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Control Approaches for Magnetic Levitation Systems and Recent Works on Its Controllers' Optimization: A Review

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Abstract: Magnetic levitation (Maglev) system is a stimulating nonlinear mechatronic system in which an electromagnetic force is required to suspend an object (metal sphere) in the air. The electromagnetic force is very sensitive to the noise, which can create acceleration forces on the metal sphere, causing the sphere to move into the unbalanced region. Maglev benefits the industry since 1842, in which the maglev system has reduced power consumption, increased power efficiency, and reduced maintenance cost. The typical applications of Maglev system are in wind turbine for power generation, Maglev trains and medical tools. This paper presents a comparative assessment of controllers for the maglev system and ways for optimally tuning the controllers' parameters. Several types of controllers for maglev system are also reviewed throughout this paper.

Keywords: Magnetic levitation; Modelling; Optimization; Nonlinear controller; PID controller.

1. INTRODUCTION

Magnetic levitation (Maglev) systems have been described for a decade as a revolutionary means of travel in science fiction. In 1726, Jonathan Swift has described the magnetic levitation system for the first time. Also, in 1842 an English clergyman, Samuel Earnshaw described the importance of Maglev and its limitation. It is shown that the system of Maglev has instability issues where the force between the static magnets and the contactless levitated part was impossible to be stable. The free levitated part has unstable displacement at least in one direction [1].

Engineering and industry fields are not the only once concerned with the maglev system. The medical and natural fields have also used Maglev in many applications. In 2010, a group of researchers from the University of Rice had developed a three-dimensional tumor model related to magnetic levitation. They had injected the cancer cells with magnetic iron oxide and gold nanoparticles. Then, by installing a coin size magnet near the infected area, they had successfully lifted the cells [2]. Recently, maglev systems have been appreciated for removing mechanical contact friction, reduce maintenance costs and achieve high-precision positioning. Maglev system has been widely used in various applications including high-speed trains, magnetic bearing systems, vibration insulation systems, stepper photolithography, and wind turbine [3].

1.1 Overview of Maglev Systems

Magnet levitation techniques can be classified into two types: Electro Dynamic Suspension (EDS) and Electro Magnetic Suspension (EMS) as shown in Figure 1. EDS systems are often known as *repulsive levitation*. Superconductivity magnets [4] or permanent magnets [5] provide corresponding levitation sources. Nevertheless, it is difficult to activate the repulsive magnet poles at the low speed of superconductivity magnets. Therefore, they are usually used in a high-speed passenger train. The EDS magnetic levitation force is partly stable and allows a high clearance. However, the magnetic materials manufacturing process is more complicated and expensive compared to the EMS system.

Attractive levitation refers to the EMS system. Inherently, the magnetic levitation force is unstable, thus controlling the system is much harder than the EDS system. The process and cost of manufacturing of EMS are lower than EDS, but additional electricity is required to maintain levitation height. Over the years, engineers and researchers have been paying great attention to stabilize the maglev system. The characteristics of the maglev system is extremely nonlinear, unstable and considerable uncertainty. One of the controllers used for the maglev system is the Proportional-Integral- Derivative (PID) controller, and it was used with several different optimization algorithms [6].

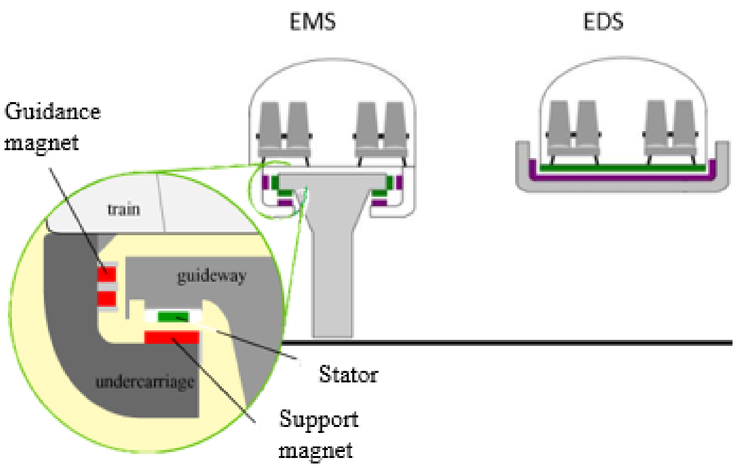

Figure 1. Attractive versus repulsive maglev system [1]

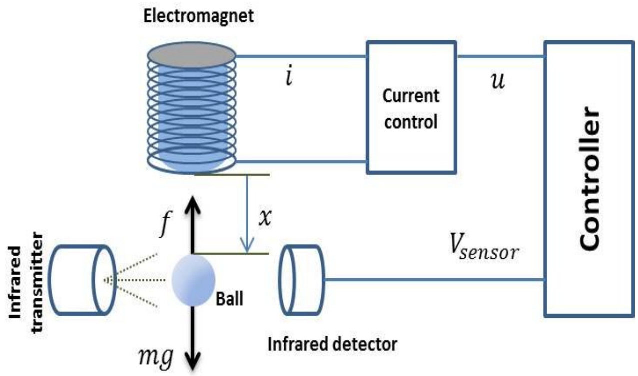

Figure 2. Magnetic levitation model

2. MAGLEV SYSTEM MODELLING

Figure 2 shows the basic construction of the Maglev system. It is a system that consists of a ferro ball that must be levitated by controlling the magnetic field. For controlling the electromagnetic field and the ferro ball position, an optical sensor can be used to measure the ball position, hence the position error can be reduced. Magnetic levitation system is a nonlinear system and by studying its characteristics, the mechanical and mathematical modelling behavior of the system can be modelled as follows:

2.1 Electrical Dynamic Equations

Using the Kirchhoff's voltage law, the electromagnetic force produced by a current within the coil can be obtained as:

$$V(t) = V_R + V_L = Ri + \frac{d\,[L(x)i]}{dt} \tag{1}$$

where V is input voltage, R is the coil's resistance, L is the inductance and i represents current through the spiral.

2.2 Mechanical Dynamic Equations

Figure 3 shows the free body diagram of the spherical ball levitated by means of harmonizing the force of gravitational, $F_{gravity}$ and the electromagnetic force, F_{em}. If the damping force and air friction are ignored, the total force, F_{acc} acting on the coil is given by the Newton's Third Law of motion as:

$$F_{acc} = F_{gravity} - F_{em} \tag{2}$$

$$m\ddot{x} = mg - k\frac{i^2}{x^2} \tag{3}$$

where m is the ball mass, k is magnetic force constant, g is gravity constant and x is the ball position.

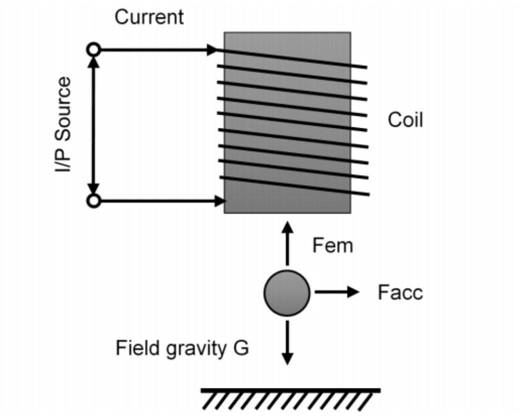

Figure 3. Free body diagram of Maglev system assembly

2.3 Mathematical Modelling in a State Space Form

By combining the related equations of mechanical and electromagnetic, the dynamic equations of Maglev system can be obtained as:

$$\frac{dx}{dt} = v \tag{4}$$

$$e = Ri + \frac{d\,[L(x)i]}{dt} \tag{5}$$

$$m\frac{d^2x}{dt^2} = mg - k\frac{i^2}{x^2} \tag{6}$$

Equation (5) stipulates $L(x)$ as a nonlinear function of the position of the ball. If the inductance varies with respect to the position of the ball, that is:

$$L(x) = L_1 + \frac{2k}{x} \tag{7}$$

where L_1 is a Maglev system parameter. By applying the value of $L(x)$ in Equation (5) yields:

$$e = Ri + \frac{d\left[(L_1+\frac{2k}{x})i\right]}{dt} \tag{8}$$

By using the product rule:

$$\frac{di}{dt} = -\frac{Ri}{L} + \frac{2kiv}{Lx^2} + \frac{e}{L} \tag{9}$$

Also, Equation (6) can be re-written as:

$$\frac{dv}{dt} = g - \frac{ki^2}{mx^2} \tag{10}$$

By considering the state vectors, $x = x_1, v = x_2, i = x_3$ and $u = e$, Equations (4), (9) and (10) can be written in a vector form as:

$$\begin{bmatrix}\dot{x_1}\\ \dot{x_2}\\ \dot{x_3}\end{bmatrix} = \begin{bmatrix} x_2 \\ g - \frac{Kx_3^2}{mx_1^2} \\ -\frac{Rx_3}{L} + \frac{2Kx_2x_3}{Lx_1^2}\end{bmatrix} x + \begin{bmatrix}0\\0\\\frac{1}{L}\end{bmatrix} u \tag{11}$$

where the output is the ball position and derived as:

$$y = x_1 = [1 \quad 0 \quad 0]x \tag{12}$$

2.4 Linearization of the System

If $x_1 = {x_1}^* = y^*$, the system can be linearized using Taylor series which gives the state vector as:

$$x_0 = [{x_1}^* \quad {x_2}^* \quad {x_3}^*]$$

The time rate of the position must be zero at steady state of the magnetic levitation for example ${x_2}^* = 0$. In addition, the current of the ball at the time of rising can be defined from Equation (3), and it must satisfy the given condition:

$${x_3}^* = y^* \sqrt{\frac{mg}{k}} \tag{13}$$

Thus, the linearized state-space modelling form can be written as:

$$A = \begin{bmatrix} 0 & 1 & 0 \\ \frac{kx_3^{*2}}{mx_1^{*3}} & 0 & -\frac{2kx_3^*}{mx_1^{*2}} \\ 0 & \frac{2kx_3^*}{Lx_1^{*2}} & -\frac{R}{L} \end{bmatrix} \tag{14}$$

By replacing the values from Equation (11) and using Equation (14) and $x_1{}^* = y^*$ yields [7]

$$\frac{kx_3^{*2}}{mx_1^{*3}} = -\frac{2}{y^*}\sqrt{\frac{gk}{m}}$$

$$\frac{2kx_3^*}{Lx_1^{*2}} = \frac{2}{Ly^*}\sqrt{gmk}$$

$$A = \begin{bmatrix} 0 & 1 & 0 \\ \frac{g}{y^*} & 0 & -\frac{2}{y^*}\sqrt{\frac{gk}{m}} \\ 0 & \frac{2}{Ly^*}\sqrt{gmk} & -\frac{R}{L} \end{bmatrix},\ B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L} \end{bmatrix}$$

$$C = [1 \quad 0 \quad 0],\ D = [0] \tag{15}$$

3. CONTROL APPROACHES FOR MAGLEV SYSTEM

3.1 Linear Controllers

PID is a linear controller and a typical method used in industrial applications. The common transfer function of the PID controller is given by:

$$U_{PID}(s) = (K_P + K_I \frac{1}{s} + K_D s)E(s) \tag{16}$$

where U_{PID} is controller output signal and $E(s)$ is the difference between input and output signals. K_P, K_I and K_D are the PID controller gains. The PID controller has been used to control a maglev plant and works based on a basic control feedback loop algorithm that is commonly used in modeling of control systems [8]. One of the methods that can be used as a linear controller has been proposed by Cohen and Coon in 1953 [9]. Ahmad et al. [10] proposed a PID controller-based maglev system, in which the overshoot of 8.4% and a settling time of 0.302 s was achieved.

Linear Quadratic Regulator **(**LQR**)** is a powerful technique for the design of controls and dynamic structures that have high performance criteria. The traditional optimum control principle is introduced in [8,11,12]. With an assumption that all state variables are available for feedback, the LQR design method starts with a defined set of states which are to be controlled. In general, the system model can be written in a state space form as

$$\dot{x} = Ax(t) + Bu(t) \tag{17}$$

The matrices Q and R are the weighting matrices and essential elements in the method of optimizing LQR. The LQR feedback, K is accomplished by choosing the specification parameters Q and R, solving algebraic Riccati equations for P and finally selecting the state variable input (SVFB) using $K = R^{-1}B^T P$. The Riccati equation is given as:

$$A^T P + PA - PBR^{-1}B^T P + Q = 0 \tag{18}$$

An LQR controller-based maglev system has been compared with the conventional PID and fuzzy logic controller in [13]. The results show that PID controller has a less rise time with 0.042 s as compared to the LQR with 0.16 s. However, the LQR controller has a better settling time of 0.166 s as compared to PID with 5.2 s. In 2016, Maji et al. [14] has proposed an LQR-based maglev controller in real time simulation and compared it with the conventional PID controller. It was found that the LQR controller provided better results in term of the stability performance. With the LQR controller, a response with a settling time of 7 s and without overshoot was obtained.

3.2 Nonlinear Controllers

There are many nonlinear controllers that have been used to control a maglev system. Backstepping is a nonlinear control technique that was proposed in the 1990s [15]. This method is sufficient for the implementation in a strict feedback form of a broad variety of linear feedback systems. In [16], Katayama et al. has proposed an integrated backstepping sliding mode algorithm to control the maglev system. The results show that backstepping technique has a better response with a settling time of 0.286 s as compared to the PI controller with a sampling time of 15.9 s. The step-back technique is a structural way to construct a control mechanism to maintain a reference signal. For a continuous-time model of a magnetic levitation system, a backstepping technique has been used to design state feedback stabilizing laws and derived high-gain observers, and the designed controller was efficient with a less steady-state error [17].

Sliding mode approach allows the mechanism of magnetic levitation to be regulated and stabilized because of its robustness and reliability in extremely nonlinear environments [18]. The sliding mode control (SMC) algorithm inherently robust in the changing of the system parameters, nonlinear models, external disturbances, and uncertainty. In [19], an SMC was proposed for a maglev system, and the results have shown that the control schemes are robust to parameter variations. The proposed method used an adaptive neural terminal SMC to overcome the chattering problem.

4. CLASSICAL TECHNIQUES FOR PID CONTROLLER TUNING FOR MAGLEV SYSTEM

4.1 Cohen-Coon Method

The tuning rules for Cohen-Coon (C-C) are sufficient for a larger range of processes than those for Ziegler-Nichols (Z-N). The Z-N technique only works well on processes in which the dead time is less than half of the time constant [16]. However, the C-C tuning rules operate exceptionally well on processes where the dead time is less than double the constant time. The process response curve is first obtained via an open-loop test and then the process dynamics are approached with first order plus dead time. Using C-C method, the process Reaction Curve (G_{PRC}) can be calculated as

$$G_{PRC}(s) = \frac{y_m(s)}{c(s)} \cong \frac{Ke^{-t_d s}}{\tau s + 1} \tag{19}$$

where k is a steady-state output, τ is the time constant for a first order response, t_d is the dead time.

The C-C method has been compared with Z-N to tune the PID controller for maglev system and the results are shown in Table 1 [20]. It was shown that the Z-N provides better results in term of the rise time and settling time. It was found that C-C intended to respond to the 4-th amplitude damping. Although the 4-th amplitude tuning system provides a very rapid rejection of disturbances, it is very oscillating and often interacts with loops similarly tuned.

Table 1. Comparison results between Z-N and C-C method by [20]

	Ziegler-Nichols [PID]	Cohen Coon [PI]
Time delay (s)	0	0
Rise time (s)	0.59	0.8
Settling time (s)	0.54	0.67
Overshoot (%)	0	0
Steady-state error	0	0

4.2 Ziegler Nichols Method

Z-N technique is by far the most used tuning method. The PID tuning method proposed by John Ziegler and Nathaniel Nichols in 1942 is still easy and yet very reliable [21]. Figure 4 shows a first-order transport system response with delay, with a transfer function as:

$$G(s) = \frac{Ke^{-sL}}{Ts+1} \tag{20}$$

where $G(s)$ is a first order transfer function, L is the delay time, T is the time constant, K is a gain and e is an error. This technique has been used to tune the PID controller of a maglev system. Ahmad et al. [22] proposed a PID tuning using Z-N and compared to a genetic algorithm for Maglev system. The results show that the PID controller based on the Z-N method had a better rise time but higher settling time than GA. Kishore and Laxmi [23] compared between Z-N one degree of freedom (1-DOF) and two degrees of freedom (2-DOF) of PID tuning for Maglev system and found that the 1-DOF has a slower settling time but faster rise time than the 2-DOF.

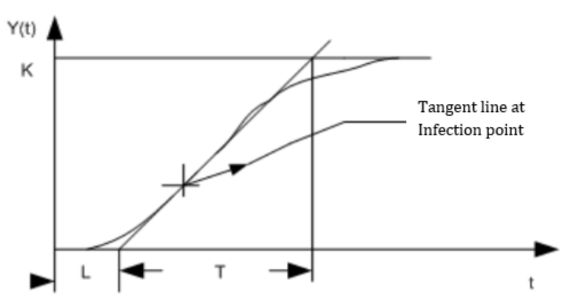

Figure 4. Ziegler-Nichols method response [24]

5. OPTIMIZATION TECHNIQUES OF PID TUNING FOR MAGLEV SYSTEM

5.1 Gradient Descent Optimization

In [25], the Gradient Descent (GD)-based convolutional neural network was used to minimize the loss function to adjust the weight parameters and enhance the accuracy of the network via iterative training. The Stochastic Gradient Descent (SGD) algorithm was used to find the minimum point from a particular function. Contrariwise, the GD is a technique used to find the maximum point close to the recent results. GD algorithm at any starting point of its function will always shift the solution to the negative direction of the gradient to get to the desired point. Alagoz et al [26] proposed PID tuning using GD algorithm, and the theoretical basis for reference gradient descent equations to determine the adaptive system, start with the cost function expressed as a square output difference as:

$$E(n) = \frac{1}{2}\, e(n)^2 = \frac{1}{2}\, (y_r(n) - y_s(n))^2 \tag{21}$$

where $E(n)$ is instant model error signal.

The function used to update rule of the control optimizer, which generates the control signals to minimize the cost function $E(n)$ is as follows:

$$\frac{\partial u}{\partial t} = -\eta_c \frac{\partial E}{\partial u} \tag{22}$$

In another work, the SGD proposed in [27] was executed by choosing a standard model for simulating the performance of the designed controller after tuning the PID controller. The MATLAB simulation was used to test the performance of the optimized controller. The optimization executed by initiating the values of the SGD Method using a trial-and-error method.

5.2 Artificial Neural Networks

The Artificial Neural Network (ANN) is a conceptual model or theoretical model used for simulation and the operation of artificial neural systems. There are many neural network structures and one of these is Radial Basis Function based Neural Networks (RBFNN) which has been proposed by Sun et al. [28]. It is a three-layer, hidden-layered feedforward neural networks. The radial base function with sliding mode controller for a maglev system has been proposed by Alias [29]. On the other hand, a maglev system based on PID tuning using RBF has been proposed by Tong et al. [30]. The inputs connected the hidden neurons has nonlinear functions, whereby the output layer is linear from the hidden layer. The ability of the RBF network to approximate any continuous function has arbitrary precision. The learning rate is greatly accelerated, and the local minimum issue is avoided. An RBFNN block diagram for PID tuning as proposed in [31] is shown in Figure 5.

Considering that the input vector of the RBFNN is $x = [x_1\,, x_2\, \dots, x_n]^T$, the neurons at the hidden layer are activated by a RBF [32]. Assuming the radial vector is $h = [h_1\,, h_2\, \dots, h_n]^T$ where h_j is a Gaussian equation expressed by the following mathematical relation:

$$h_j = \exp\left[\frac{\|x - c_j\|^2}{2b_j^2}\right], j = 1,2,\dots,m\,. \tag{23}$$

Similarly, authors in [33, 30] used radial basis neural networks to auto-adjust the maglev suspension of a train and compared them to a relay system proposed by Astrom and Hagglund, in which better results were achieved. In another work, comparisons of PID control using Neural Networks and Support Vector Machine (SVM) show that the neural network-based controls provided a better system performance under noiseless settings, but less performance than SVM in noisy conditions [34].

5.3 Genetic algorithms

Genetic algorithm (GA) is a technique of optimization influenced by evolution. It is considered as an important optimization technique since it has been implemented in several different fields to solve complicated optimization problems [35]. Based on the natural selection mechanisms of shape and advancement, GA has shown an incredibly stable methodology in determining the ideal global position. GA is not a single-phase method. It consists of a variety of measures or approaches centred on stochastic optimization concepts and names extracted from genetics. A flow chart in Figure 6 explains the implementation of GA to a maglev system. To apply the GA for optimization process, it requires addressing the following important steps: a) Representation, b) Genetic operators, c) Formulation of the fitness function.

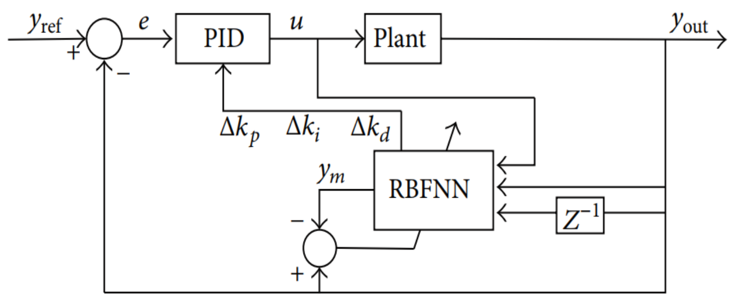

Figure 5. RBF neural network based PID tuning diagram [31]

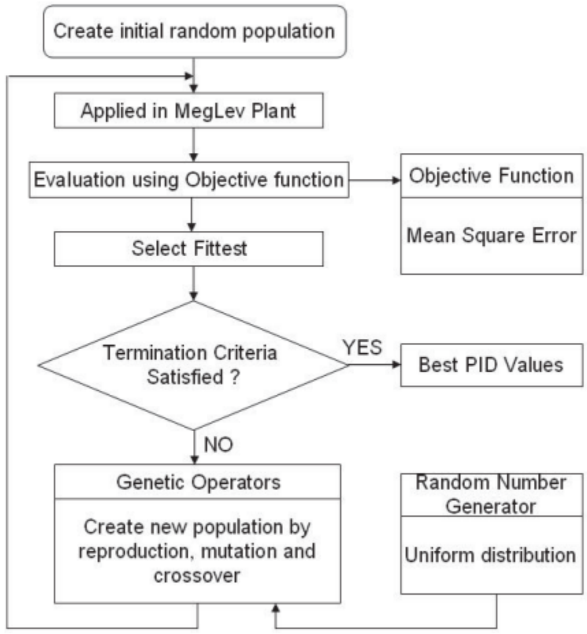

Figure 6. Flow chart of GA [22]

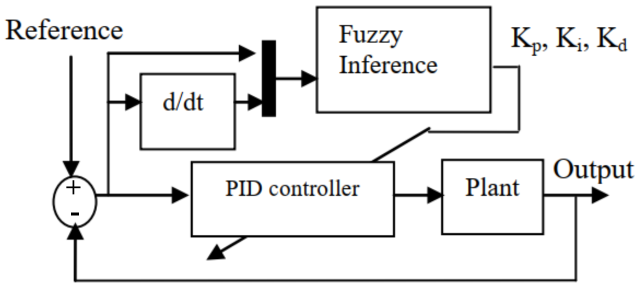

Figure 7. Block diagram of FLC-based PID controller [24]

Ahmad at el. [22] proposed a GA-based PID optimization and compared to a Z-N method. It was found that the settling time is faster than Z-N and the ball levitation is more stable. Altintas and Aydin [36] proposed an optimization method using GA for a maglev system and the results shows that GA has a better tuning flexibility than the conventional methods, as it has five parameters that can be modified.

5.4 Fuzzy Logic

Fuzzy logic controller (FLC) is one of the methods used to interface between artificial intelligence and control engineering. The FLC uses the standard PID controller to change the PID controller parameters online and to modify the signals error and the change of the error. FLC configuration requirements differ with the plant in use, and the PID controller parameter in conjunction with the plant to be used [34, 37].

There are two standard models mostly used with a fuzzy interface which are the Mamdani model or Sugeno model. The operation of the Mamdani rule can be divided into four parts:

1) Fuzzification is mapping each of the crisp inputs and determine the degree to which these inputs belong to each of the proper fuzzy sets.
2) Rule’s evaluation: the output of each rule will be determined by its fuzzy antecedents.
3) Aggregation of the rule outputs: defining the aggregate output of all fuzzy rules.
4) Defuzzification: mapping the fuzzy output to crisp output.

The fuzzy rules are decided by the plant to be managed and the form and practical experience of the controller [38]. The probably most challenging part is to design essential rules bases. Therefore, PD fuzzy system and integrated error control are the perfect design. There are also examples where a PI-based FLC controller and a PD-like FLC controller are used to achieving a PID-based controller.

Ataşlar-Ayyıldız and Karahan [39] proposed a FLC for a maglev system based on Cuckoo Search algorithm and obtained an outstanding performance as compared to fractional order PID (FOPID). An and Chen [40] proposed an FLC-based PSO and PID, where the results are superior than the conventional PID. The proposed methodology is shown in Figure 7, where the error and the derivative of the error are the inputs to the fuzzy interface.

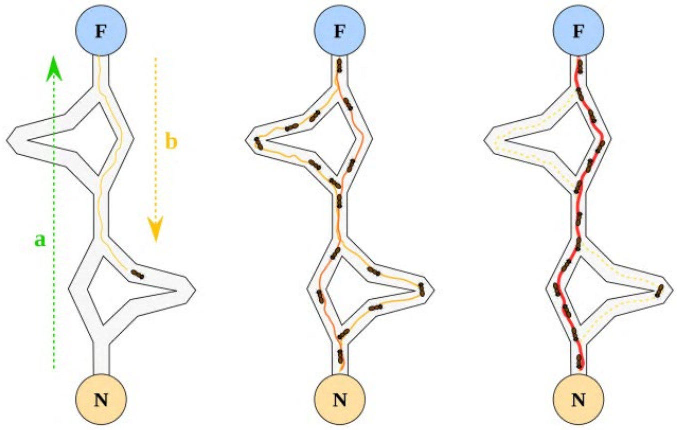

Figure 8. Ant colony optimization algorithm process [41]

5.5 Ant Colony Optimization

Ant Colony Optimizations (ACOs) are particularly well adapted to solving a variety of optimization tasks. An artificial ant colony collaborates to find good solutions, which is an emergent characteristic of their cooperative interaction. Ant algorithms are adaptable and resilient and would be used to multiple versions of the same task as well as distinct optimization problems, thanks to their natural resemblance to ant colonies. The ACO technique is ideal for a variety of optimization tasks. The key to finding the best answer is for a colony of ants to work together [42]. The natural behavior of ants inspired the nature-inspired ant colony algorithm. This method is strong and adaptable, and it may be used to solve a variety of problems [43]. Artificial ants have the following characteristics:

- Artificial ant colonies exist to facilitate inter-individual cooperation.
- Pheromone deposition is a way of communication that is used in an indirect manner.
- A sequence of local movements is used to find the shortest path between the starting and destination points. Using just local knowledge, a stochastic decision policy is used to determine the optimal solutions. The mathematical optimization of the ACO technique is shown in Figure 8.

The movement of ants is controlled by the local stochastic search strategy, which is influenced by local environmental information, pheromone trails, and internal states [44]. The ants use private or public information to select the place and timing for releasing pheromones into the environment. In most cases, the quality of an ant's movement is directly related to the number of pheromones emitted.

The following six stages are used to implement the ACO algorithm on the FOPID controller:

1. Initialize the heuristic value, pheromone trail, and potential solutions for the FOPID parameter (K_P, K_I, K_D, λ, μ).
2. The heuristic value obtained is connected to the error-minimization target and the Y th ant is placed on the node.
3. Using evaporation rate of pheromones equation, the population of pheromones is regulated, and poor choices are permitted to be removed.
4. The resulting solutions are assessed in relation to the goal.
5. The optimized parameters' optimal value is produced.
6. Globally, pheromones are updated based on the data acquired in step 5. The procedure is restarted from step 2 until the best result, or the maximum number of iterations is achieved. Figure 9 illustrates the flow chart for the whole process of the ACO algorithm for the FOPID controller.

5.6 Particle Swarm Optimization

Particle swarm optimization (PSO) is a standard method used to optimize PID controller parameters. This technique was developed in 1995 by Eberhart and Kennedy [45]. PSO technique is a population of particles that moves to the solution area to find the target, where the system keeps on changing and track for the best solution found by the individuals [46]. Moreover, these particles move to a new position based on velocity and current position. Authors in [47, 48] proposed a robust design of PSO technique to tune the PID parameter and control Maglev system, for nonlinear optimization problem includes the restrictions without the objective function. The involved equations used are:

$$V_{id} = w \times V_{id} + C_1 \times r_1(p_{id} - x_{id}) + C_2 \times r_2(p_{gd} - x_{id}) \tag{24}$$

$$Gx_{id} = x_{id} + V_{id} \tag{25}$$

where x is current position, V_i is the velocity, p_{id} is the article local best position and G is the global best among all particles. w is the inertia weight, $C_1$and C_2 are positive constants, r_1 and r_2 are random numbers generated by PSO and d is the dimensional vector space.

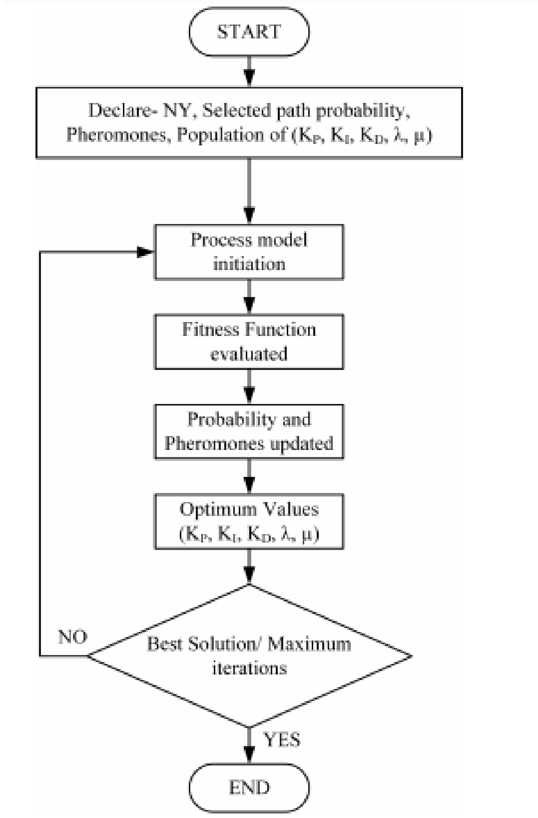

Figure 9. Flow chart of ACO algorithm for FOPID controller [49]

The PSO is designed to decide the optimum set of PID controller parameters. The way the control system finds optimum parameters is converted into a solution optimization problem that is solved by the PSO equation, and it has demonstrated its excellent results by enhancing the stationary error and that the peak overlap. PSO-based tuning for high-performance maglev systems was proposed in [50]. PSO has also been used in position control of maglev system in [51]. Furthermore, it shows a better result when compared with a real coded genetic algorithm.

6. CONCLUSION

This paper describes linear and nonlinear controllers for maglev system. For a linear controller, PID and LQR controllers are discussed, whereas back stepping and sliding mode control are discussed for nonlinear controllers. Tuning of PID-based controllers are divided into two types: classical tuning method which consists of Ziegler Nichols and Cohen Coon, and the intelligent tuning method which consists of radial basis function, fuzzy logic control, genetic algorithm, and particle swarm optimization. Each controller has been explained in this review and some of the algorithms have been compared to others. A few works using intelligent-based PID tuning for Maglev system shows a better result, more stable and efficient performance.

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