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Control of Magnetic Levitation System Based on NARMA-L2 Controller under Load Variation

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ABSTRACT: Magnetic suspension or magnetic levitation (Maglev) is a technology that enables objects to float in the air using the action of magnetic fields, annulling physical contact and friction. This project explores the principles, modeling and control mechanisms of basic maglev system based on MATLAB simulation. A prototype model was developed and simulate based on real implementation components (using electromagnets, position sensors and a feedback control system) in other to stabilize a ferromagnetic object (ball) in mid-air. The project demonstrates clearly the feasibility of Maglev technology in applications such as high-speed transportation, vibration-free platforms and contactless bearings. The maglev system was mathematically modeled and simulated using MATLAB software. Results achieved indicate that a neural Network Based controller called Non-Autoregressive Moving Average Level 2 controller (NARMA L2) effectively stabilizes the levitated object under controlled conditions. Validation was made using Proportional-Integral-Derivative (PID) controller which indicate the effectiveness of the NARMA L2 over PID controller in maintaining equilibrium.

KEYWORDS: Maglev, NARMA-L2, PID, EMSS, EMInd, .

INTRODUCTION

Right from its discovery, magnetic fields have been found very vital for a variety of several applications and the number is still growing at staggering rate [1]. Lot of today's electrical applications utilizes magnetic field technologies [2]. Such applications include all electromechanical systems, the cathode ray tubes and even electromagnetic suspension system (EMSS) [3]. The Maglev is becoming increasingly popular in urban transportation owing to its high-speed capabilities [4]. Compared with the wheel/rail trains [5][6] which are propelled typically by electric motors and adhesive forces [7], the maglev vehicles are certainly suspended in the air based on electromagnetic induction (EMInd) [8] and are actually more sensitive to internal and external excitations, circuit fluctuations, air gap floating and as well bridge vibrations [9][10]. Fig. 1 shows a simple maglev system.

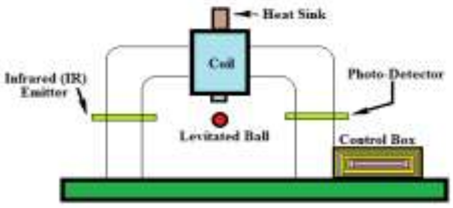

Fig. 1: Structure of Magnetic Levitation Device

In view of that, maglev technology can be viewed as technology that completely revolutionized present day transportation (as in high-speed trains e.g., Shanghai Maglev) [11] and is increasingly used in aerospace, precision instrumentation and industrial automation [12][13].

Maglev systems can be categorized into two: the electromagnetic suspension system (EMS) [14] and the electrodynamic suspension (EDS) [15]. The EMS uses the concept of attractive forces from electromagnets to pull object upward [16][17]. So, the electromagnetic attraction type maglev uses magnetic forces to counteract the effect of gravity [18] and suspend an object (mass) without any mechanical support, a principle of EMS [6][19][20]. It leverages the concept of repulsive or attractive forces between magnets and the controlled electromagnetic fields [21]. The levitated object attains steady position when magnetic force (f_m) and gravitational force (f_g) are equal and opposite [22][23]. Hence a proper current flow through the electromagnet coil is necessary in suspending [24] the object at the desired position which is achieved by a controller [25]. The EDS uses repulsive forces from induced currents in conductive materials [26][27][28].

As the use of maglev is becoming more and more popular [14][28]; not only has it found its way into the transportation sector with the maglev vehicles [29], but also for further research into nuclear fusion reactors [30] where maglev is used for controlling the reactor's extremely hot plasma. The two primary issues involved in magnetic levitation are lifting forces [31][32]: providing an upward force sufficient to counteract gravity, and stability [33]: ensuring that the system does not spontaneously slide or flip into a configuration where the lift is neutralized [34].

Actually, maglev system forms the prime technology of electric train today and they are good proving ground for advanced control [35]. Maglev has major practical control issue, which is to come up with control action that suitably positions the magnet to suspend above an electromagnet [36], where the magnet is constrained so that it can only move in the desired direction [35]. The conventional constant gain feedback controller (as in PID) fails to maintain the performance of the system at acceptable levels [36]. So, in order maglev to function efficiently on a job, it must have a special controller to work with [37]. This project proposed an artificial neural network controller called Non-Autoregressive Moving Average Level Two (NARMA-L2) controllers to improve the dynamic properties of the system and also improve the system performance [38]. This paper investigates the control of a metal ball in a maglev system using two distinct strategies: a classical PID controller (as base-line control strategy) and a neural network-based NARMA-L2 controller. The scope is limited to simulation-based analysis using MATLAB 2025a, focusing on key performance metrics such as rise time, peak overshoot, settling time and steady-state error. Hardware implementation, multi-axis control and external disturbances are excluded. The findings aim at highlighting the comparative effectiveness of intelligent nonlinear control system (the NARMA-L2) against the traditional linear methodology (PID) in precision positioning applications. The paper holds significance in advancing control strategies of a nonlinear dynamic system, particularly the maglev technology. Through the following:

- Comparing the performance of a classical PID controller with a neural network-based NARMA-L2 controller and highlights numerous limitations of traditional linear control methods and demonstrates clearly the potentialities of intelligent, data-driven control approach in achieving higher precision and better stability.
- The findings contribute to the development of more robust and adaptive control systems for applications maglev for transportation, industrial automation and where contactless and highly responsive control is essential.

- Furthermore, the simulation-based methodology provides a cost-effective and scalable framework for academic research and engineering education in modern control theory.
- Obviously, the comparison used in this work provides good insight into controller selection for engineers working on real-world MAGLEV systems or relevant nonlinear applications. This demonstrates how machine learning techniques (like the NARMA-L2) can be integrated into real control systems for better adaptability and precision.

LITERATURE REVIEW

Over the last three decades, magnetic levitation systems have gain significant attention in both academia, research agencies and industries due to their unique contributions to achieve high precision, contactless motion and minimal mechanical wear. The control of the maglev system, particularly the vertical positioning of a metal ball, presents complex challenging task because of nonlinear nature of the electromagnetic forces and the gravitational dynamics involved. Over the years of intense research, various control strategies have been proposed to address this challenge, ranging from the classical linear control techniques (PID) to more advanced nonlinear and intelligent methods that including neural network-based controllers.

Magnetic levitation systems have presented unique control challenges due to their inherently nonlinearity and unstable in dynamics [7][39]. Over the years, researchers have proposed a range of control strategies to address these complexities, beginning with classical linear techniques and evolving toward intelligent nonlinear approaches [40]. PID controller remains one of the most widely adopted schemes due to its simplicity and ease of implementation [41]. Even with its effectiveness in linear systems, PID control strategy often struggles with the nonlinear characteristics of nonlinear systems (such as maglev) [42], leading to limitations in accuracy, precision and stability problem under varying operating conditions [6][28].

To overcome these limitations, researchers have explored nonlinear neural network-based control strategies such as the NARMA-L2 controller. This approach models the nonlinear dynamics of the maglev system and generates control signals that adapt to changing systems conditions. From the literature, it has been shown that NARMA-L2 controllers offer better and superior performances in terms of reduced overshoot coupled with improved steady-state accuracy compared to the PID counterparts [42].

In [44], the paper proposes an organizes control methods into categories such as classical linear controllers (such as PID), adaptive controllers, robust controllers (such as H-infinity) and intelligent controllers (such as fuzzy logic, neural networks, and hybrid neuro-fuzzy systems). They compare the strengths and weaknesses of each approach in terms of computational complexity, robustness, stability and real-time applicability. While their review was thorough and informative, several limitations are evident, its lack of experimental support and limited quantitative analysis suggest that further empirical studies are required to validate and extend of its findings. [25] proposed a review paper that provides a comprehensive and systematic analysis of magnetic levitation control methods for low- and medium-speed EMS. The limitation of the work is restriction to EMS-type maglev systems, excluding EDS systems and hybrid configurations, which may also benefit from advanced control strategies. In [45], PID, fuzzy logic, and linear quadratic (LQR) controllers are compared for a maglev system using MATLAB simulations. While the comparison is useful, the study lacks experimental validation and never explores hybrid or adaptive tuning methods.

Also, [8] presented a work on a fuzzy-PID controller for maglev trains, improving adaptability and reducing overshoot. The early work with limited computational modeling actually lacks robustness analysis under disturbances. [46] proposes a work on technological evolution, operational principles coupled with the global deployment of both maglev and hyperloop systems aimed at contextualizing these emerging transport technologies as alternatives to the conventional rail systems. However, for engineers or developers seeking technical implementation guidance, deeper studies and experimental validations would be necessary. [47] presented a work that offers real and practical implementation-focused contribution of maglev control engineering, especially for low-speed urban transit systems; but future work could benefit from integrating nonlinear or intelligent control strategies and providing comparative performance data.

Another work [22], rigorous experimentally validated contribution to maglev control based on Global Fast Terminal Integral Sliding Mode Control (GFTISMC) was proposed. The goal was to enhance robustness, response speed and steady-state accuracy in the presence of nonlinear dynamics and as well external disturbances. However, its practical deployment may need further simplification, sensor calibration and wider benchmarking to fully realize its potentials in real-world applications. Another approach that presents a comprehensive literature review of control strategies applied to electromagnetic levitation (EML) systems, which are inherently nonlinear and unstable. The authors aim to categorize the existing control methods, highlight their strengths and weaknesses, and identify research gaps in the field. Although intelligent methods are employed, the work lacks technical depth on architecture design, training procedures, and computational complexity [44].

[42] work on the reviewing the solid foundational resource for understanding the landscape of maglev control strategies and optimization techniques. It effectively maps out classical and intelligent approaches. The review does not include key performance metrics such as rise time, overshoot or settling time to objectively compare control methods. In [33], real-time adaptive control strategy for maglev system was designed to handle large variations in load mass, such as those caused by passenger numbers fluctuating in urban transit. This is with the aim of maintaining stable levitation performance even under large internal disturbances. While their work makes good practical contribution, two major limitations were noted. Firstly, the adaptive control strategy focuses mainly on mass variation; as other real-world disturbances like sensor noise, track irregularities and external vibrations are not addressed, Again, the system model focuses on single-axis control and tested for vertical levitation only, while multi-axis control that essentially considered for full vehicle stability has not been considered.

Futhermore, [48] proposed work that study how to tackle the challenges for controlling of medium and low-speed EMS maglev trains with open-loop instability, strong nonlinearities and good sensitivities to external disturbances. They used adaptive Sliding Mode Control (SMC) strategy enhanced by a Linear Extended State Observer (LESO) and compared with PID controllers. It was shown that proposed LESO estimates the total disturbances; including unmodeled dynamics and the external noise in real time, hence allows SMC to compensate effectively; which PID struggles to maintain the performance under such conditions. But the effectiveness of LESO actually depends on the accurate disturbance estimation, because in highly nonlinear or time-varying environments, such assumptions may not hold. [41] review different control techniques for Maglev vehicle EMS-type system. But the experimental validation scope is limited to specific operating conditions.

RESEARCH METHODOLOGY

This research focused on the simulation-based approach to evaluate the performance of PID and NARMA-L2 controllers in controlling the vertical position of a metal ball within a maglev system. A nonlinear mathematical model of the system was developed based on physical laws governing electromagnetic force and the gravitational dynamics. The PID controller was manually tuned and then implemented in MATLAB 2022a, while the NARMA-L2 controller was pre-rained using MATLAB Neural Network (NN) Toolbox which obviously handles the system nonlinear behavior. The simulations are conducted under ideal conditions over a fixed time horizon, with both controllers subjected to the same reference input. Performance is assessed using key metrics including rise time, peak overshoot, settling time and as well the steady-state error. The methodology employed facilitates a comparative analysis of the classical and intelligent control strategies; hence highlighting their effectiveness in nonlinear system environments (like the maglev).

Materials

The experimental Setup for simulation prototype construction was: electromagnet mounted vertically, steel ball placed below, IR sensor aligned to measure ball position and Arduino programmed with PID logic and the NARMA L2 control [1].

For the testing;
Initial drop test: Ball levitated at 12 mm (approx.).
Disturbance test: A Light tap caused oscillation; hence system recovered in < 0.5 s.
The stability: Maintained ball levitation for > 5 minutes continuously.

Modeling of the Maglev

To analyze the maglev system, it required mathematical modeling which involved the various components of the system [28]. The circuit equations are written for voltage balance (Wang et al., 2020). Consider a free-body diagram of maglev system in Figure 9(a) which translates to schematic of Figure 9(b) showing input parameter as voltage (V) and output as the ball position (x). Also, consider the free-body diagram of maglev device levitating an object of mass, m vertically under the influence of gravitational field, g as shown in Fig. 2, for the force between an electromagnet and a ferromagnetic object from the part inside the box:

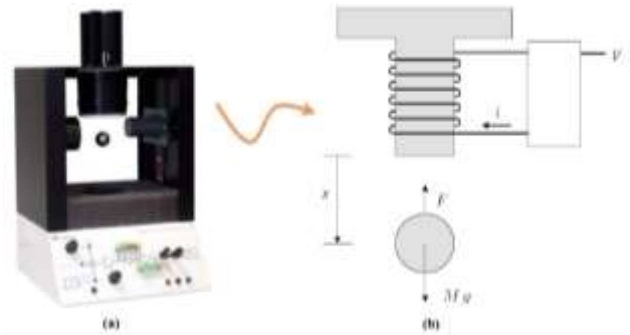

Fig. 2: Magnetic Levitation System

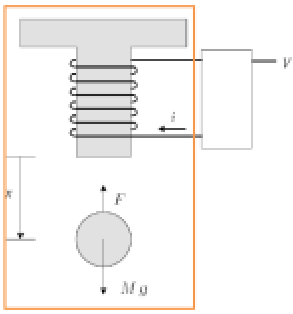

Fig. 3: Free Body Diagram for the Force between Electromagnet and Ferromagnetic Object

The magnitude of the force exerted across the air-gap, x by an electromagnet through which current, i flows can be described in Equations (3). Equation (4) and (5) are obtained from Ampere's circuital law and the Faraday's inductive law:

$$m\ddot{x} = mg - F(x,i) \qquad (1)$$

The force between an electromagnet and a ferromagnetic object is given by:

$$F = \frac{\mu_o N^2 I^2 A}{2x^2} \qquad (2)$$

Where: F = Magnetic force (N), μ_o = Permeability of free space ($4\pi\times10^{-7}$ H/m), N = Number of coil turns, I = Current (A), x = Air gap (m) and A = Cross-sectional area (m^2). The total inductance, $L(x)$ is given in Equation (6) as:

$$L(x) = L_C + \frac{L_o x_o}{x} \qquad (4)$$

Where LC is the electromagnet (coil) inductance in the absence of levitated object, L_o is the additional inductance contributed by its presence and $L_o x_o$ define the operating points. Substituting Equation (3) into Equation (4), Equation (5) is obtained.

$$\Rightarrow F(x,i) \cong \frac{L_o x_o}{2} \frac{i^2}{x^2} \qquad (5)$$

$$\therefore F(x,i) \cong K_L \frac{i^2}{x^2} \qquad (6)$$

Where $K_L = \frac{L_o x_o}{2}$ is determine experimentally.

The force equation can be linearized to obtain Equation (7):

$$F = K_L\left(\frac{I_o}{X_o}\right) + \left(\frac{2K_L I_o}{X_o^2}\right)i - \left(\frac{2K_L I_o^2}{X_o^3}\right)x \qquad (7)$$

Where: I_o and X_o are the equilibrium values, while i and x are the incremental values.

At the equilibrium point, the gravitational force is balanced by the magnetic force on the levitated object, f_o, which is the first term on the RHS of Equation (7). Now, the incremental magnetic force needed to maintain equilibrium, f_1, is given in Equation (8) as:

$$f_1 = \left(\frac{2K_L I_o}{X_o^2}\right)i - \left(\frac{2K_L I_o^2}{X_o^3}\right)x \qquad (8)$$

Where:

$$f_1 = F - f_o \qquad (9)$$

The total inductance $L(x)$ is expressed in Equation (10):

$$L(x) = L_C + \frac{L_o x_o}{2} \qquad (10)$$

Substituting Equation (5) into Equation (1), we have Equation (11) as:

$$m\ddot{x} = mg - K_L \frac{i^2}{x^2} \qquad (11)$$

Consider Fig. 4 for the free body for the voltage-current relationship for the electromagnet with the assumption that the levitating object remains close to its equilibrium.

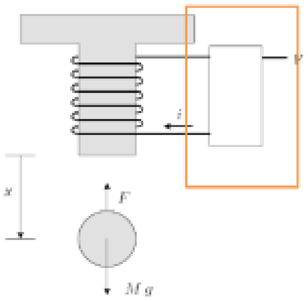

Fig. 4: Free Body Diagram for the Maglev Voltage-Current Relationship

The input voltage (on assuming no dynamics) for the electromagnetic voltage-current relationship is modeled as series combination of resistors and inductors[34] which is given in Equation (14):

$$v = iR_C + L(x)\frac{di}{dt} \cong K_C i \qquad (14)$$

From Equation (14), R_C is the coil resistance. Under the equilibrium assumption, $x = x_o$, thus $L(x) = L_C + L_o$. Further assumption is that, $L_C >> L_o$, so Equation 14 can be rewritten as Equation (15):

$$v = iR_C + L_C\frac{di}{dt} \qquad (15)$$

Using Newton's second law of motion, as the governing equation for the Levitated object [34]; the one degree of freedom system has the force balance [31] equation is given by Equation (16) as:

$$m\ddot{x} = -f \qquad (16)$$

Also, on modeling the sensor voltage, vs as a single gain as in Equation (17) as follows:

$$v_s = k_s x \qquad (17)$$

Where: k_s is the sensor gain.

Clearly, from Equation (13), the motion of the levitated object is governed by Newton's second law of motion [14] and that it is inherently unstable and really requires real-time control. As such, a closed-loop control system using a position sensor (e.g., Hall effect sensor) [33] can be employed to measure the gap and then adjusts the electromagnet current using a microcontroller (such as Arduino) for the PID algorithm and then NARMA-L2 controller. The general block diagram of the maglev control system is shown in Fig. 5:

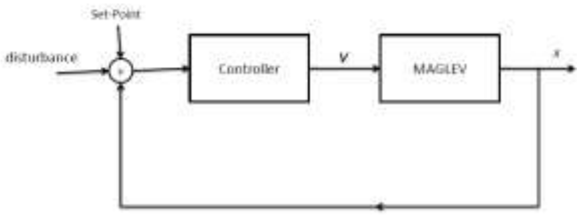

Fig. 5: Block Diagram of the Maglev System.

The full and detailed block diagram of the maglev system is shown in Fig. 6.

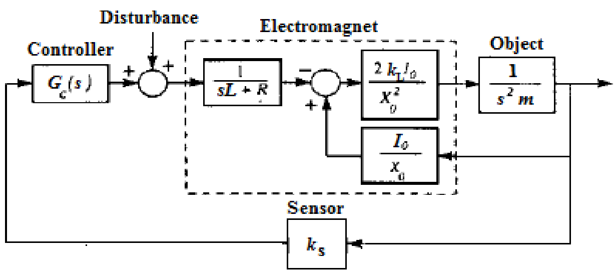

Fig. 6: Detailed Block Diagram of the Maglev System

RESULTS AND DISCUSSION

This section presents the results of the performance of a maglev system using PID (tuned based on Zeigler-Nichol's method) and NARMA-L2 control strategies evaluated on the basis of rise time, settling time, maximum over shoot and steady state error. The various and far-reaching simulation results so obtained for the conventional PID and the NARMA-L2 controllers are documented herein. In the subsequent sections, the various results are further highlighted. In this work, linearization was made around an operating point for the PID controller but uses the full nonlinear model for NARMA-L2 controller. The NARMA-*L2* is a model-based neural network control strategy which converts a nonlinear system into a linear-like form. This makes the control a lot easier.

Simulation of both controllers under single and then varying load masses were made and finally made a performance comparison using the response metrics: rise time, overshoot, settling time and steady-state error. The maglev used in the course of this project work has the following detail dimension specified in Table 1.

Table 1: Details Dimension and Design Specification of the Maglev

Dimension	Value (mm)
A	50
B	25
C	150
D	30
E	100
Y	10
Sensing coil	$R = 15\ \Omega$, $L = 0.136\ H$
Lifting coil	$R = 5\ \Omega$, $L = 0.7\ H$
Electromagnet	$12V$, $1A$, iron core
Levitated object	($20mm$ diameter)
Power supply	12V (DC)

A MATLAB Code (2022-Compatible) was employed for the simulation. In this work, linearization was made around an operating point for the PID controller but uses the full nonlinear model for NARMA-$L2$ controller. The NARMA-$L2$ is a model-based neural network control strategy which converts a nonlinear system into a linear-like form. This makes the control a lot easier. MATLAB (2022-Compatible) was employed for the simulation.

Determination of PID Parameters

With K_I and K_D zero and the value of proportional gain K_P is adjusted to get minimum steady state error possible. With increase in K_P, the settling time decreases but the steady state value remains unchanged. A value of K_P was chosen as: $K_P = 272$. The value of K_P at that oscillatory response is the ultimate gain, K_u. At that sustained oscillation, the K_P that yields ultimate gain is the period of self-sustained oscillation, T_u.

$$T_u = X_2 - X_1$$

$$X_1 = 1600 \text{ and } X_2 = 800$$

$$\Delta X = 800$$

Using Table 1,

$$K_P = \frac{K_P}{1.7} = \frac{272}{1.7} = 160,$$

$$K_I = \frac{T_U}{2} = \frac{800}{2} = 400,$$

$$K_d = \frac{T_U}{8} = \frac{0.0001}{8} = 0.0001$$

$K_p = 160$; $K_i = 400$ and $K_d = 0.0001$.

The NARMA Training

After carrying out the maglev ball analysis and verifying the validity of the artificial neural network (ANN) model, the NARMA-L2 based controller MATLAB code was generated. So, the oscillation of a maglev has been successfully controlled by using a neural network-based NARMA-L2 technique. Using ANN, there is no need to calculate the parameters of the maglev. The network training was carried out using the Levenberg-Marquardt (LM) standard back-propagation algorithm; this is due to its high speed of convergence and accuracy. The stopping criteria were based on the mean-square error (MSE) analysis. Fig. 7 shows the trained data generated for the ANN.

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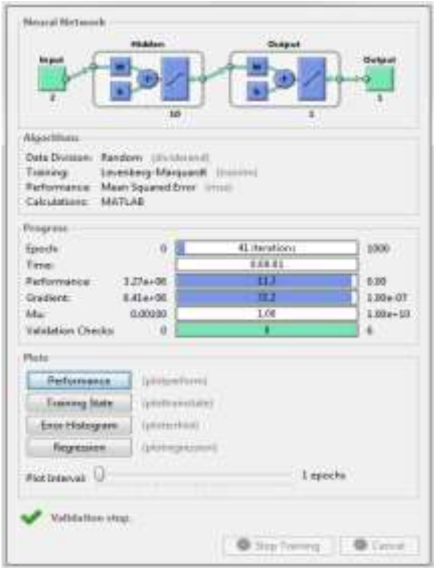

Fig. 7: Training Data Generation for ANN Controller

Simulation of Ball Position Tracking and Coil Current

The Maglev system dynamics is modeled as a nonlinear control system implemented with a standard PID controller and compared with NARMA L2 controller (a nonlinear neural network based adaptive controller). Both controllers are simulated on the same system for a step or reference trajectory input. The design and comparison of the performance of a PID controller and the NARMA-L2 controller for stabilizing a magnetic levitation system under disturbances and nonlinear dynamics was simulated using MATLAB. The plot for the ball position tracking, control input was shown in Fig. 8.

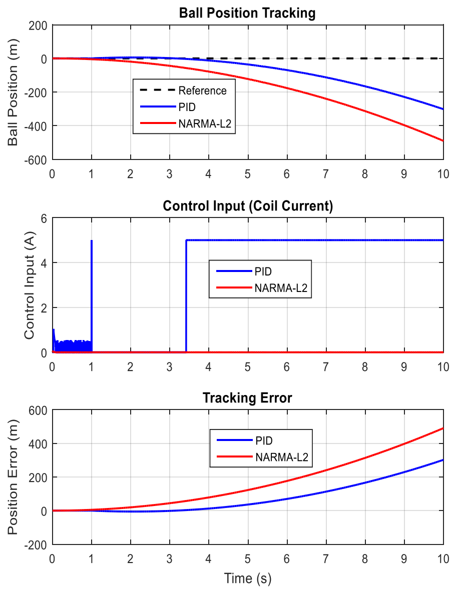

Fig. 8: Plot for the Ball Position, Control Input and Tracking Error

From Fig. 8, the top plot shows the position tracking of the metal ball for both controllers (PID and NARMA L2) against the step reference, the middle plot indicates the control input (coil current) for each controller and the bottom plot shows the position tracking error for both controllers (PID and NARMA L2). The Figure shows maglev position tracking and the performance of the maglev system under large load disturbances based on the two control strategies. The ball position swings larger ($2.2\times10^{-6}mm$) and smaller ($1.0\times10^{-6}mm$) after 5 seconds for PID and NARMA L2 controllers respectively. This indicates that NARMA-L2 controller has advantages over the PID in terms of control, higher flexibility, better dynamics and good static performance.

Fig. 9 shows the simulation and plot the performance of a magnetic levitation system under large load disturbances using the two control strategies: the PID controller and NARMA-L2 controller.

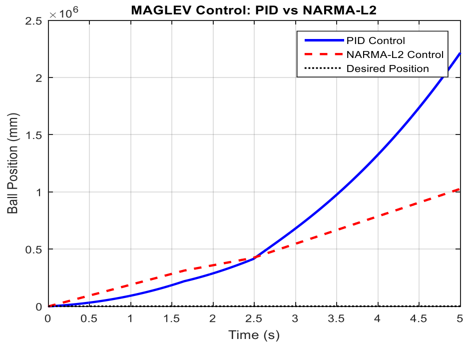

Fig. 9: Plot of the Performance of a Maglev System for Large Load Disturbances

Also, Fig. 10 simulation includes a load disturbance which mimics real-world maglev conditions like in passenger variation of electric train.

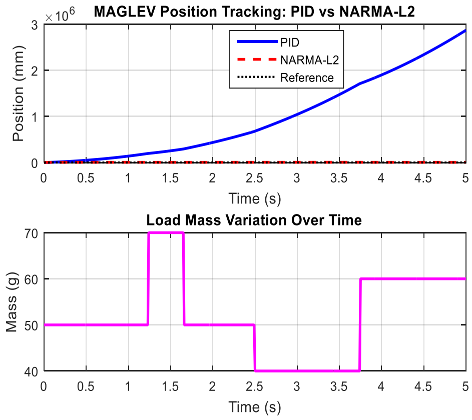

Fig. 10: The PID versus NARMA-L2 with Parameter Variations

Table 2 depicts the PID and NARMA-L2 controller response, for stabilizing the maglev system under disturbances and nonlinear dynamics.

Table 2: The PID and NARMA-L2 Controller Response Metrics.

Metric	PID Controller	NARMA-L2 Controller
Rise Time, T_r (s)	0.09	0.36
Peak Time, T_p (s)	0.25	0.70
Overshoot, M_p (%)	73.41	32.97
Settling Time, T_s (s)	3.04	0.39
Steady- State Error, E_{ss}	0.0020	0.0002

Table 2 depicts qualitatively the comparative result for the maglev system response result with the performance metrics (rise time, peak time, overshoot, settling time and steady-state error) for control assessment using PID and NARMA L2. As the mass of the levitating ball increases, the overall system dynamics change. This is because heavier masses introduce more inertia, hence, making it very hard for the controller to stabilize the levitating ball quickly and accurately. On how quickly the ball reaches close to the target height (the rise time) are 0.09s and 0.36s for PID and NARMA L2 controller. The time the levitated ball reaches its highest point before settling (the peak time) are 0.25s and 0.75s for PID and NARMA L2 respectively. Also, for how much the levitated ball exceeds the desired position (overshoot) are 73.41% and 32.97% for PID and NARMA L2 respectively. Again, the time taken for the ball to stay within of the target value without any further oscillation (settling time) is 3.04s and 0.39s for PID (takes a longer settle) and NARMA L2 respectively. Furthermore, the final value between the targeted (desired) and the actual position (steady state error) is; 0.0020 and 0.0002 for PID and NARMA L2 controllers respectively. Clearly, the results of the metrics show that, NARMA-L2 controller is the better controller than PID in maglev system, which provides satisfactory performance and good response. The results show that the implementing NARMA-L2 controller is given simple data processing, effective solution and can be implemented easily in real time maglev system like the electric train.

Fig. 11 depicts PID and the NARMA-L2 controller performances for the maglev system under varying load mass and then calculates and plots key performance metrics: rise time, peak time, maximum overshoot and settling time.

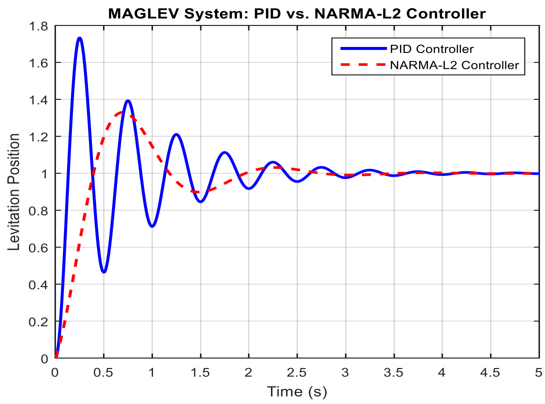

Fig. 11: Response of PID and NARMA-L2 Controllers for Maglev

For the case of the Maglev system under varying ball masses (0.05kg, 0.1kg and 0.15kg) using both PID and NARMA-L2 controllers, increasing the mass certainly affects the stability and as well the tracking performance. Figure 18 depicts the two sub-plots for vertical position of the levitating ball over time for different masses using PID and the NARMA L2 controllers. The top plot is the PID controller response showing the vertical position of the levitating ball over time for different masses (0.05 *kg*, 0.1 *kg* and 0.15 *kg*). The vertical-axis shows the ball position in meters, while the horizontal-axis displays the time in seconds. Each colored line represents a different mass. Also, for same setup but using NARMA-L2 controller in this case, the vertical-axis represents the ball position in meters while the horizontal-axis is the time in seconds. The dashed lines represent each mass. Clearly, the PID controller shows longer rise and settling times, especially for heavier mass and with higher overshoot. In the same vain, NARMA-L2 controller typically translates to faster rise, lower overshoot and better steady-state accuracy across all the masses.

Fig. 12 depicts the two sub-plots for vertical position of the levitating ball over time for different masses using PID and the NARMA-L2 controllers.

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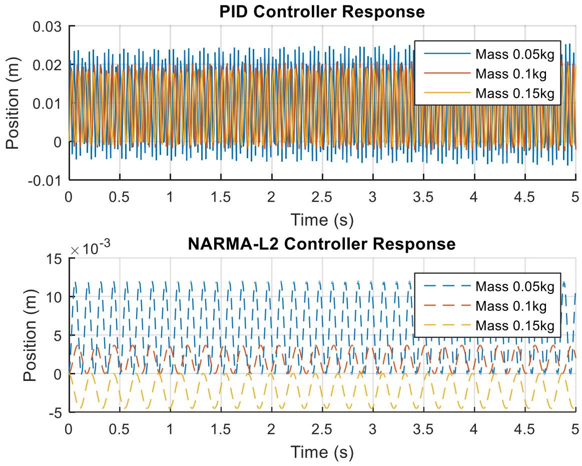

Fig. 12: Response of PID and NARMA-L2 Controllers for Maglev with Different Masses.

The top plot is the PID controller response showing the vertical position of the levitating ball over time for different masses (0.05 kg, 0.1 kg and 0.15 kg). The vertical-axis shows the ball position in meters, while the horizontal-axis displays the time in seconds. Each colored line represents a different mass. Also, same setup as the top plot, but using NARMA-L2 controller in this case, the vertical-axis represents the ball position in meters while the horizontal-axis is the time in seconds. The dashed lines represent each mass. Clearly, the PID controller shows longer rise and settling times, especially for heavier mass and with higher overshoot. In the same vein, NARMA-L2 controller typically translates to faster rise, lower overshoot and better steady-state accuracy across all the masses. This is shown in Table 3, the performance metric Table.

Table 3: The PID and NARMA-L2 Controller Response for Different Ball Masses Metrics.

Mass (kg)	Controller	Rise Time (s)	Peak Time (s)	Overshoot (%)	Settling Time (s)	Steady-State Error
0.05	PID	0.42	0.86	12.6	2.2	0.0003
0.05	NARMA L2	0.28	0.64	2.0	1.1	0.0001
0.10	PID	0.54	1.07	18.8	2.9	0.0005
0.10	NARMA L2	0.35	0.74	3.3	1.4	0.0002
0.15	PID	0.67	1.26	25.4	3.6	0.0007
0.15	NARMA L2	0.42	0.84	4.6	1.7	0.0003

CONCLUSION

This research presented the capabilities of intelligent NARMA-L2 controller for the control of maglev system compare to the system response obtained by classical PID controller. Ultimately, it is clear that PID controller exhibits simplicity and works well near operating points but certainly struggles with nonlinearity and disturbances. On the other hand, NARMA-L2 learns the maglev system dynamics and then adapts control in real time and also adapts better to mass the changes. This makes it an ideal controller choice for nonlinear systems (including maglev). Even though the neural controller (NARMA L2) requires training data and more computational resources, but it offers superior performance in terms of metrics used in quantifying controller performance in this work (rise time, peak time, maximum overshoot, settling time and steady-state error). Also, it was shown that with NARMA L2 controller, even with the heavier masses the system reaches the desired position far quicker (faster convergence) than with the PID controller coupled with less overshoot. In addition, with the NARMA-L2 controller better stability across varying masses is maintained. This implied robustness to system nonlinearities; a property which PID controller does not possessed. Furthermore, NARMA L2 controller exhibit smoothness property than PID controller. This is because the response curves in NARMA L2 are smoother and more consistent than PID, especially for higher masses. So, in real-world maglev systems like electric train, adaptive controllers (like NARMA-L2) are certainly preferred. Obviously, it is to be concluded that the proposed artificial neural network-based controller -(NARMA-*L*2) is clearly superior, particularly in the case of non-linearities, parameter variations and with the case of changing the levitating ball masses. This is mainly attributed to its weights and biases updating feature that made it possible to compensate for both parameter changes and disturbances during operation. The whole work proposed the use of NARMA-L2 controller for the control of maglev developed using MATLAB software.

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