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Design & Development of Maglev Girder Bridge & Vehicle

Md Zeeshan Alam[1], Sagar Kumar Malakar[2], Sumit Saurabh[3], Sourabh Singh[4], Tabish Quadari[5] Anuj Sharma[6]
[1,2,3,4] *Student at CIVIL Engineering Dept., Greater Noida Institute of Technology, Greater Noida, UP-201310, India.*
[5,6] *Assistant Professor, CIVIL Engineering Dept., Greater Noida Institute of Technology, Greater Noida, UP-201310, India.*

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Abstract: *A high-speed maglev vehicle is an innovative transportation technology that uses a magnetic levitation and propulsion system, and its guideway design is an important feature of this project that accounts for around 60-80 percent of the original infrastructure development expenses. Under external forces, the allowable variations of such structural parts are extremely minimal. It is critical to be able to precisely estimate the guideway response to the action of high-speed maglev vehicles in order to control the magnitude of guideway displacement and vibration. The vehicle and guideway form a linked system, resulting in precisely defined guideway stiffness needs. To evaluate a wide range of guideway designs for varied operating situations, a reliable simulation technique for the dynamic interaction system must be developed. The major goal of this research is to investigate the dynamic properties of the maglev guideway and to create a reliable numerical approach for simulating the coupled maglev system. External actions on maglev guideways have been summarized as well. The possibilities of modelling the vehicle/guideway interaction system that is influenced by high-speed loadings are then explored. In MATLAB/Simulink, a method to the dynamic response of the coupled system is devised. Five numerical models with varying degrees of precision are built. A series of simulations are run based on these models to investigate the dynamic characteristics of the maglev system. In Simulink, a surface roughness model is constructed to analyze the impact of guideway irregularity, and in Midas/Civil, finite element models matching to the first three numerical models are created. The goal of developing a FE model like this is twofold. On the one hand, the finite element method will be utilized to validate Simulink numerical models. Midas' accuracy in analyzing dynamic properties of guideways under high-speed vehicles, on the other hand, can be validated.*

Key Word: *Maglev; Neural Networks; NARX; MATLAB/Simulink; MSE; MIDAS/CVIL; Autoregressive; FE;*

I. INTRODUCTION

The maglev technology relies heavily on guideway design. The infrastructure for Maglev development is projected to cost between 60 and 80 percent of the initial investment. As a result, guideway design is a crucial cost-cutting area. When a maglev vehicle's speed is increased to 300-500 km/h, or a guideway is made lighter and more flexible to save money, dynamic interactions between vehicles and guideways become a significant issue. It will play a key role in determining vehicle suspension requirements and specifications such as guideway stiffness, length, and other factors. The major goal of this project is to talk about the issue of guideway design and modelling vehicle/guideway interactions. To simulate the dynamically coupled system, a numerical approach to simulating a complicated coupling system is created. The first section will provide an overview of the maglev guideway's development at the Emsland Test Facility during the last twenty-five years. For an optimum structural design, the benefits and drawbacks of experience are critical. Following that, three types of guideways utilized in the Shanghai and Munich projects are examined, which are thought to represent the state of the art in maglev guideway design at this time. Following that, we'll research and design complex loading instances on guideways in accordance with industry standards. Using the software MATLAB/Simulink, five numerical models for vehicle/guideway interaction analysis will be built at different degrees of precision. A series of numerical simulations are run based on them to investigate the dynamic properties of the maglev system. A surface roughness model is also produced in Simulink to mimic guideway irregularity and evaluate its impact on guideway displacement and vehicle acceleration, as well as finite element models using the software Midas/Civil to investigate the guideway's dynamic response. The goal of creating a FE model like this is to validate the numerical models that have been created in Simulink. Midas' accuracy while evaluating the guideway dynamic characteristics under a high-speed vehicle, on the other hand, can be validated. The difficulties of modelling the maglev guideway in Midas will be investigated

II. MAGLEV MODELLING WITH NEURAL NETWORKS

Modelling with Maglev

Here, we build a neural network that can predict the dynamic behaviour of a magnet levitated using a control current. The system is characterized by the magnet's position and a control current, both of which determine where the magnet will be an instant later. This is a more or like a study of a time series problem, where past values of a feedback time series (the magnet position) and an external input series (the control current) are used to predict future values of the feedback series. A NARX (Nonlinear AutoRegressive with External Input) neural network is used to model a magnet levitation dynamical system in this study.

Preparing the Data

Data for function fitting issues is organised into two matrices, the input time series X and the target time series T, and then fed into a neural network.

- The input series X is a row cell array, with each element representing a control current timestep.
- The target series T is a row cell array, with each member representing a levitated magnet position timestep. A dataset of this type is loaded here.

```
[x,t] = maglev dataset;
```

The sizes of the inputs X and targets T may be seen. There are 4001 columns in both X and T. This represents 4001 control current and magnet position timesteps.

```
size(x)
ans = 1×2
        1      4001
size(t)
ans = 1×2
        1      4001
```

III. USING A NEURAL NETWORK TO MODEL TIME SERIES

The next stage will be to build a neural network that will learn to model how the magnet moves. The outcomes of this study will vary significantly each time it is run because the neural network starts with random initial weights. To avoid this randomness, the random seed is set. However, for your own applications, this is not required.

```
setdemorandstream(491218381)
```

Two-layered (i.e., one-hidden-layer) Given enough neurons in the hidden layer, **NARX** neural networks can suit any dynamical input-output relationship. Hidden layers are layers that are not output layers. For this research, we'll use a single hidden layer with ten neurons. More neurons and possibly more layers are required for more challenging issues. Less neurons are required for simpler issues. We have also experimented with two tap delays for the external input (control current) and feedback (magnet position). The network can mimic more complex dynamic systems with more delays. Because the network has not yet been setup to match our input and target data, the input and output have sizes of 0. This will occur once the network has been taught. The delayed form of the output y(t) is fed back into the network as an input.

```
net = narxnet(1:2,1:2,10);
view(net)
```

Before we can train the network, we must fill the two tap delay states with the first two timesteps of the external input and feedback time series. In addition, we must employ the feedback series as both an input and a target series. **PREPARETS** creates time series data for us to use in simulations and training. Xs will be given to the network as shifted input and target series. The first input delay states are represented by Xi. Ts is the shifted feedback series, and Ai is the layer delay states (empty in this case because there are no layer-to-layer delays).

```
[Xs,Xi,Ai,Ts] = preparets(net,x,{},t);
```

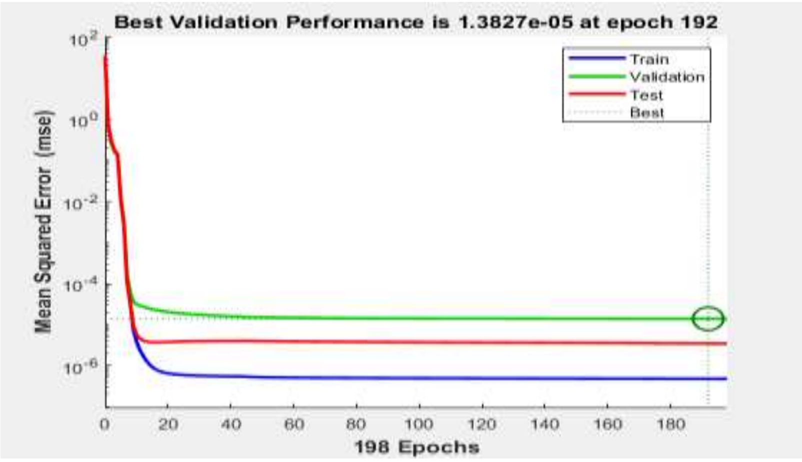
The network is now ready for training. Training, validation, and test sets are created automatically from the timesteps. The network is taught using the training set. Training will continue as long as the network's validation set performance improves. The test set gives an objective assessment of network accuracy. The Neural Network Training Tool displays the network being trained as well as the training algorithms. It also shows the current condition of training, with the criteria that caused training to be stopped highlighted in green. The bottom buttons open handy charts that can be accessed both during and after training. The plot buttons and links next to the algorithm names open documentation on those topics.

```
[net,tr] = train(net,Xs,Ts,Xi,Ai);
```

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	198	1000
Elapsed Time	-	00:00:04	-
Performance	36.3	4.75e-07	0
Gradient	73.2	2.96e-05	1e-07
Mu	0.001	1e-07	1e+10
Validation Checks	0	6	6

Click the "Performance" button in the training tool or call PLOTPERFORM to see how the network's performance increased throughout training. Performance is expressed as a log scale and quantified in terms of mean squared error. As the network was taught, it progressively reduced. Each training, validation, and test set's performance is displayed.

```
plotperform(tr)
```



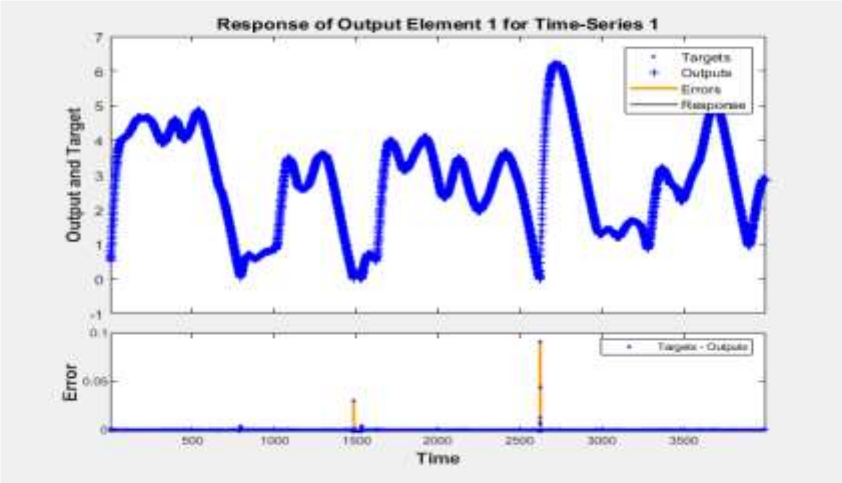
IV.TESTING NEURAL NETWORK

The trained neural network's mean squared error for all timesteps may now be calculated.

```
Y = net(Xs,Xi,Ai);
perf = mse(net,Ts,Y)
perf = 2.9245e-06
```

PLOTRESPONSE will display the network's reaction in relation to the magnet's actual position. The '+' points will track the diamond points if the model is accurate, and the inaccuracies in the bottom axis will be minimal.

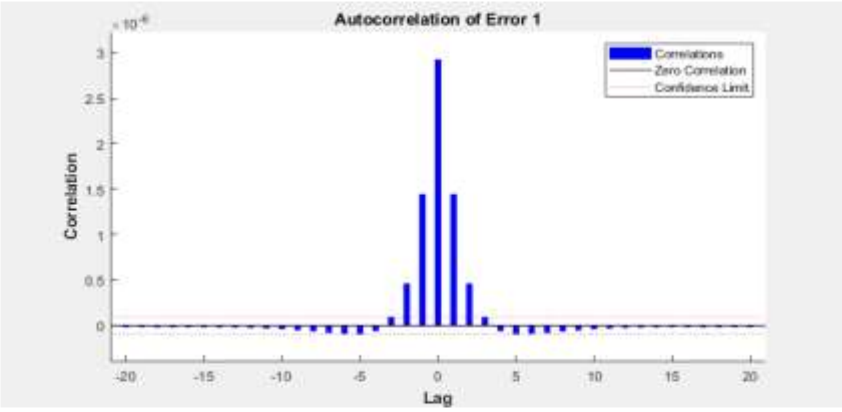
```
plotresponse(Ts,Y)
```



PLOTERRCORR displays the relationship between errors at time t, e(t), and errors at different lags, e(t+lag). The mean squared error is shown in the center line. All other lines will be substantially shorter if the network has been properly trained, and most, if not all, will fall under the red confidence boundaries. The error is calculated using the GSUBTRACT function. To support disparities across cell array data, this method generalizes subtraction.

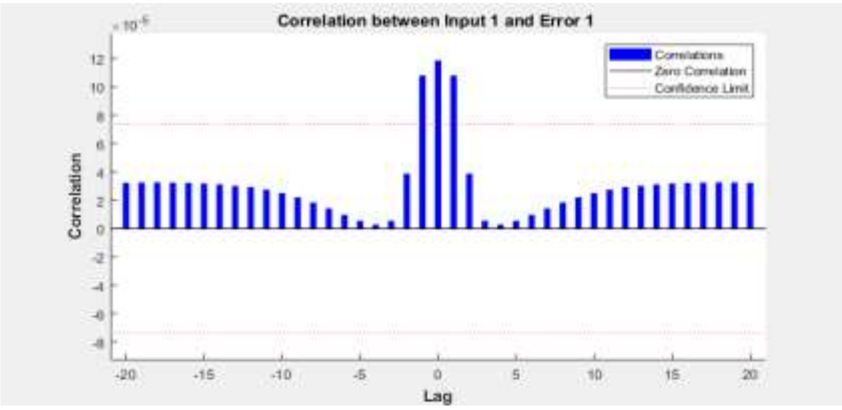
E = gsubtract(Ts,Y);

ploterrcorr(E)



PLOTINERRCORR, on the other hand, displays the error correlation with regard to the inputs, with variable degrees of latency. In this situation, most or all of the lines, including the centre line, should fall inside the confidence boundaries.

plotinerrcorr(Xs,E)



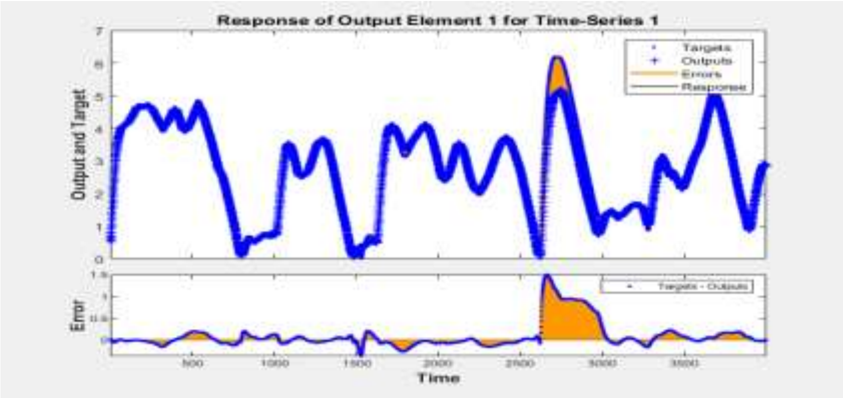
Targets were employed as feedback inputs in the open loop training of the network. The network can also be turned into a closed loop, with its own predictions acting as feedback.

net2 = closeloop(net);

view(net2)

In closed loop mode, we can mimic the network. The network is only given starting magnet positions in this scenario, and it must then recursively predict new places using its existing anticipated positions. This quickly leads to a mismatch between the expected and actual reaction. Even if the model is excellent, this will happen. However, it's fascinating to see how many steps they match before they separate. PREPARETS prepares the time series data for us again, this time taking into account the changed network.

```
[Xs,Xi,Ai,Ts] = preparets(net2,x,{},t);
Y = net2(Xs,Xi,Ai);
plotresponse(Ts,Y)
```

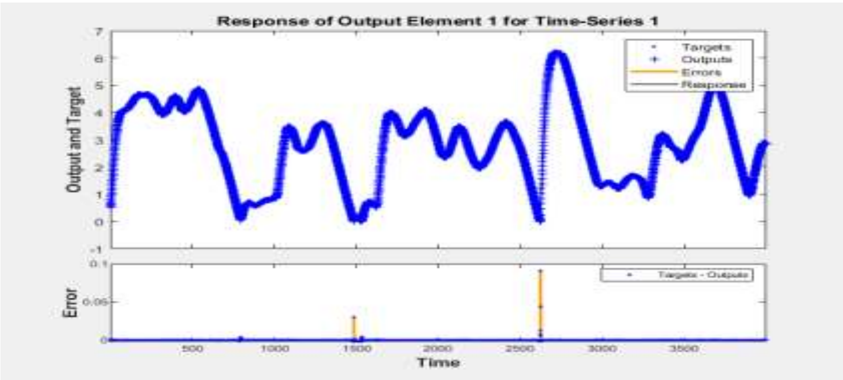


If we need to access the anticipated magnet position a timestep before it happens, we can remove a delay from the network so that the output at any given time t is an estimate of the position at time t+1.

```
net3 = removedelay(net);
view(net3)
```

PREPARETS is used to prepare the time series for simulation once more. The network is extremely accurate this time because it is performing open loop prediction, but the result has been shifted one timestep.

```
[Xs,Xi,Ai,Ts] = preparets(net3,x,{},t);
Y = net3(Xs,Xi,Ai);
plotresponse(Ts,Y)
```



V. CONCLUSIONS AND RECOMMENDATIONS

- Maglev Modelling with NARX gives us the to model the dynamic simulation models for future time series data with the model trained on past time series data.
- With the NARX Neural Network trained with MATLAB, we have achieved 4.0323e-07 MSE performance.
- The numerical method presented in this research is both versatile and efficient. one of the input factors is the guideway's span length, which may be easily changed. the levitation frame, surface roughness, and guideway model are all packed as easy-to-change subsystems. to analyse a wide range of guideway designs for varied supporting schemes and operating situations, the governing equation and boundary conditions can be replaced.
- at v = 175 m/s, the numerical models with a single moving force (model i-1) or a single moving oscillator (model ii-1) have the largest dynamic factor, b (g,z) = 1.72. the oscillator model's dynamic factor decreases faster than the force model's after the highest value. these two models are simple to construct, but when the traversing velocity is between 50 and 200 m/s, they provide a substantial dynamic response. as a result, they are ineffective for studying both guideway dynamic displacement and vehicle acceleration.

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