time of the system's response, showcasing its superiority over the other algorithms considered.

Future research directions for the study include enhancing the FFA for greater efficiency and applicability, integrating it with machine learning for adaptive control in dynamic environments, validating proposed control strategies in real-world systems, exploring multi-objective optimization to address conflicting control objectives simultaneously, extending HBA-based control strategies to diverse fields beyond the studied system, and assessing the robustness of FFA-based controllers against uncertainties and disturbances for real-world deployment. These efforts aim to advance control theory and contribute to the development of more efficient and adaptive control systems across various domains.

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APPENDIX

MATLAB program for the minimization of error

Below is the program for minimization of error for PD controller

```
function F = tracklsq(pid)

         Kp =
         pid(1);
         Kd =
         pid(2);

         sprintf('The value of interation Kp=
%3.0f,Kd= %3.0f', pid(1),pid(2));
         simopt =
simset('solver','ode45','SrcWorkspace','Current','Dst
W orkspace','Current');  % Initialize sim options
         [tout,xout,yout] =
sim('Maglev_PD_model',[010],simopt);
         F=e;

    end
```

Below is the program for minimization of error for PID controller

```
function F = tracklsq(pid)

         Kp     =
         pid(1);
         Ki     =
         pid(2);
         Kd     =
         pid(3);

         sprintf('The value of interation Kp=
%3.0f,Ki=%3.0f, Kd= %3.0f', pid(1),pid(2),pid(3));
         % Compute function
         valuesimopt =
simset('solver','ode45','SrcWorkspace','Current','Dst
W orkspace','Current');  % Initialize sim options
         [tout,xout,yout] =
sim('Maglev_PD_model',[010],simopt);
         F=e ;

    end
```

MATLAB program of FFA for the minimization of error

```
function [best_params, best_error] =
firefly_algorithm_for_pid()
    % Firefly Algorithm parameters
    num_fireflies = 10;
    max_generations = 5;
    alpha = 0.2; % Light absorption coefficient
    beta_0 = 1.0; % Initial attractiveness

    % PID parameter limits
    Kp_min = 0;
    Kp_max = 15;
    Ki_min = 0;
    Ki_max = 10;
    Kd_min = 0;
    Kd_max = 1;

    % Initialize fireflies
    fireflies = rand(num_fireflies, 3) .* [Kp_max, Ki_max,
Kd_max];

    % Evaluate initial fireflies
    [best_params, best_error] =
evaluate_fireflies(fireflies);

    % Main loop
    for generation = 1:max_generations
        % Update attractiveness
        beta = beta_0 * exp(-alpha * generation);

        % Move fireflies towards brighter ones
        for i = 1:num_fireflies
            for j = 1:num_fireflies
                if i ~= j
                    % Calculate Euclidean distance
                    distance = norm(fireflies(i,:) -
fireflies(j,:));

                    % Update position based on attractiveness
                    if evaluate_error(fireflies(i,:)) >
evaluate_error(fireflies(j,:))
                        fireflies(i,:) = fireflies(i,:) +
beta * (fireflies(j,:) - fireflies(i,:)) + randn(1,3);
                    end
                end
            end

            % Ensure parameters stay within bounds
            fireflies(i,1) = max(min(fireflies(i,1), Kp_max),
Kp_min);
            fireflies(i,2) = max(min(fireflies(i,2), Ki_max),
Ki_min);
```

```
            fireflies(i,3) = max(min(fireflies(i,3), Kd_max), 
Kd_min);
        end

        % Evaluate fireflies
        [new_params, new_error] = 
evaluate_fireflies(fireflies);

        % Update best solution
        if new_error < best_error
            best_params = new_params;
            best_error = new_error;
        end

        % Display best error in each generation
        disp(['Generation ', num2str(generation), ', Best 
Error: ', num2str(best_error)]);
    end

    disp('Optimization complete.');
end

function [best_params, best_error] = 
evaluate_fireflies(fireflies)
    best_error = Inf;
    best_params = zeros(1,3);
    for i = 1:size(fireflies, 1)
        params = fireflies(i,:);
        error = evaluate_error(params);
        if error < best_error
            best_error = error;
            best_params = params;
        end
    end
end

function error = evaluate_error(params)
    % This function should evaluate the error of the system 
with the given PID parameters (Kp, Ki, Kd)
    % For example, you can use the tracklsq function here
    error = tracklsq(params);
end
```