Nonlinear Model Predictive Controller for Maglev Systems : A Support Vector Machine Approach Optimized with Particle Swarm Optimization

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Abstract:-Model Predictive Control is employed by the plant's linear model, which incorporates a multilayer feed-forward network for predictive control. The inclusion of Particle Swarm Optimization as the optimization technique results in a significant decrease in the required convergence iterations. This paper presents a new approach that uses Particle Swarm Optimization as the reduction technique in conjunction with SVM-generalized predictive control. This study employs a mathematical model based on a Support Vector Machine, with the objective function optimization model being Particle Swarm Optimization. The strategy utilizing SVM exhibits a high level of accuracy, as the controller's precision is contingent upon the quality of the model. Simulation findings show that an acceptable solution can be reached in just two iterations. empirical proof also supports real-time control's feasibility.

Keywords:*Model Predictive Control (MPC), Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Maglev System, Artificial Neural Network (ANN)*

1. Introduction

The magnetic levitation system, or Maglev, utilizes electromagnetic forces to suspend ferromagnetic balls. This technology boasts advantages such as low noise, precise positioning, and effective operation in high vacuum conditions, all due to its minimal friction properties. The magnetic levitation system presents a challenge due to its nonlinear and inherently unstable dynamics under open-loop conditions. Notwithstanding its drawbacks, magnetic levitation technology finds many uses. They include the development of ultra-fast trains, friction-reducing bearings, magnetic levitation-powered trains, satellite launchers, earthquake-dampening devices, and frictionless wind turbines. (1),(2). The adoption of automatic control techniques is crucial for expanding the system's usability.

Designing control algorithms for magnetic levitation is intricate due to its nonlinear and unstable characteristics. Model Predictive Control (MPC) poses a particular challenge for Maglev systems, despite its effectiveness in handling complex processes and constraints on system inputs and outputs (3). This modern optimization technique is widely applied in both linear and nonlinear control scenarios (4) – (6), utilizing past and future system behavior to generate control actions (7). While there are few studies exploring MPCs for magnetic levitation control, notable efforts have been made. For instance, one study (8) developed a multiple MPC approach using linearized models to adapt to various environmental conditions. Another focused on customizing MPC specifically for Maglev systems (9). Additionally, a significant study (10) outlines the real-time functionality of a magnetic levitation system, employing a distinctive control technique named model predictive control. With an induction-motor-powered electric vehicle (EV), this work focuses on implementing model predictive torque and flux control, or MPTFC. Since MPTFC is quick and can increase the EV's propulsion system's efficiency, it was selected (11). The method outlined in this study employs fuzzy gain scheduling of a PI controller (FGS-PI) alongside model predictive direct torque control (MPDTC) to regulate the rotational speed of an induction motor (IM). Instead of relying on conventional hysteresis-based Direct Torque Control (DTC), MPDTC employs a cost function (12). An autonomous sleep stage classification system was implemented and a fuzzy kernel SVM with SRN for classifying the retrieved features [13]. With SVM, a more accurate transformer incipient defect prediction is being attempted in this work. The process involved collecting and analyzing DGA data from various transformer oil samples (14) to determine the most suitable SVM kernel function and kernel factor, as well as to evaluate prediction accuracy.

The paper starts with an introduction in Section I, followed by a depiction of the Maglev system closed-loop control with MPC in Section II. Section III provides an overview of the Magnetic Levitation system, while Section 4 elaborates on the Simulink model of the Maglev system. The V section covers the training of support vector machines. Lastly, Section VI concludes the proposed work.

2. Maglev system closed loop control using mpc

Fig.1 illustrates the closed-loop control of the Maglev system using SVM and Extended Predictive Control. The factory to be controlled, a reference model to indicate the plant's favored activity, an SVM to represent the unit, and the Reductions of Cost Function technique to estimate the volume of work to achieve the plant's desired level of performance are all taken into account. The two separate parts of the SVM Extended Predictive System are the parameters modification block and the SVM block. The methodology of SVM Extended Predictive Control, which begins with the message signal r, can be used by the reference model (n). The ym(n) reference signal is produced by this system used as an input to the cost function reduction block. The output of the cost function reduction techniques is employed as the plant's feed or design. Once the optimal input, u(n) has been determined through cost function reduction, it is applied using a double pole double throw switch, denoted as S to configure the unit. The selection of the suitable plant model is determined by the position of switch S. Utilizing the cost function reduction technique, the subsequent control signalu(n+l)is computed, thereby prompting the expected response from the linear system. Once the cost function has been minimized, this refined data is then fed into the respective plants for implementation.

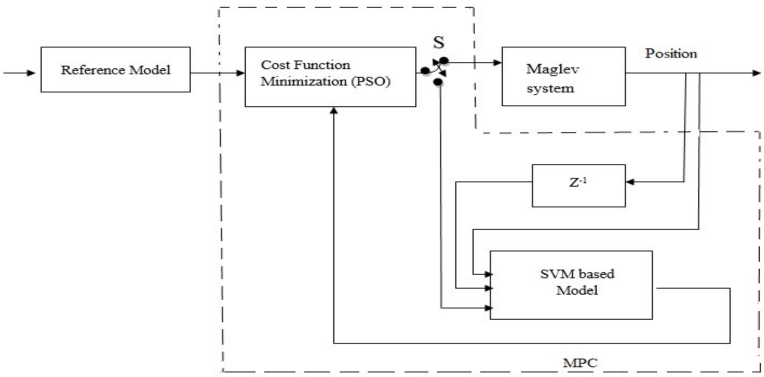

Figure 1: Magnetic levitation system using MPC

3. Magnetic levitation system

Magnetic levitation employs magnetism to suspend an object either in air or in a vacuum. The body does not require any further support to stay hung in the air, other than from magnetic forces. To counteract gravitational forces and other external influences on the object, magnetic attraction and repulsion forces are utilized. Suspension is used when the force is attraction, and levitation is used when the force is repulsion. Floating is another term for levitation. Figure 2 depicts the magnetic configuration of the maglev system.

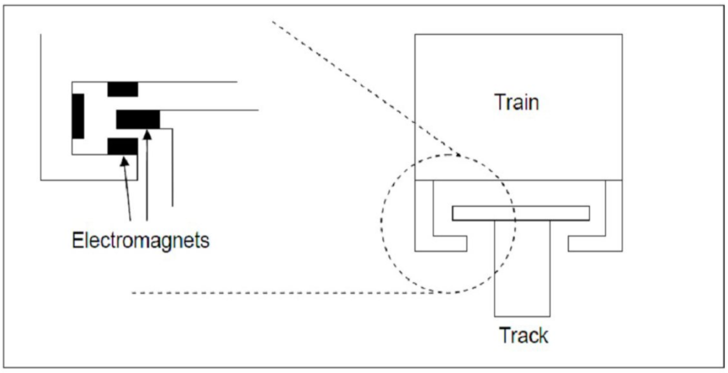

Figure 2: Maglev system's magnetic arrangement

A physical model is a representation of a physical process in its ideal, whereas a mathematical model is a mathematical statement that represents a physical model. To simulate a maglev system, magnetic force leakage was ignored, a constant magnetic force was kept inside the insulating material, the reluctance in the insulating material among the magnet spheres was solely considered, and all electromagnetic forces were focused in the spherical core. Suppose that the sphere is undisturbed by factors other than the magnetic and forces of attraction. In the vertical position, the dynamic formula can be expressed as

$$m\frac{d^2}{dt^2}x(t) = F(i,x)+\mathrm{mg} \tag{1}$$

and

$$F(i,x) = C\left(\frac{i}{x}\right)^2 \tag{2}$$

$$e=Ri+\frac{d(Li)}{dt} \tag{3}$$

As L(x) is non linear function of x and it is given by

$$e=Ri+L\frac{di}{dt}\left(\frac{L_0}{x^2}x_0\right)\frac{dx}{dt} \tag{4}$$

We can get the following state formulas by writing and u=e.

$$\frac{dx_1}{dx} = x_2 \tag{5}$$

$$\frac{dx_2}{dx} = g - \frac{C}{m\left(\frac{x_3}{x_1}\right)^2} \tag{6}$$

$$\frac{dx_3}{dt} = -\frac{Rx_3}{L} + 20\frac{\left(\frac{x_2x_3}{x_1{}^2}\right)}{L} + \frac{u}{L} \tag{7}$$

4. Maglev system simulink model

A. Magnetic levitation system modelling

This section presents the simulation results obtained from modeling the magnetic levitation system. The state equation is used to create a Simulink model of the maglev system. Figure 3 shows an open loop unstable nonlinear system.

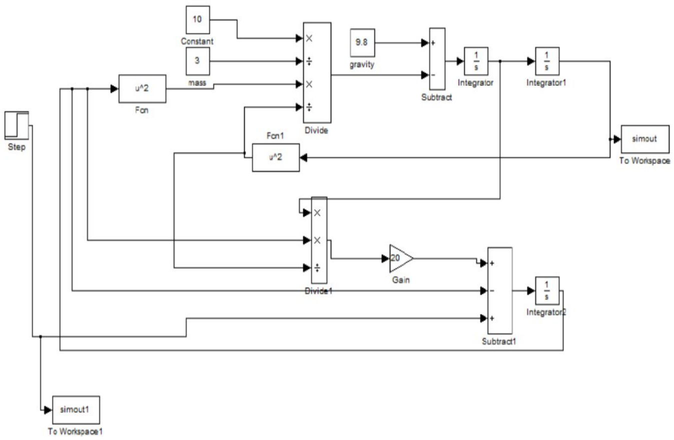

Figure 3. Maglev System Simulink Model with Step Input Signal

Figure 4 depicts its step reaction. As a result, feedback must be used to keep the closed loop stable.

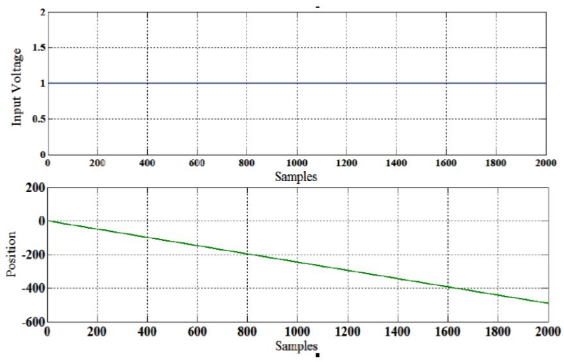

Figure 4. Maglev System Input and Output behavior for step response

B. Generation of training data

Providing a randomly generated input voltage within the range of 0V to 5V to the configured Simulink model generates the input-output dataset.

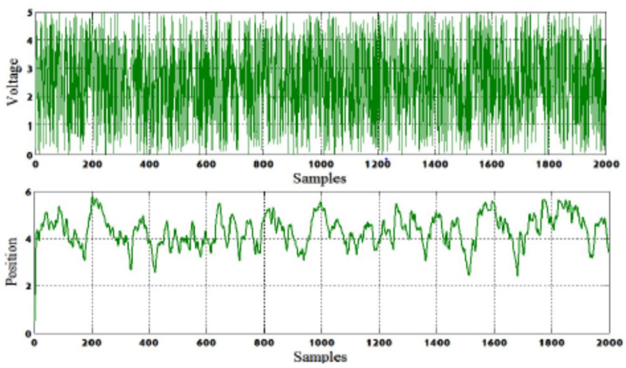

Figure 5. Maglev System Response for random input

Figure 5 depicts a sketch of unpredictable input data from a built Maglev system.

5.Training of support vector machine

A multilayered feed backward design is used to build the model in this section. The model architecture consists of a single input datum, a hidden layer comprising one neuron with five hidden units, and an output vector connected to a biological neuron. Tansig activation can be found in the buried layer, although purelinactivation can be found in the output neuron. The graph is created using the Levenberg-Marquardt learning algorithm and a sequence of 2000 samples. The steps in the training procedure are as follows:

- Arrange the data in such a way that the predictors and predicted variables are stored in a file with one sample per row.
- Data can be divided into two groups: a test set and a training set.
- Check the information, provide the analyst with data, and then output the relative value as the estimated values using SVM.
- Make a forecast and compare the SVM's output to the desired outcome.
- The weights are adjustable.
- Display the document's following sample.
- Keep going until the error exclusion stops decreasing – If feasible, cease when the trial error is minimized.

The training of the SVM model is visualized in Figure 6. The model is used to obtain actual input and output data. The data in the input and output should be in synchronization with the characteristics of the unit to be regulated. The identical input u is given to both the plant and the SVM model (t). Another support vector machine input is responsible for monitoring unit characteristics and ensuring stable operation. This data originates from either the output of the physical plant, labeled as y(t), or from the output of the Support Vector Machine (SVM), also denoted as y(t). Training an SVM involves fine-tuning the weights assigned to each input until the desired output is attained.

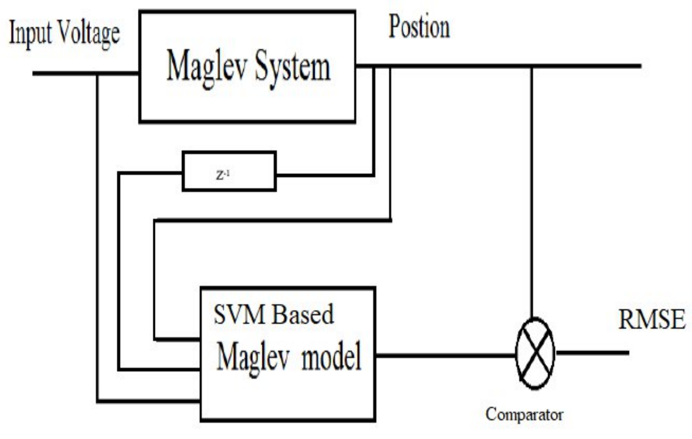

Figure 6. SVM Model Training

A. The created model's training efficiency

The suggested feed forward SVM design uses three parameters: the first is the current plant data, the second is the previous plant input with unit delay, and the third is the current process result. The training accuracy of the SVM model is depicted graphically in Fig7.

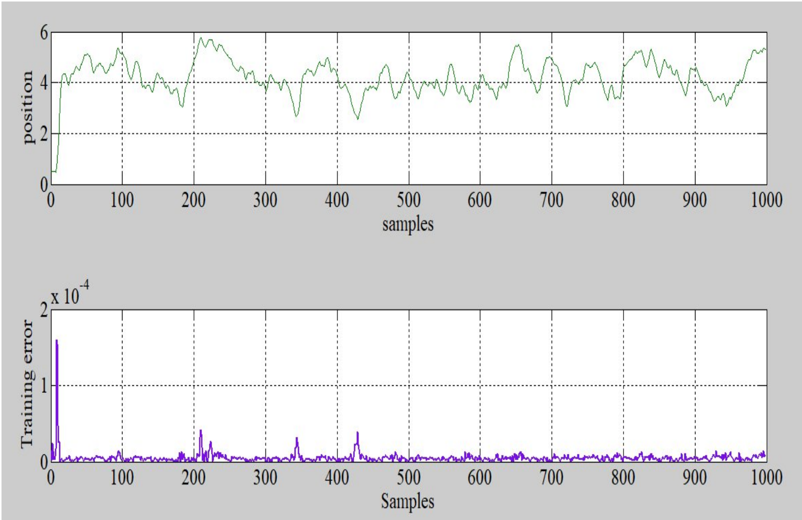

Figure 7. SVM model Training accuracy

A. Predictive Accuracy of SVM Model

Once the training phase is completed, the predictive accuracy of the model of the constructed SVM models is evaluated. The generated SVM models predict the accuracy of the model output using an unknown 200 set of data. Fig. 8 depicts the predictive performance of the created SVM model of a Maglev system.

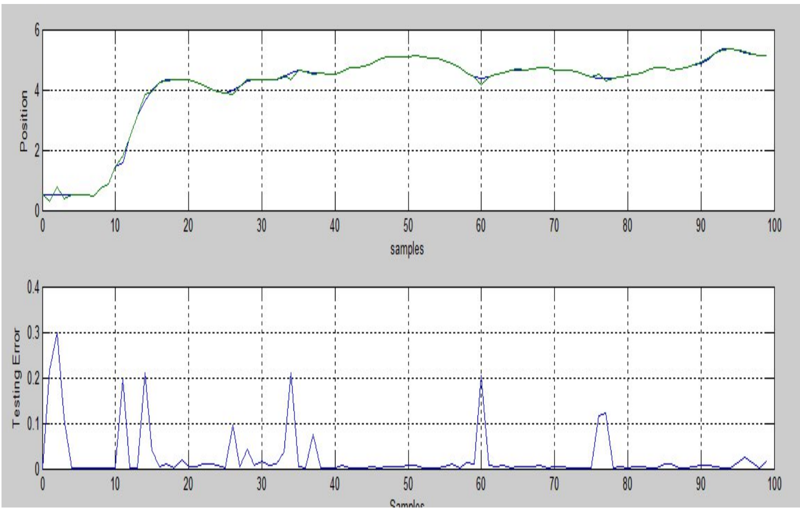

Figure 8: Prediction accuracy of the SVM Model

C. Cost Performance Simplification and Specification

The primary objective of the MPC controller is to minimize the cost function governing the constraints.

$$J=\sum_{k=1}^{N_p}(\hat{y}-r)^{T}Q(\hat{y}-r)+\sum_{k=1}^{Nc}\Delta u^{T}R\Delta u \tag{8}$$

Where,

Np – Horizontal prediction

Nc – Horizontal control

r – Set point

y – Process output predicted

Q — Weighted output error matrix

R stands for the control weight matrix.

Several algorithms are available for reducing cost functions such as,

• Ant colony

• Optimization algorithm

• Self-propelled nanoparticles

• Boids is artificial life software

In this study, the PSO algorithm is used as an optimization technique which yields the optimal solution for the proposed work.

D. Predictive Control of the Maglev System with a SVM Based Model and the PSO Algorithm

The command settings must be adjusted prior executing the primary software for operating the Magnetic levitation Prototype system. A significant amount of parameter adjustment is required for the optimal controlling action. After much experimenting, the ideal values for many factors can be found, resulting in a well-controlled action. The best known parameter values for the Maglev SIMULINK model depicted are listed below.

• The minimum prediction horizon is set to one.

• The maximum prediction horizon spans seven years.

• Horizontal control=3

• On the differenced control signal, a 0.005 charge function is calculated.

• Minimum rate will change: -5; maximum control input: 5

• Time spent sampling =0.01 seconds

The proper control input should be from the Maglev unit throughout order to manage it for the stated reference and the governed result is visualized in Fig 9.

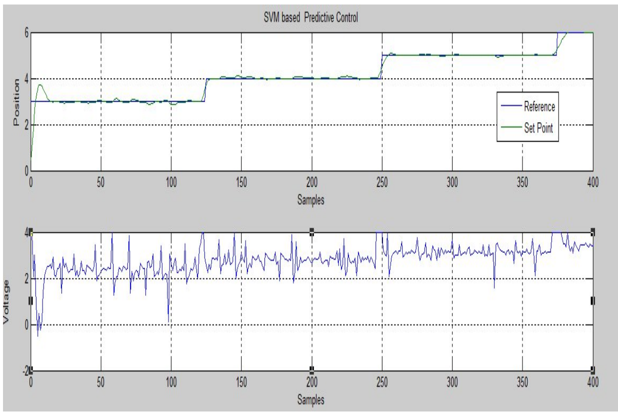

Figure 9. SVM-based MPC of maglev system using PSO Algorithm

As a result, the Magnetic Maglev system's directional result can follow the steady state value with great precision. After that, the generated SVM model's prediction accuracy improves, and the PSO algorithm's improvement ability improves.

6. Conclusion

This study constructs and simulates a Nonlinear Model Predictive Controller for a Maglev system. The mathematical model employed is SVM, and the optimization of the objective function is conducted using PSO.

Strategy based on SVM has a high degree of accuracy because the accuracy of the controller is controlled by the model's quality. In MPC, ANN Models are used as statistical models. The SVM algorithm is also user-friendly and has a high degree of consistency. The following conclusions can be taken from the preceding research:

- The effectiveness of model predictive controller is influenced by the model's accuracy.
- Choosing the right evolutionary programming technique can speed up the optimization process.

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Authors' contributions

Dr. Haewon Byeon: Supervision

Dr. M.S Sivagama Sundari (Corresponding Author): Conceptualization, Methodology, Writing- Original draft preparation.

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