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BORANG PENGESAHAN STATUS TESIS

JUDUL: MODELLING THE MAGNETO RHEOLOGICAL DAMPER USING RECURRENT NEURAL NETWORK METHOD

SESI PENGAJIAN: 2011/2012

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MODELING THE MAGNETO- RHEOLOGICAL DAMPER USING
RECURRENT NEURAL NETWORK METHOD

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This thesis is submitted as partial fulfillment of the requirements for the award of the
Bachelor of Mechanical Engineering

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I certify that the project entitled "*Modeling the Magneto-Rheological damper using Recurrent Neural Network method*" is written by Muhammad Afiq Naquiddin. I have examined the final copy of this project and in my opinion; it is fully adequate in terms of scope and quality for the award of the degree of Bachelor of Engineering. I herewith recommend that it be accepted in partial fulfillment of the requirements for the degree of Bachelor of Mechanical Engineering.

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DEDICATION

I specially dedicate to my beloved parents

*(**ABD RAHMAN B NAWAWI and NORESAH BT AHMAD**),*

My siblings,

My supervisor and those who have guided

And motivated me for this project

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ABSTRACT

This thesis is study about modeling the Magnetorheological damper using Recurrent Neural Network method. Five different values of current were used in order to modeling the MR damper, which are 0.0 ampere, 0.5 ampere, 1.0 ampere, 1.5 ampere and 2.0 ampere. In order to modeling the MR damper, the graph of simulation damper will be compared with the experimental damper. The results will get the Square Error for the simulation damper. Then, the Root Mean Square Error will be calculated to get the difference between the simulation damper and experimental damper. The results show that the lowest RMSE for the simulation damper were value 0.4008, while the highest RMSE is 1.9882. From the results also, the better current value to modeling the MR damper is using the MR damper with the lowest RMSE.

ABSTRAK

Tesis ini merupakan kajian tentang pemodelan peredam Magnetorheological menggunakan kaedah Rangkaian Neural Berulang. Lima nilai-nilai arus yang berbeza telah digunakan untuk memodelkan peredam MR, yang 0,0 ampere, 0,5 ampere, 1.0 ampere, 1,5 ampere dan 2.0 ampere. Dalam untuk memodelkan peredam MR, graf peredam simulasi akan dibandingkan dengan peredam eksperimen. Keputusan akan mendapat Ralat Square untuk peredam simulasi. Kemudian, Akar Min Ralat Square akan dikira untuk mendapatkan perbezaan di antara peredam simulasi dan peredam eksperimen. Keputusan menunjukkan bahawa RMSE terendah untuk peredam simulasi ialah nilai 0,4008, manakala RMSE tertinggi adalah 1,9882. Daripada keputusan yang diperolehi juga, nilai yang lebih baik semasa memodelkan peredam MR ialah dengan menggunakan peredam MR dengan RMSE yang paling rendah.

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LIST OF ABBREVIATIONS

RNN	Recurrent Neural Network
MR	Magneto Rheological
ER	Electro Rheological
RMSE	Root Mean Square Error

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF STUDY

Damper was used in most of the machine that we used every day in our daily life, including car suspension system and clothes washing machine. The suspension system is one of the most important parts in vehicles, while the damper is the most important part in suspension system of the vehicles. Hit a bump without dampers, and the suspension would continue to bounce up and down uncontrollably. The job of a car suspension is to maximize the friction between the tires and the road surface, to provide steering stability with good handling and to ensure the comfort of the passengers besides it also provide a safety to a driver. For a clothes washing machine, damper function is to reduce the noise make by that machine. In a civil engineering field, the damper was also used widely. We can saw that damper was used widely to build the bridge and building. For a bridge, damper is so effective to improving bridge performances. In other words, the damper could result in simple connection and lower construction cost.

Meanwhile, for building, in order to reduce the resonance effect, it is important to build large dampers into their design to interrupt the resonant waves. If the dampers were not used in building, the buildings can be shaken to the ground especially when earthquake happens.

Most of the thing used in this world is purpose to easier the human work, so are damper. It is used because of its advantage. One of the advantage of using damper is because, damper provide a safety for the machine or one system. For example, a building, it used a damper for a safety of the people in the building. The other advantage of the damper is to provide comfort for the user. For example, in vehicles, dampers were mostly used to provide a comfort for the driver and passengers. Besides that, dampers also were used because of the capability of it to reduce the cost.

There were several types of damper, one of type of damper is magnetorheological damper or can be simplify as MR damper. A magnetorheological (MR) damper consists of a hydraulic cylinder containing a solution that, in the presence of a magnetic field, can reversibly change from a free flowing, linear viscous fluid to a semi-solid with controllable yield strength. This solution is called MR fluid and is composed of micron-sized magnetically polarizable particles dispersed in a carrier medium such as water, mineral or synthetic oil. Typically, it contains 20 to 40% by volume of relatively pure carbonyl iron with 3 to 5 microns in diameter (Yang, 2001). MR fluid is normally a free flowing viscous fluid, but the presence of a magnetic field causes the particles to form chains and increase the fluid viscosity, until it becomes a semi-solid. Additives are commonly added to discourage settling, improve lubricity, modify viscosity, and reduce wear.

1.2 PROBLEM STATEMENT

To fulfill the objective of this project, which is to modeling the MR damper using recurrent neural network, Besides, the input and also the updated equation in the recurrent neural network method should been have any mistake. Besides that, MR fluid also got unique characteristic which is it has a nonlinear characteristic. If the modeling method is accurate the MR damper will achieve high damping control system performance.

1.3 OBJECTIVE

1) To model the magnetorheological (MR) damper.
2) To analyze the equation of simulation so that the graph of MR damper model is almost same as theoretical damper.

1.4 SCOPE OF PROJECT

1) Design the model simulation of magnetorheological (MR) damper using MATLAB software.
2) Analyze the equation of simulation using Recurrent Neural Network method.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, the MR damper, MR fluid and the method used which is recurrent Neural Method will be discussed. Literature study is one of the initial steps toward the understanding of this project. The information was collected from many resources such as journals and thesis. From this literature study, the problem statements have been noted, the objectives of the project been set and the scope of the projects has been specified.

2.2 MR DAMPER

2.2.1 Damper background

Damper is a mechanical device that functional to flatter the impulse and to dissipate kinetic energy. The damper in automotive consist of spring loaded check valves to control the flow of fluid trough an internal piston. From the study of the damper, there are three types of damper that can be concluded. The type of the damper is passive, active and the semi- active damper.

Passive controller or passive damper is set of system that does not require a power source to operate. The passive control dampers produce fixed design, so the damper will not be optimal when the system or the operating condition changed. The advantages of the passive damper are the design simplicity and cost effectiveness. Besides that, the passive damper also avoided the performances limitation due to the lack of damping force controllability.

The active control damper is a device that required a power to operate and apply force directly into the system. The advantage of an active damper is that, it can adapt for system variation. Besides, the active control damper also can provided high control of performances in wide frequency range. The active control damper also can be much more effective than the passive damper. However, the active dampers were having some lack besides of the high power sources. The other disadvantage of the active damper is it has many sensors and complex actuators.

The semi-active damper is devices that combine the best feature of the passive and active characteristics (Spencer et al, 1996). The semi active damper is resolution of the disadvantage of both active and passive damper. The semi active damper has the reliability of the passive damper, while maintaining the versatility and the adaptability of the active damper characteristics (Liao and Lai, 2002). The semi active damper has a very low power requirement (Ashfak et al., 2009), it is important when the main power source for the structure is fail function. Because of the widely used for the semi- active damper, the study for the semi- active damper were made and the results show that the semi- active damper can potentially achieve the majority of the performance of fully active system.

One of the classes of semi- active damper is the dampers that use controllable fluids. The benefits of using the controllable fluids damper is their ability to reversible change from a free- flowing to a semi- solid with a controllable yield strength in millisecond when exposed to the magnetic or electric field (Bahar et al., 2009). Two fluids that been widely used for this type of damper is the Electro Rheological (ER) damper and the MR damper.

2.2.2 MR damper background

The MR damper in general is a damper filled with MR fluid. The MR damper is a control devices that consist of hydraulic cylinder filled with magnetically polarized particle in a liquid (Karla, 2002). The essential characteristic of MR damper is the ability to reversibly change from free flowing, linear viscous fluid to a semi solid with a controllable yield strength in millisecond when exposed to magnetic field. MR fluids are the magnetically polarized particle that spread in a carrier medium such as mineral or silicone oil. The figure 2.1 shows the MR damper structure in general.

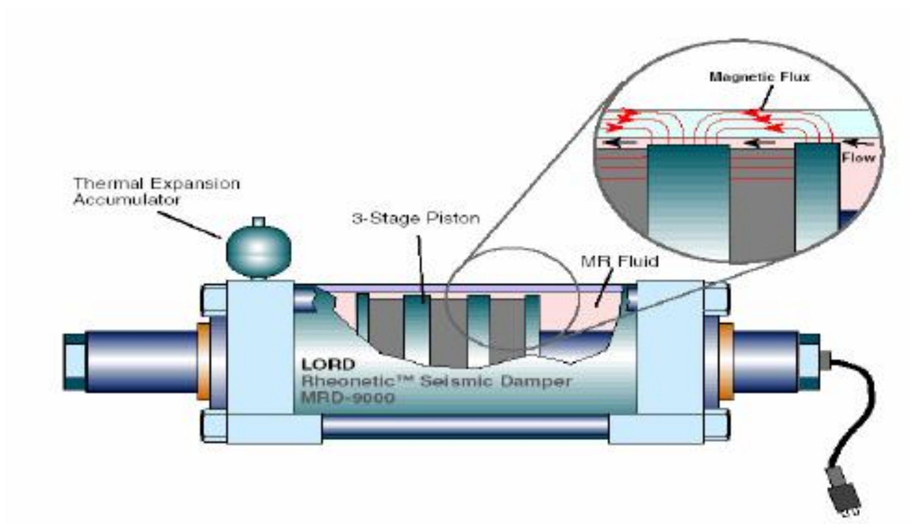

Figure 2.1: MR fluid damper (Yang, 2001).

2.2.3 Operation of MR Damper

MR damper consist of electromagnetic coils in the piston, and MR fluids reservoirs. The magnetic fields will be created to the electromagnetic coils when voltage is supply between the housing and the piston.

When the piston rod enters the housing, MR fluid will pass through the annular orifice gap to the other side of the reservoir. There will be two magnetic fields, as the damper in compressed mode. The damper will resist the flow of fluid from one side to other side of the piston when applied to magnetic field.

The MR fluids will become solid when it exposed to magnetic field. The magnetic field will change the shear strain of the MR fluid. When magnetic strength increased the resistances to the fluids flow also will be increased until it reach some limit. Resistance in the MR damper will cause it to produce damping force. Figure 2.2 shows the phenomenal behavior of the MR fluid when the no magnetic field applied, while figure 2.3 shows the phenomenal of the MR fluid when magnetic field is applied.

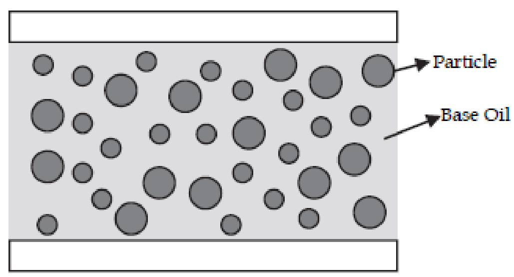

Figure 2.2: Phenomenal Behavior of MR fluid when no magnetic field applied (Seong et al., 2011)

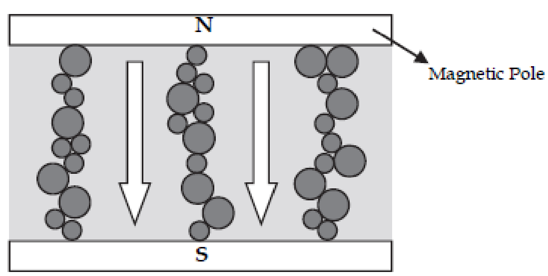

Figure 2.3: Phenomenal behavior of MR fluid when magnetic field applied. (Seong et al., 2011)

2.2.4 MR damper application

MR damper were used widely because of the advantages that this damper has. The application for MR damper were used in so many field such as mechanical engineering, military and defense field, optics area, automotive and aerospace area, human prosthesis and many more.

As in mechanical engineering, the MR dampers are widely used in heavy industry with applications such as heavy motor damping. Besides that, the MR dampers also were used as an absorbing detrimental shock waves and oscillation within the building (Hung, 2007). The ability of the MR damper that earthquake resistant is why this type of damper is widely used to building the structure. In the military and defense area, the MR dampers were used to make an absorber for the military vehicles. Besides that, the applications of the MR fluid were used to build body armor for the soldiers.

As in optics area, the MR fluids were used as the construction of as a corrective lens for the telescope. The MR damper was used widely in automotive and aerospace area in building the suspension system for the vehicles. The BMW, Audi and Ferrari, is one of the company that used the knowledge of the MR fluid or MR damper to manufactures cars using their own property version of this device. While Porsche has used the MR to build the MR engine for Porsche GT3 and GT 2 model. The engine that Porsche build will get stiffer to provide a more precise gearbox shifter. As in human prosthesis field, the MR damper used to build the human prosthetic legs. The damper in prosthetic legs is functional to reduce the shock deliver to the patient leg when walking or jumping.

As from the example above, the application of the MR damper and MR fluids has been widely used. The MR dampers were used for the benefits to human itself. The knowledge for the MR damper should be used to build and create more beneficial devices for human.

2.3 MR FLUID

MR fluids, consisting of small magnetic particles dispersed in a liquid, these material properties are controllable through the application of an external magnetic field. Under a high magnetic field, the magnetic particles have been observed to aggregate into elongated clusters aligned along the magnetic field direction. This macrostructure is responsible for the solid like rheological characteristics and is hereby denoted the ground state of the MR fluids at the high field limit. The structure of the MR fluid ground state has been the subject of prior experimental and theoretical studies, but with conflicting conclusions in regard to both the observations and the governing physics.

MR fluids are considerably less well known than their ER fluid. Both fluids are non colloidal suspensions of polarizable particles having a size on the order of a few microns. The initial discover and developer for MR fluid was Jacob Rabinow at the US National Bureau of Standards in the late 1940s. Thanks to him, the MR fluids have enjoyed recent commercial success. A number of MR fluids and various MR fluid-based systems have been commercialized including an MR fluid brake for use in the exercise industry, a controllable MR fluid damper for use in truck seat suspensions and an MR fluid shock absorber for oval track automobile racing.

2.3.1 Properties of MR fluid

Typical magnetorheological fluids are the suspensions of micron sized, magnetizable particles (mainly iron) suspended in an appropriate carrier liquid such as mineral oil, synthetic oil, water or ethylene glycol. The carrier fluid serves as a dispersed medium and ensures the homogeneity of particles in the fluid. A variety of additives (stabilizers and surfactants) are used to prevent gravitational settling and promote stable particles suspension, enhance lubricity and change initial viscosity of the MR fluids. The stabilizers serve to keep the particles suspended in the fluid, whilst the surfactants are adsorbed on the surface of the magnetic particles to enhance the polarization induced in the suspended particles upon the application of a magnetic field.

Table 2.1: Summary of the properties of MR fluids (Kciuk and Turczyn, 2006).

Property	Typical value
Initial viscosity	0,2 – 0,3 [Pa·s] (at 25˚C)
Density	3 – 4 [g/cm3]
Magnetic field strength	150 – 250 [kA/m]
Yield point	50 – 100 [kPa]
Reaction time	few milliseconds
Typical supply voltage and current intensity	2 – 25 V, 1–2 A
Work temperature	-50 do 150 [˚C]

2.4 RECURRENT NEURAL NETWORK

Recurrent Neural Networks (RNN) is nonlinear or linear dynamic systems. They can be simulated in software on computers or implemented in hardware (analog or digital). A first property that can be used to distinguish RNN in two distinct groups is the representation of time in the system such as continuous-time systems and discrete-time systems.

A second property is the representation of signals in the system. The signals can be real-valued and quantized. A system can be real-valued if implemented in analog hardware. All digital implementations use quantized values since values are stored in a finite number of bits. However, a digital implementation is often analyzed as if it were real-valued in case that the error introduced by the quantization is too small to be noticed.

The above properties of the system do not say much about the intended application of the RNN. All possible applications of RNN can be grouped into two broad categories.

Recurrent neural networks can be used as associative memories and sequence mapping systems. Recurrent neural networks used as sequence mapping systems are operated by supplying an input sequence, which consists of different input patterns at each time step (in case of a discrete time system), or a time-varying input pattern over time (in case of a continuous-time system).At each time instant, an output is generated which depends on previous activity of the system and on the current input pattern. The entire output sequence generated over time is considered the result of the computation.

The class of sequence mapping systems is interesting for practical applications in sequence recognition, generation or prediction and it will be examined in the next chapter. Sequences mapping neural networks are nearly always implemented in software or clocked digital hardware (both have a discrete representation of time). This report will focus on recurrent neural networks used as sequence mapping systems. Using the common ways of implementation these networks are discrete-time systems. Therefore, all treatment of recurrent neural networks in the next chapters will be restricted to discrete-time systems. Some examples of recurrent neural networks used as associative memories will be given now.

Recurrent neural networks used as associative memories are operated by applying a fixed input pattern (that does not change over time). Then the network is operated according to a set of equations describing the network dynamics. Internal signals and the network outputs will change over time. Under certain conditions (and waiting for a sufficient time interval), the network. This means the systems output has converged to some static pattern which is considered the result of the computation performed by the system. This result is some association made by the system in response to the input, hence the name associative memories.

The difference with sequence mapping systems lies in supplying a static input to the network (not a sequence) and only using the final output values of the network as a result (and not the output sequence over time). So both input and output are static patterns whereas for the sequence mapping systems, both input and output are sequences.

These recurrent neural network architectures were proposed to create associative content addressable memories. They were used in Artificial Intelligence research and they contributed to research about the way the (human) brain works. Associative memories are sometimes implemented in analog hardware, but generally for research purposes a software implementation is favored because it is more convenient and flexible. Examples of these architectures are the Brain-State-in-a-Box neural network and the Hopfield network. The Hopfield network model was later on extended with neurons that operate in a stochastic manner (using theory from the field of statistical mechanics) which are called Boltzmann machines (Hertz et al., 1991).

2.4.1 Recurrent Neural Network background

The recurrent neural network can be used to approximate any finite function when there are a set of hidden nodes, such as when the function have a fixed input space then there are always ways of encoding those function with recurrent neural network. For recurrent neural network, to make the equation it must consist of two layers network. The first layer is input layer and the other layer is either hidden or state or output layer. Each layer will have its own index variable: k for output nodes, j (and h) for hidden, and i for input nodes. In a feed forward network, the input vector, x, is propagated through a weight layer, V. Where n is the number of inputs, Ɵj is a bias, and f is an output function (Bodén, 2001). The figure 2.4 shows a feed forward network.

$$y_j(t) = f(\, net_j(t)) \tag{2-1}$$

$$net_j(t) = \textstyle\sum_i^n x_i\,(t) v_{ji} + \theta_j \tag{2-2}$$

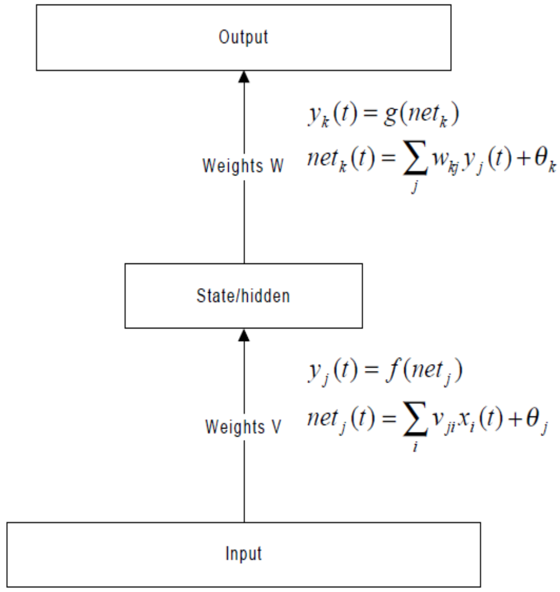

Figure 2.4: A feed forward network (Bodén, 2001).

In a simple recurrent network, the input vector is similarly propagated through a weight layer, but also combined with the previous state activation through an additional recurrent weight layer, U. where m is the number of ’state’ nodes (Bodén., 2001).

$$net_j(t) = \sum_i^n x_i(t) v_{ji} + \sum_h^m y_h(t-1) u_{jh}) + \theta_j \tag{2-3}$$

The output of the network is determined by the state and a set of output weights, W. Where g is an output function same as f. As can see from Figure 2.5, it show the recurrent neural network (Bodén, 2001).

$$y_k(t) = g(net_k(t)) \tag{2-4}$$

$$net_k(t) = \sum_j^m y_j(t) w_{kj} + \theta_k \tag{2-5}$$

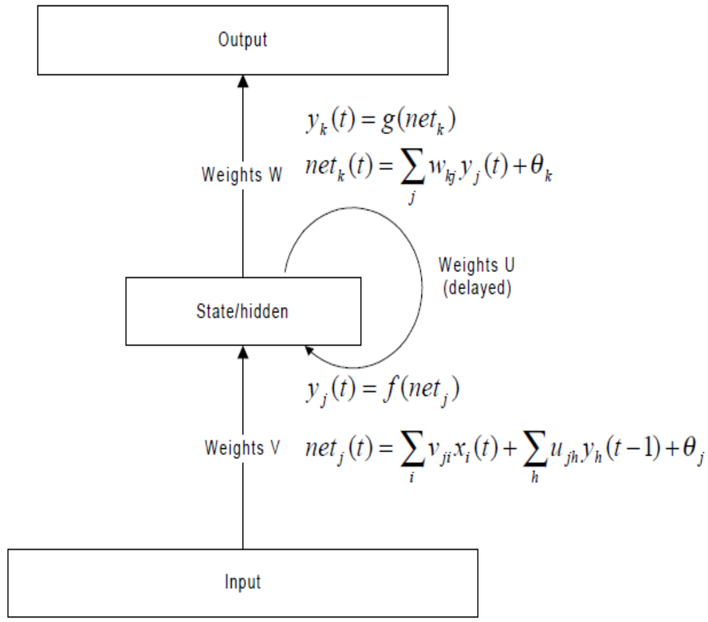

Figure 2.5: Simple Recurrent Neural Network (Bodén, 2001).

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This chapter provided on a review and step by step procedure to complete the objective and scope of the project entitled modeling the MR damper using recurrent neural network. It will cover the overall procedures, subjects of study and data collection.

3.2 FIELD OF STUDY

This study was carried out to modeling the MR damper using Recurrent Neural Network method. Therefore, it will concern on the differences and comparison results between the simulation and experimental damper. If the differences between the simulation dampers are slightly small, then the method using which is Recurrent Neural Network is valid or can be use to modeling the MR damper.

3.3 SUBJECT OF STUDY

Since this study is based to modeling the MR damper, the data from the experimental damper is used to compare with the output of the simulation damper.

3.4 PROCEDURE OF STUDY

The first step for this project is modeling the MR damper simulation block using the MATLAB software. For this step, the required parameters data such as velocity, displacement and forces for the actual damper were taken from the experiment. The next step is, make the equation for the output of the simulation damper. For this step the Recurrent Neural Network method is required, the equation is used to make a coding for simulation damper output. After that, the experiment is run to test if the is an error in the coding. Then, when there are no error for the simulation, the next step is to tuned the X (initial value) parameters and the W (weight) in the coding so that the graph for simulation damper is almost as the same as experimental damper. The number for X parameters for Recurrent Neural Network is 25 and the ranged for the values of X is between -1 until 1. For the W value there is no range but the value is so small. The tuning steps were using try and error method. Then, after get the results which is to get the graph for simulation damper as same as theoretical damper, the results for square error were obtained. The tuning step will continue as to reduce the square error. The results for the square error show that the difference between the simulation damper and experimental damper. If the square error is slightly small the result for the graph of simulation damper will become almost as the same as experimental damper. Then after getting the results for square error, the data of square error obtained were used to calculating the value of Root Mean Square Error of the simulation damper. The first step which is modeling the simulation block until calculating the value of Root Mean Square Error were repeated, but using the different value of current. The value of the current for MR damper using in this project is 0.0, 0.5, 1.0, 1.5 and 2.0 Ampere. For different values of current, the data for each MR damper for experimental damper such as velocity, displacement and force will be different.

3.5 FLOW CHART

To reach the objective of the project, the methodology is based on the scope of project as a guiding principle to formulate this project become success. The important of this project is to compare the parameters between the modeling damper and the theoretical damper. Hence, to accomplish the objective, a flow chart had been made to done the project in certain timing.

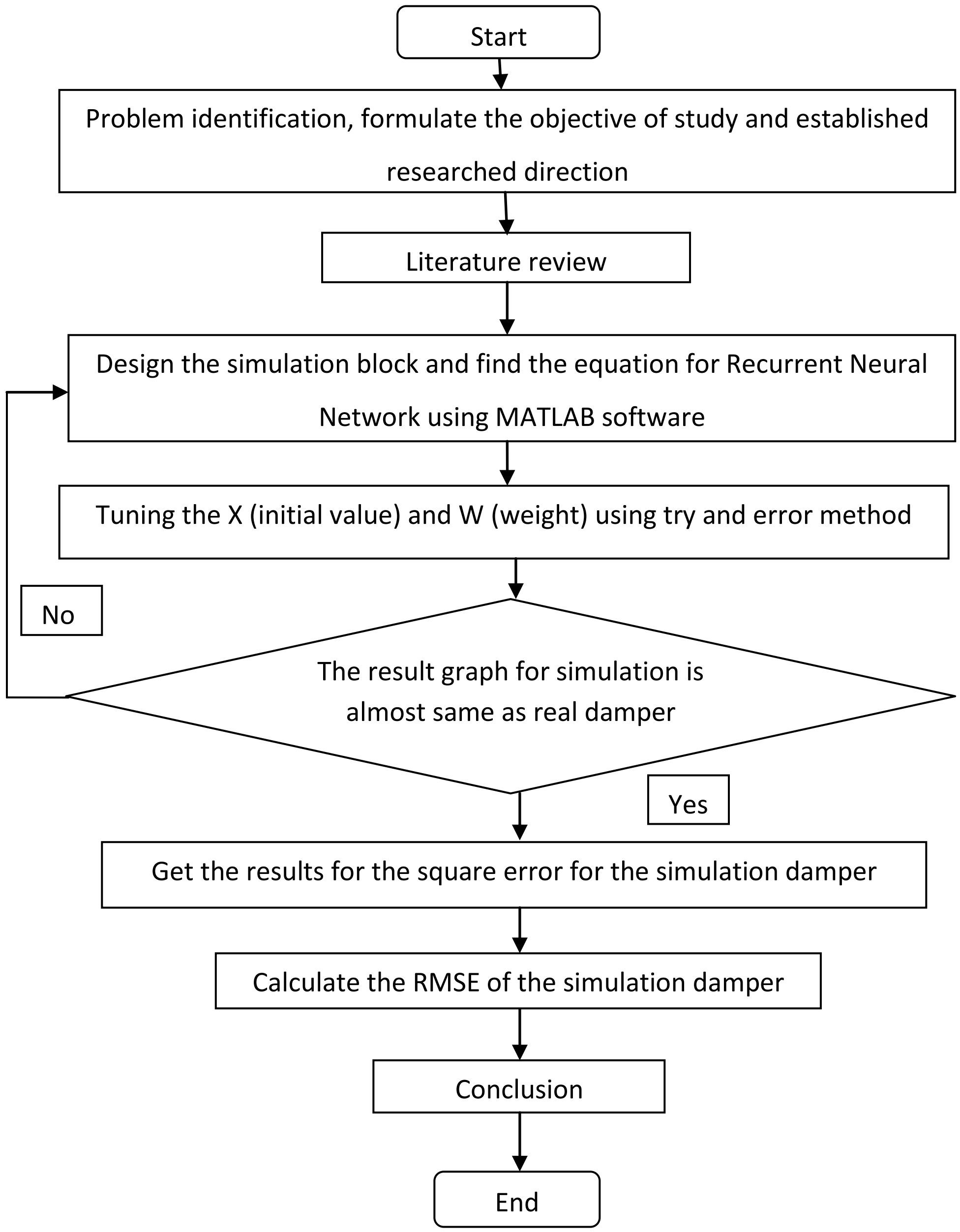

Figure 3.1: Flow chart for the final year project

3.6 Modeling the MR damper simulink block

This method is the first step in order to modeling the MR damper. The data from the experimental damper will be used to build this simulink block. In order to run this simulink block the equation of simulation need to design or build using recurrent neural network.

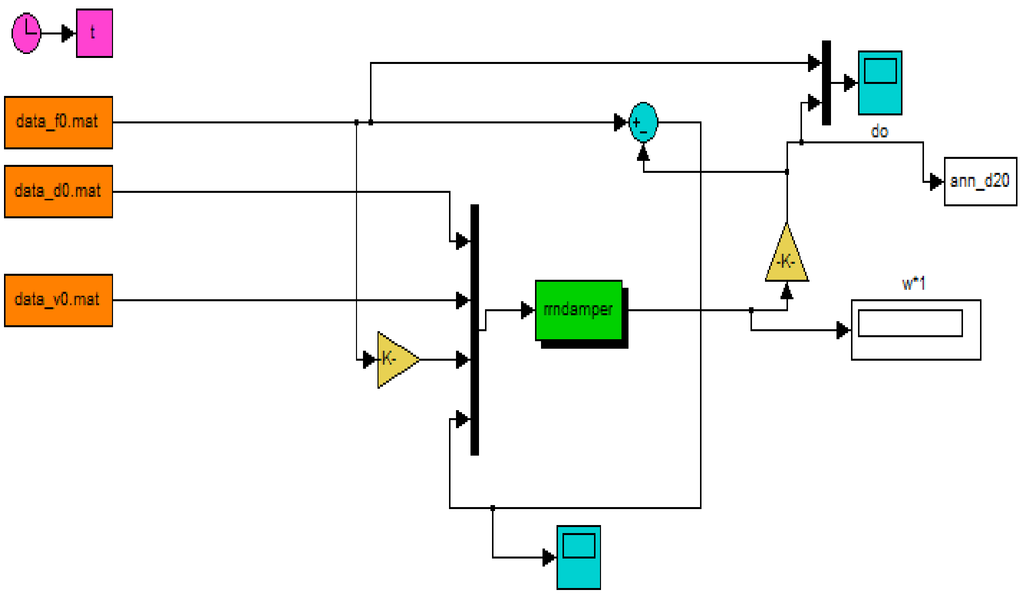

Figure 3.2: The model simulink of the MR damper.

Based on the figure 3.2, the overall simulink model represents the MR damper model. The orange blocks represent the input from the experimental damper while the blue block represents the output of the simulation damper. The output of the simulation will be in term of graph comparison between the simulation damper and experimental damper.

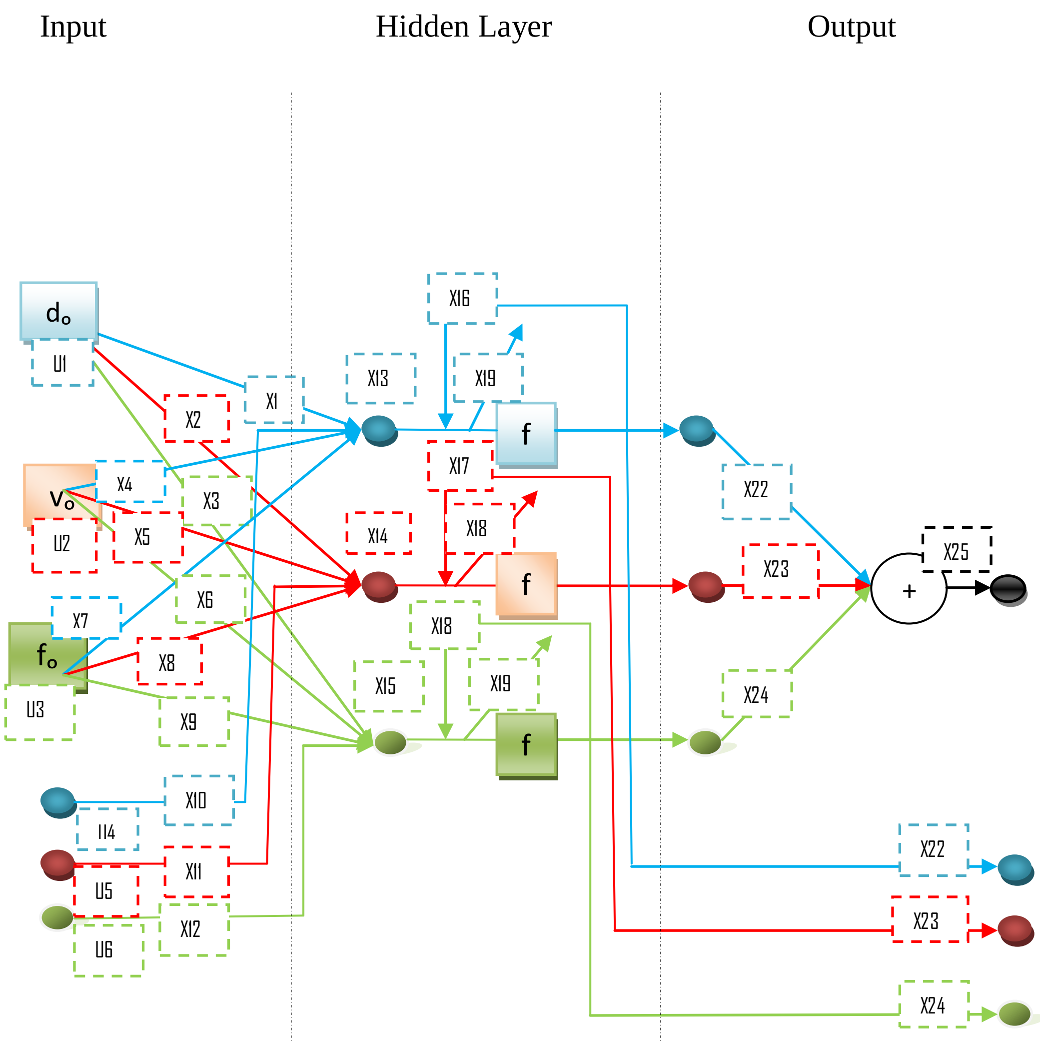

Figure 3.3: Recurrent Neural Network

The figure 3.3 shows the basic draft or diagram to make an equation for the output for the MR simulation block. The output for the simulink block using Recurrent Neural Network will be like these:

$$X19 = (U1 \times X1) + (U2 \times X4) + (U3 \times X7) + X13 + (X22 \times X10)$$

$$X20 = (U1 \times X2) + (U2 \times X5) + (U3 \times X8) + X14 + (X23 \times X11)$$

$$X21 = (U1 \times X3) + (U2 \times X6) + (U3 \times X9) + X15 + (X24 \times X12)$$

$$X22 = \frac{2}{1 + e^{-2(X19)}} - 1$$

$$X23 = \frac{2}{1 + e^{-2(X20)}} - 1$$

$$X24 = \frac{2}{1 + e^{-2(X21)}} - 1$$

$$X25 = (X16 \times X22) + (X17 \times X23) + (X18 \times X24)$$

Then the output that been build using Recurrent Neural Method will be used as output of the simulink block for MR damper.

```
function sys = mdlOutputs(t,x,u)

    x(19)=(u(1)*x(1))+(u(2)*x(4))+(u(3)*x(7))+x(13)+(x(22)*x(10));
    x(20)=(u(1)*x(2))+(u(2)*x(5))+(u(3)*x(8))+x(14)+(x(23)*x(11));
    x(21)=(u(1)*x(3))+(u(2)*x(6))+(u(3)*x(9))+x(15)+(x(24)*x(12));
%     x(22)=1/(1+exp^(-x(19)));
%     x(23)=1/(1+exp^(-x(20)));
%     x(24)=1/(1+exp^(-x(21)));
    x(22)=(2/(1+exp(-2*x(19))))-1;
    x(23)=(2/(1+exp(-2*x(20))))-1;
    x(24)=(2/(1+exp(-2*x(21))))-1;
    x(25)=(x(16)*x(22))+(x(17)*x(23))+(x(18)*x(24));

  sys=x(25);
```

Figure3.4: The coding for the output of simulink block

3.7 Tuning the value of A and X_o

The method for tuning the value of A and X_o is a process to obtained a desire damping results. The A value is the weight while the X_o value is the initial value. The results from this method will produce the graph for the simulation graph compare to the experimental damper graph. The method for the tuning of value A and X_o value is done using try and error method. The range for X_o is between the -1 until 1. For the Recurrent Neural Network method the number of X_o value to be determine or tuneis is 25. For the tuning process for determine the suitable for value A, the range for A value is fom 0 until 0.1 (McClusky, 1993).

```
sys = simsizes(sizes);
str = [];
x0=[-0.2853 0.0999997 0.55 0.800001 -0.534 0.239999 0.1025 0.958 0.97939
ts  =[-1 0];                    % inherited sample time

function sys = mdlUpdate(t,x,u)
    A = 0.00000000000000000111;
```

Figure 3.5: The A and X_o value

3.8 Root Mean Square Error

RMSE is used to measure the average magnitude of the error. The RMSE were used in this project because to modeling the MR damper, the difference between simulation damper and experimental damper is needed to be so small. The formula used to calculate the value of RMSE for simulation MR damper is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}} \tag{3-1}$$

$(Frnn - Fact)^2$: Square error

N: Number of data

To construct the RMSE of the simulation damper, the value of square error or residual is needed. The square error is obtained as the output data from the simulation, while, the value for N for this simulation is same for the entire simulation damper which is 1001.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

The results and discussion chapter present and described the results obtained through the simulation of MR damper model. The simulations were compared to experimental data from the experiment in order to determine whether the modeling of MR damper is success or not. The MR damper was simulated between 0.0 Ampere current until to 2.0 Ampere current range. The results were obtained from the study is model of the simulink block, the graph for the experimental damper parameter, the comparison graph between the experimental damper and simulation damper, the square error graph and the root mean square error.

4.2 RESULTS DATA AND GRAPH.

4.2.1 Result for 0.0 Ampere MR damper.

(a) The model of simulink block for 0.0 Ampere damper.

The modeling of simulation block was model using the MATLAB software. The differences between the simulink block models are the input, whereas the orange block in the model simulation block shows the input. The inputs for the simulation were taken from the data from experimental damper. The modeling for the simulink block were done with different value of current which is 0.0 Ampere, 0.5 Ampere, 1.0 Ampere, 1.5 Ampere, and 2.0 Ampere. Figure 4.1 shows the simulink block for 0.0 Ampere damper.

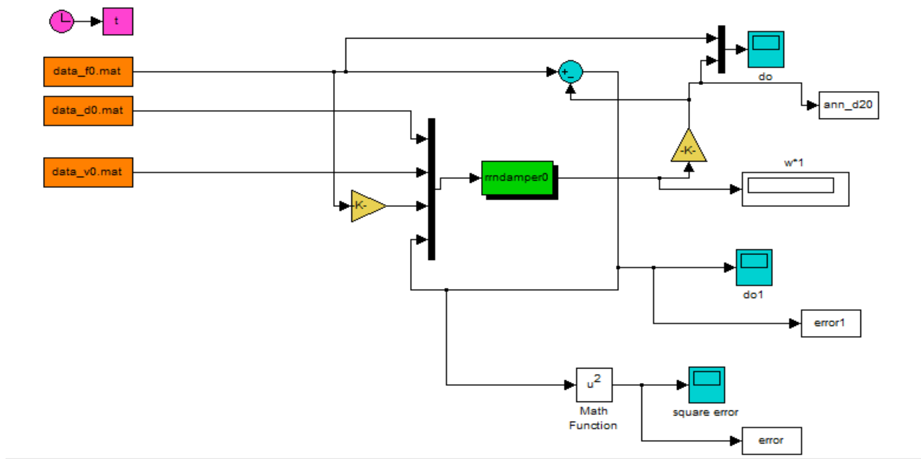

Figure 4.1: The simulink block for 0.0 Ampere damper

(b) The parameters graph for 0.0 Ampere damper

The parameter of experimental damper data is obtained from the experiment. The parameter used for these experiments is velocity, displacement and force. The results will only show the results data experiment by graph. The parameter of experimental damper data will be used as input in the simulation process. The figure 4.2 shows the displacement graph for 0.0 Ampere damper, the figure 4.3 shows the velocity graph, while the figure 4.4 shows the force graph for 0.0 Ampere damper.

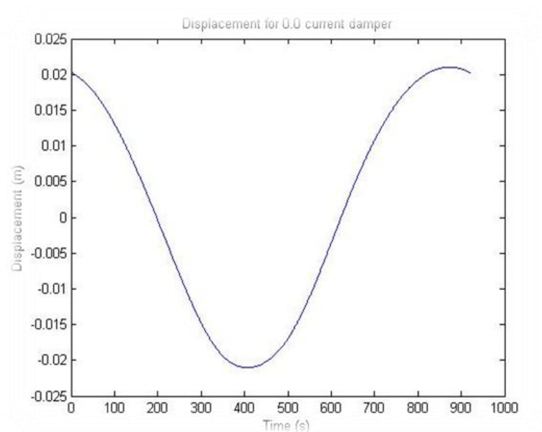

Figure 4.2: Displacement graph for 0.0 Ampere damper

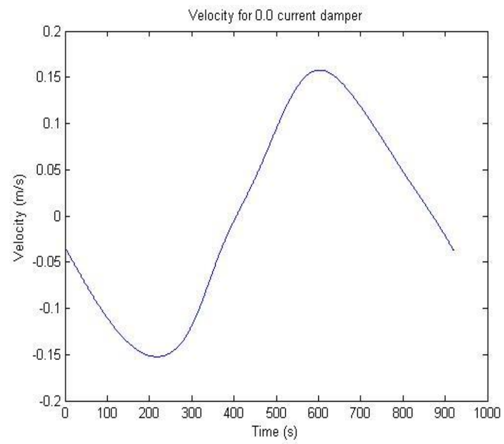

Figure 4.3: Velocity graph for 0.0 Ampere damper

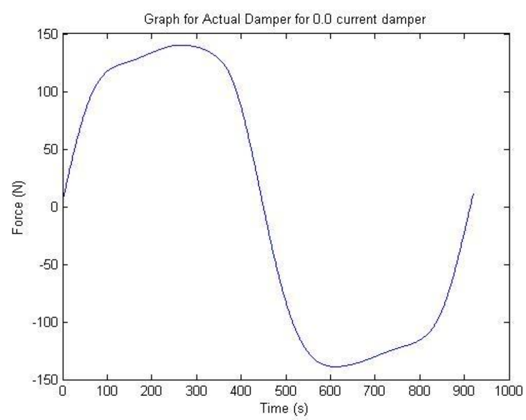

Figure 4.4: Force graph for 0.0 Ampere damper

(c) The comparison graph between simulation and experimental damper

The comparison of the experimental and the simulation were obtained in term of the force graph. The Y-axis was represent the forces in Newton unit, while the X-axis were represent the time taken using second as a unit. The yellow line is the experimental damper data, while for the simulation damper is purple line. The figure 4.5 shows the comparison graph between the experimental damper and simulation damper for 0.0 Ampere.

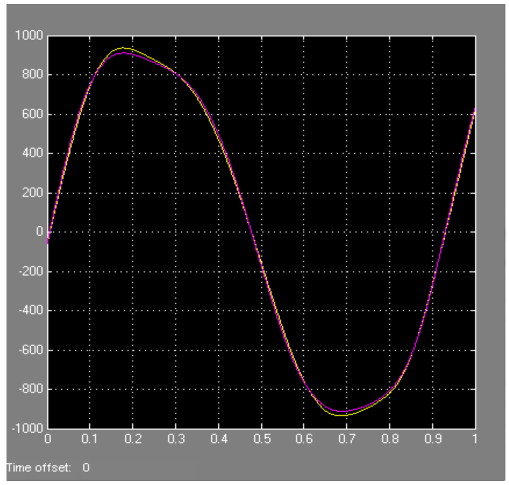

Figure 4.5: The experimental damper and simulation damper comparison graph for 0.0 Ampere damper.

(d) Square error for 0.0 Ampere damper.

The results for square error will determine whether the method used which is Recurrent Neural Network can be use to modeling the MR damper. If the square error results from the simulation are small the modeling is successful. The data from the square error will be used to determine the value for Root Mean Square Error for the simulation damper. Figure 4.6 shows the RMSE for the 0.0 Ampere damper.

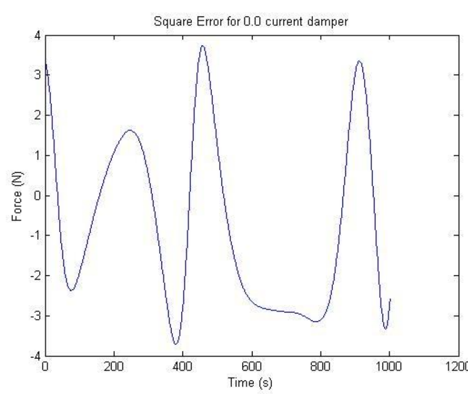

Figure 4.6: Square error graph for 0.0 Ampere damper

(e) Results for RMSE for 0.0 Ampere damper:

Root Mean Square Error is used to measure the difference or error between value from the experimental and the value from the simulation that being modeled. The Root Mean Square Error values will determine whether the Recurrent Neural Network method can be use to modeling the MR damper.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}}$$

Square error for 0.0 Ampere damper: 750.669
No of data, N: 1001

$$RMSE = \sqrt{\frac{(750.669)}{1001}}$$

$$RMSE = 0.8659$$

4.2.2 Result for 0.5 Ampere MR damper

(a) The modeling of simulation block for 0.5 Ampere damper.

The modeling of simulation block was model using the MATLAB software. The differences between the simulink block models are the input, whereas the orange block in the model simulation block shows the input. The inputs for the simulation were taken from the data from experimental damper. Figure 4.7 shows the simulink block for the 0.5 Ampere damper.

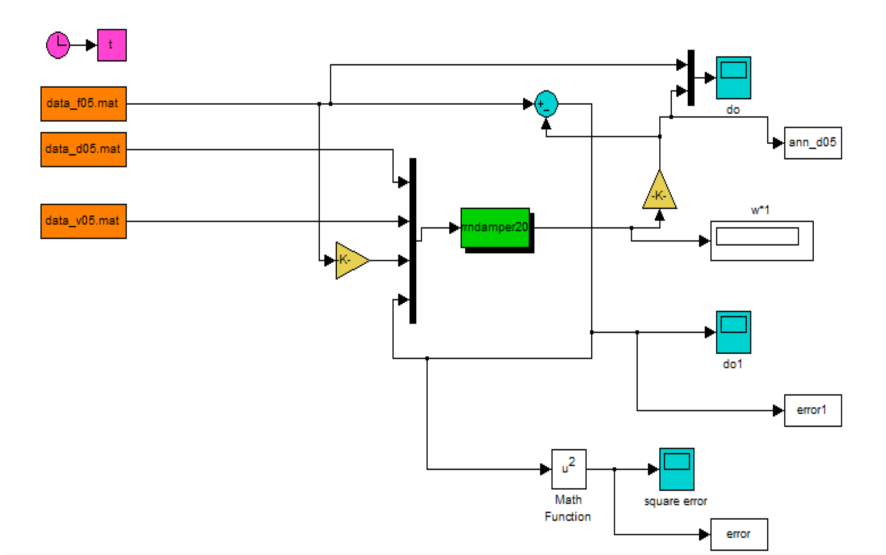

Figure 4.7: The simulink block for 0.5 Ampere damper

(b) The parameters graph for 0.5 Ampere damper

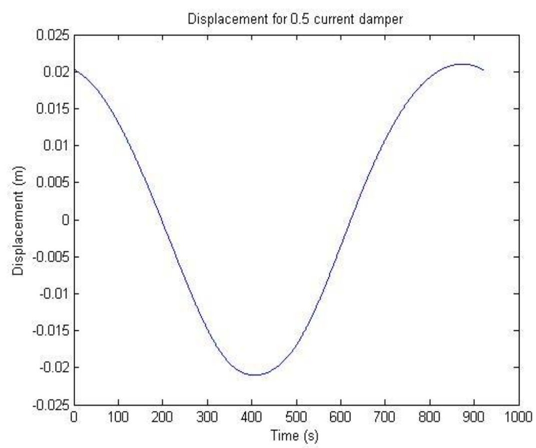

Figure 4.8: Displacement graph for 0.5 Ampere damper

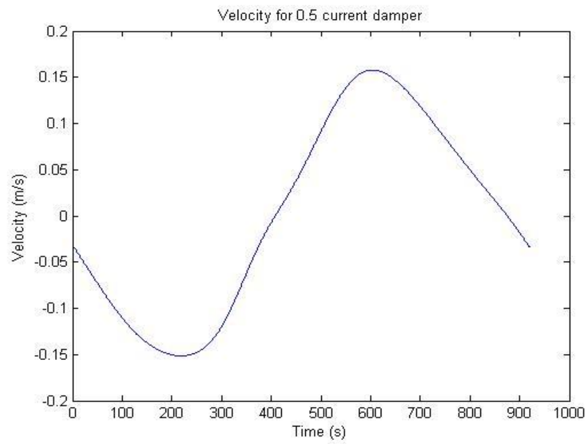

Figure 4.9: Velocity graph for 0.5 Ampere damper

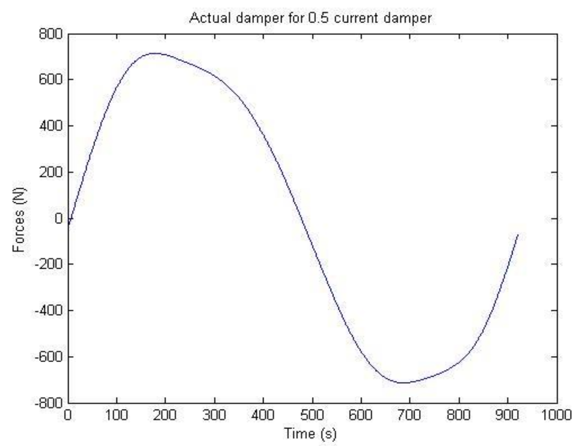

Figure 4.10: Force graph for 0.5 Ampere damper

The parameter of experimental damper data is obtained from the experiment. The results parameter from the experiment is velocity, displacement and force. The results will only show the results data experiment by graph. The parameter of experimental damper data will be used as input in the simulation process. The figure 4.8 shows the displacement graph for 0.5 Ampere damper, the figure 4.9 shows the velocity graph, while the figure 4.10 shows the force graph for 0.5 Ampere damper.

(b) The comparison graph between simulation and experimental damper

The comparison of the experimental and the simulation were obtained in term of the force graph. The Y-axis was represent the forces in Newton unit, while the X-axis were represent the time taken using second as a unit. The yellow line is the experimental damper data, while for the simulation damper is purple line. The figure 4.11 shows the comparison graph between the experimental damper and simulation damper for 0.5 Ampere.

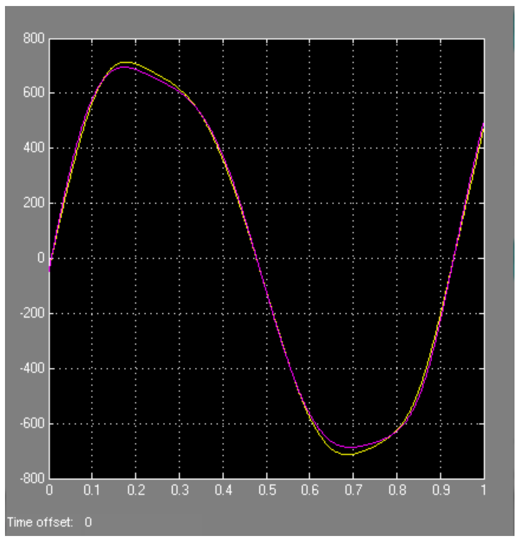

Figure 4.11: The experimental damper and simulation damper comparison graph for 0.5 Ampere damper.

(d) Square error for 0.5 Ampere damper.

The results for square error will determine whether the method used which is Recurrent Neural Network can be use to modeling the MR damper. If the square error results from the simulation are small the modeling is successful. The data from the square error will be used to determine the value for Root Mean Square Error for the simulation damper. Figure 4.12 shows the RMSE for the 0.5 Ampere damper.

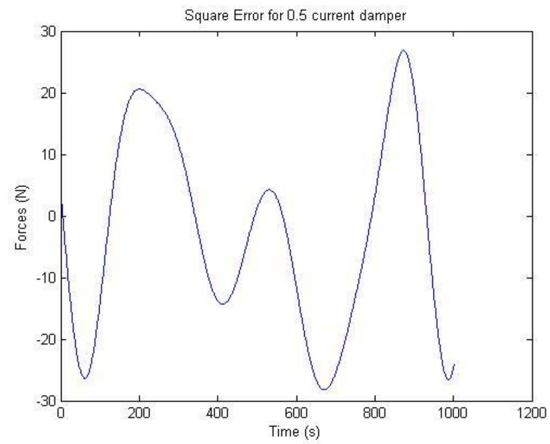

Figure 4.12: Square error graph for 0.5 Ampere damper

(e) Results for RMSE for 0.5 Ampere damper:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}}$$

Square error for 0.5 Ampere damper: 2857.25

No of data, N: 1001

$$RMSE = \sqrt{\frac{(2857.25)}{1001}}$$

$$RMSE = 1.6895$$

4.2.3 Result for 1.0 Ampere MR damper

(a) The modeling of simulation block for 1.0 Ampere damper.

The modeling of simulation block was model using the MATLAB software. The differences between the simulink block models are the input, whereas the orange block in the model simulation block shows the input. The inputs for the simulation were taken from the data from experimental damper. Figure 4.13 shows the simulink block for the 1.0 Ampere damper.

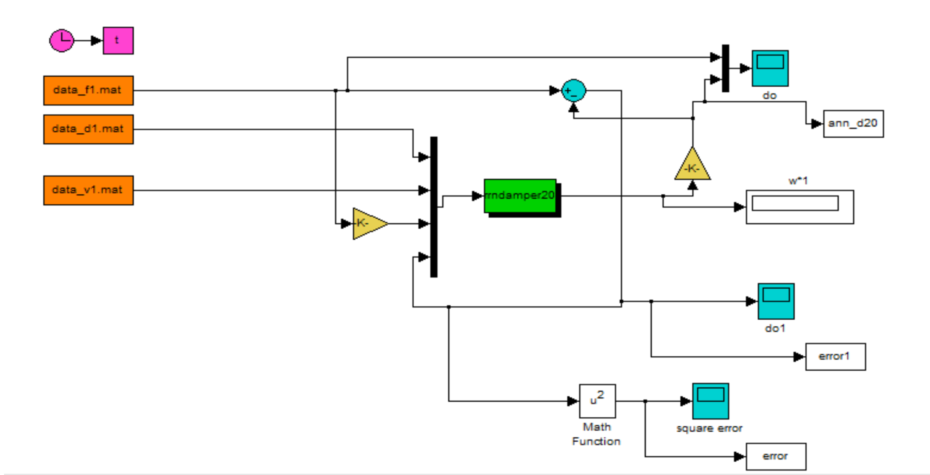

Figure 4.13: The simulink block for 1.0 Ampere damper

(b) The parameters graph for 1.0 Ampere damper

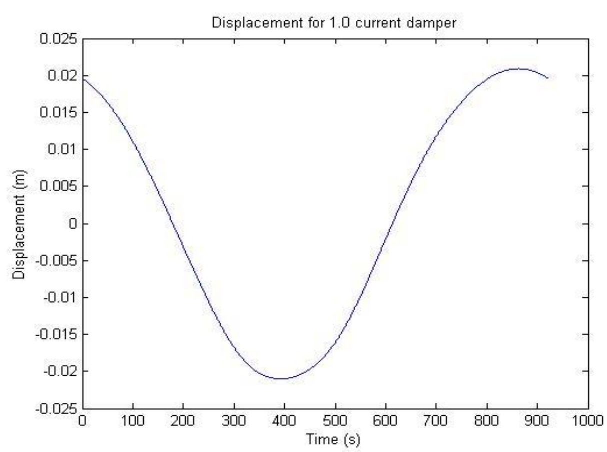

Figure 4.14: Displacement graph for 1.0 ampere damper

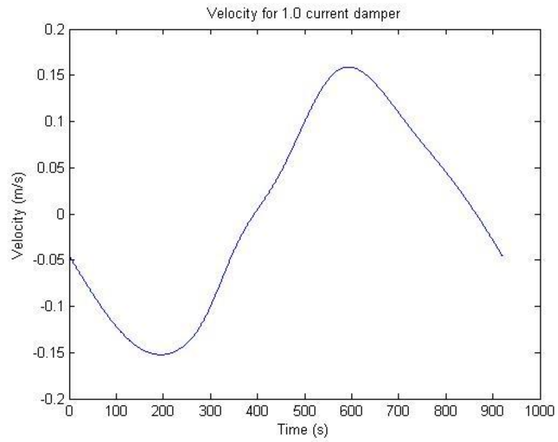

Figure 4.15: Velocity graph for 1.0 Ampere damper

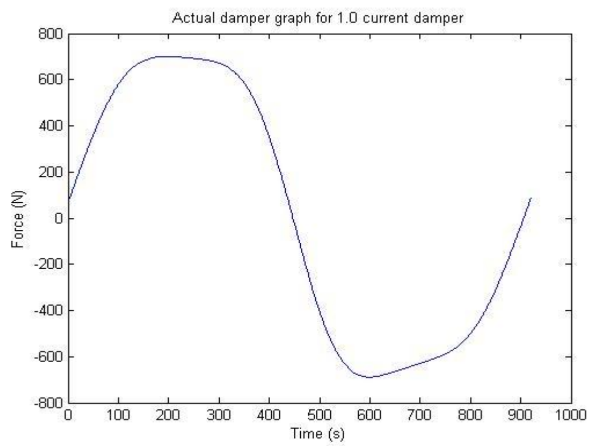

Figure 4.16: Force graph for 1.0 Ampere damper

The parameter of experimental damper data is obtained from the experiment. The results parameter from the experiment is velocity, displacement and force. The results will only show the results data experiment by graph. The parameter of experimental damper data will be used as input in the simulation process. The figure 4.14 shows the displacement graph for 1.0 Ampere damper, the figure 4.15 shows the velocity graph, while the figure 4.16 shows the force graph for 1.0 Ampere damper.

(c) The comparison graph between simulation and experimental damper

The comparison of the experimental and the simulation were obtained in term of the force graph. The Y-axis was represent the forces in Newton unit, while the X-axis were represent the time taken using second as a unit. The yellow line is the experimental damper data, while for the simulation damper is purple line. The figure 4.17 shows the comparison graph between the experimental damper and simulation damper for 1.0 Ampere.

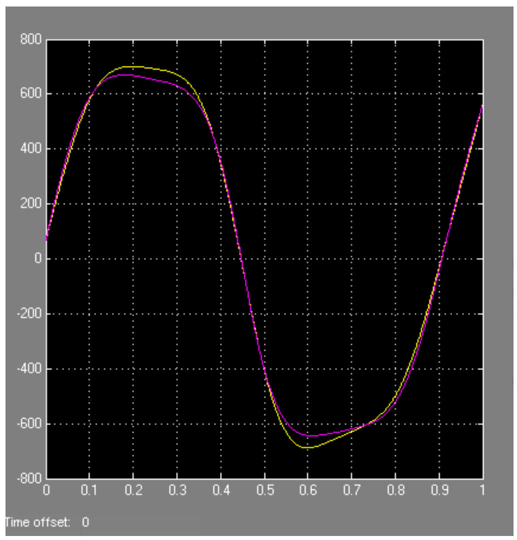

Figure 4.17: The experimental damper and simulation damper comparison graph for 1.0 Ampere damper.

(d) Square error for 1.0 Ampere damper.

The results for square error will determine whether the method used which is Recurrent Neural Network can be use to modeling the MR damper. If the square error results from the simulation are small the modeling is successful. The data from the square error will be used to determine the value for Root Mean Square Error for the simulation damper. Figure 4.18 shows the RMSE for the 1.0 Ampere damper.

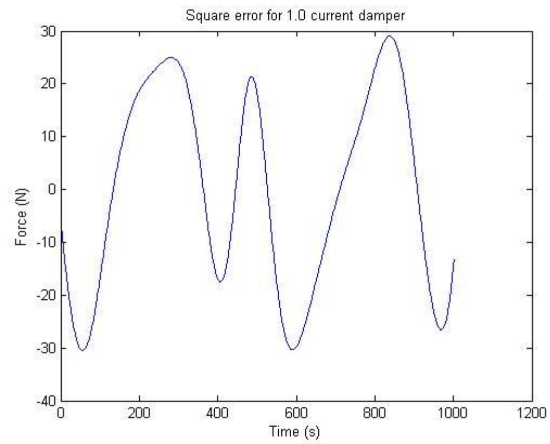

Figure 4.18: Square error graph for 1.0 Ampere damper

(e) Results for RMSE for 1.0 Ampere damper:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}}$$

Square error for 1.0 Ampere damper: 160.81
No of data, N: 1001

$$RMSE = \sqrt{\frac{(160.81)}{1001}}$$

$$RMSE = 0.4008$$

4.2.4 Result for 1.5 Ampere damper

(a) The modeling of simulation block for 1.5 Ampere damper.

The modeling of simulation block was model using the MATLAB software. The differences between the simulink block models are the input, whereas the orange block in the model simulation block shows the input. The inputs for the simulation were taken from the data from experimental damper. Figure 4.19 shows the simulink block for the 1.5 Ampere damper.

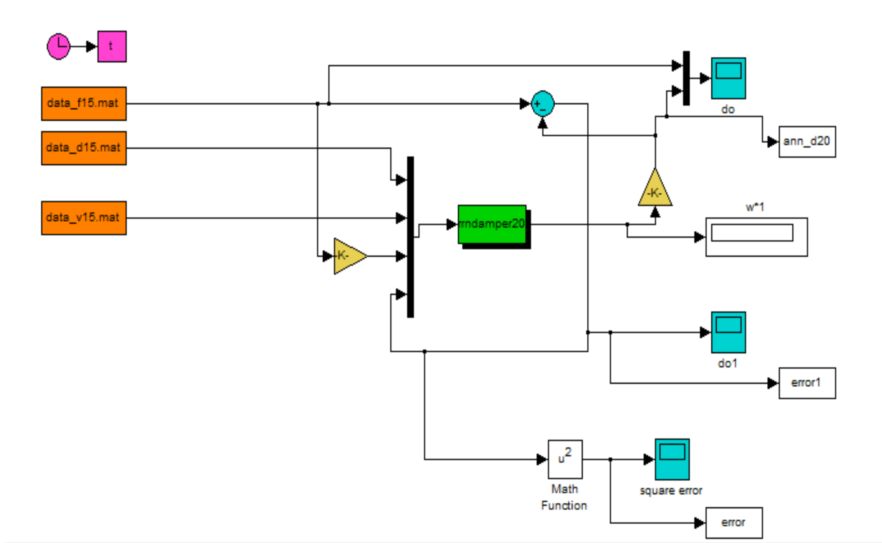

Figure 4.19: The simulink block for 1.5 Ampere damper

(b) The parameters graph for 1.5 Ampere damper

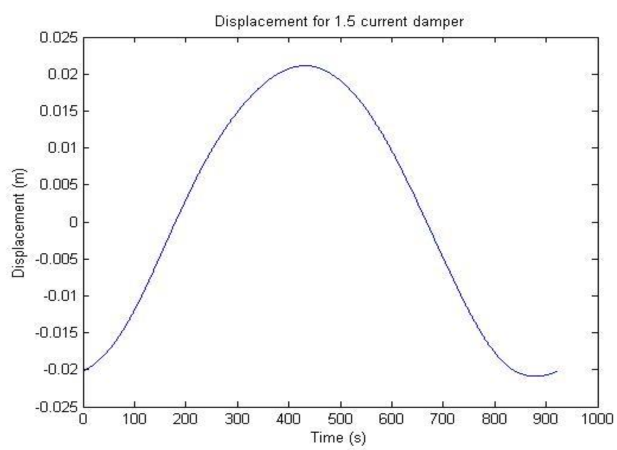

Figure 4.20: Displacement graph for 1.5 Ampere damper

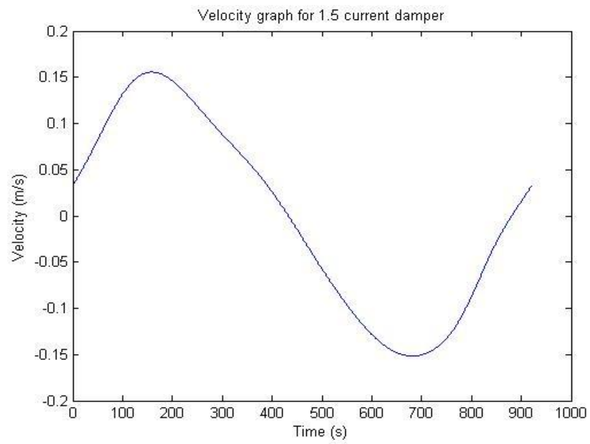

Figure 4.21: Velocity graph for 1.5 Ampere damper

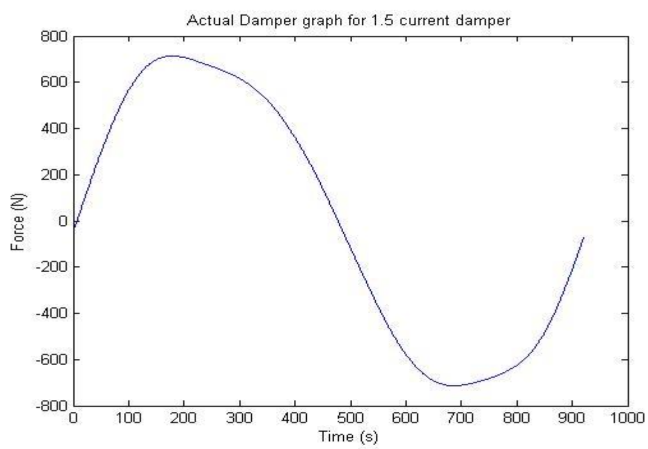

Figure 4.22: Force graph for 1.5 Ampere damper

The parameter of experimental damper data is obtained from the experiment. The results parameter from the experiment is velocity, displacement and force. The results will only show the results data experiment by graph. The parameter of experimental damper data will be used as input in the simulation process. The figure 4.20 shows the displacement graph for 1.5 Ampere damper, the figure 4.21 shows the velocity graph, while the figure 4.22 shows the force graph for 1.5 Ampere damper.

(c) The comparison graph between simulation and experimental damper

The comparison of the experimental and the simulation were obtained in term of the force graph. The Y-axis was represent the forces in Newton unit, while the X-axis were represent the time taken using second as a unit. The yellow line is the experimental damper data, while for the simulation damper is purple line. The figure 4.23 shows the comparison graph between the experimental damper and simulation damper for 1.5 Ampere.

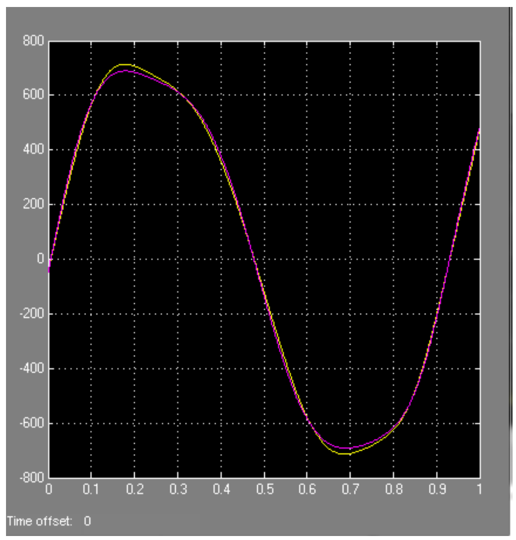

Figure 4.23: The experimental damper and simulation damper comparison graph for 1.5 Ampere damper.

(d) Square error for 1.5 Ampere damper.

The results for square error will determine whether the method used which is Recurrent Neural Network can be use to modeling the MR damper. If the square error results from the simulation are small the modeling is successful. The data from the square error will be used to determine the value for Root Mean Square Error for the simulation damper. Figure 4.24 shows the RMSE for the 1.5 Ampere damper.

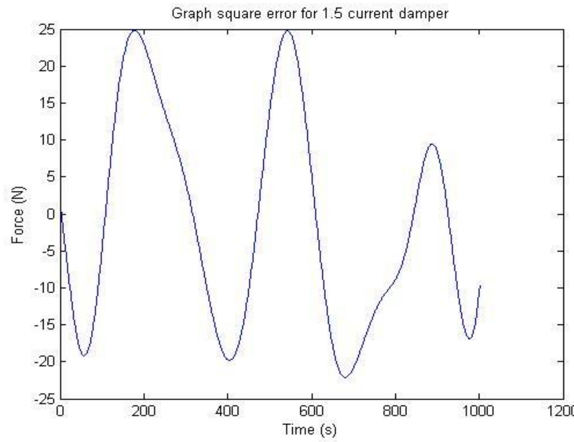

Figure 4.24: Square error graph for 1.5 Ampere damper

(e) Results for RMSE for 1.5 Ampere damper:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}}$$

Square error for 1.5 Ampere damper: 1412.76

No of data, N: 1001

$$RMSE = \sqrt{\frac{(1412.76)}{1001}}$$

$$RMSE = 1.1880$$

4.2.5 Result for 2.0 Ampere MR damper

(a) The modeling of simulation block for 2.0 Ampere damper.

The modeling of simulation block was model using the MATLAB software. The differences between the simulink block models are the input, whereas the orange block in the model simulation block shows the input. The inputs for the simulation were taken from the data from experimental damper. Figure 4.25 shows the simulink block for the 2.0 Ampere damper.

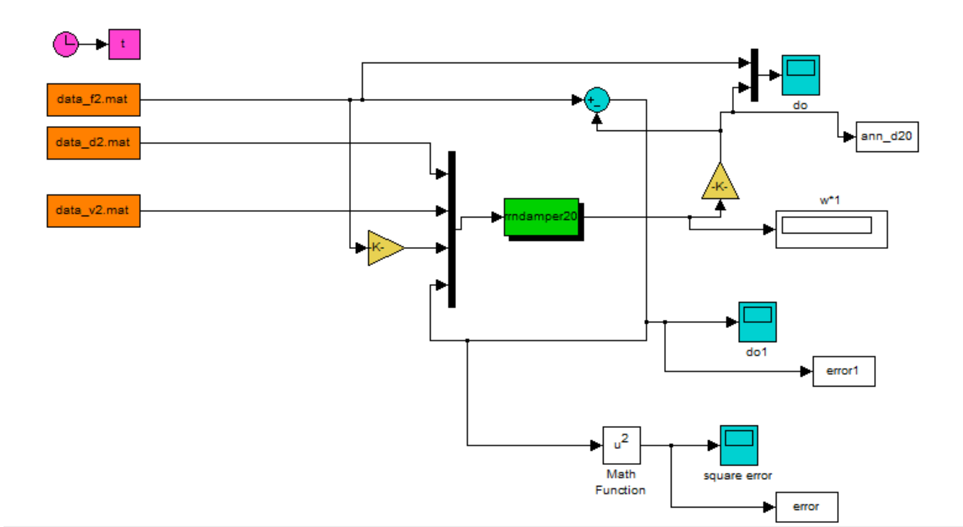

Figure 4.25: The simulink block for 2.0 Ampere damper

(b) The parameters graph for 2.0 Ampere damper

The parameter of experimental damper data is obtained from the experiment. The results parameter from the experiment is velocity, displacement and force. The results will only show the results data experiment by graph. The parameter of experimental damper data will be used as input in the simulation process. The figure 4.26 shows the displacement graph for 2.0 Ampere damper, the figure 4.27 shows the velocity graph, while the figure 4.28 shows the force graph for 2.0 Ampere damper.

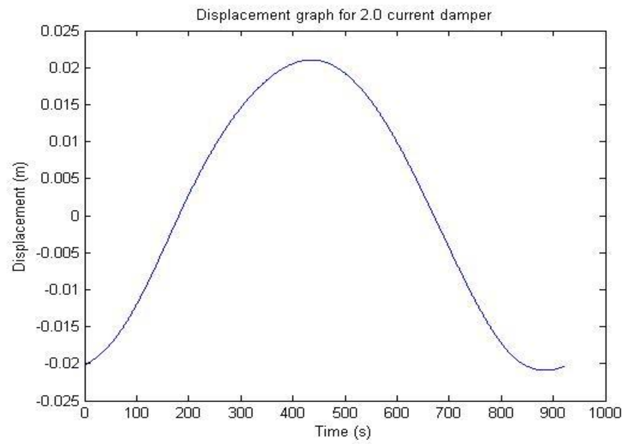

Figure 4.26: Displacement graph for 2.0 Ampere damper

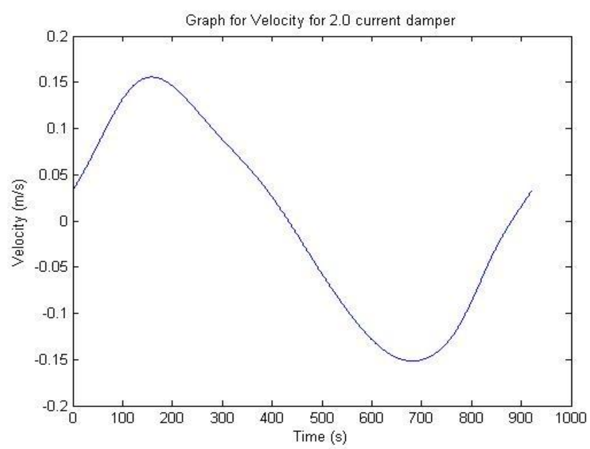

Figure 4.27: Velocity graph for 2.0 Ampere damper

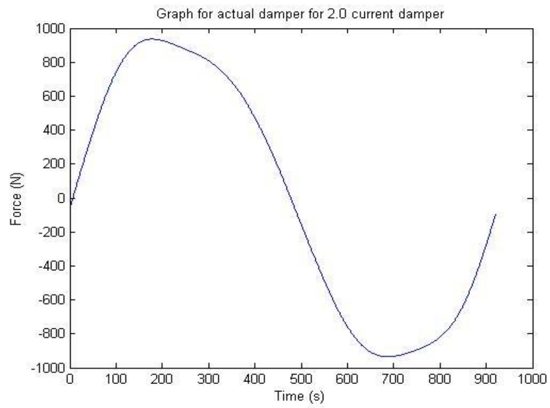

Figure 4.28: Force graph for 2.0 Ampere damper

(c) The comparison graph between simulation and experimental damper

The comparison of the experimental and the simulation were obtained in term of the force graph. The Y-axis was represent the forces in Newton unit, while the X-axis were represent the time taken using second as a unit. The yellow line is the experimental damper data, while for the simulation damper is purple line. The figure 4.29 shows the comparison graph between the experimental damper and simulation damper for 2.0 Ampere.

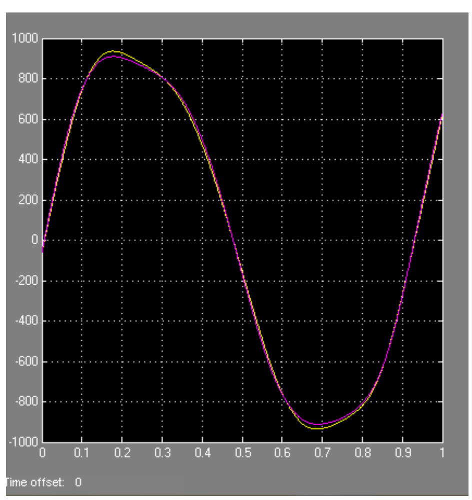

Figure 4.29: The experimental damper and simulation damper comparison graph for 2.0 Ampere damper.

(d) Square error for 2.0 Ampere damper.

The results for square error will determine whether the method used which is Recurrent Neural Network can be use to modeling the MR damper. If the square error results from the simulation are small the modeling is successful. The data from the square error will be used to determine the value for Root Mean Square Error for the simulation damper. Figure 4.30 shows the RMSE for the 2.0 Ampere damper.

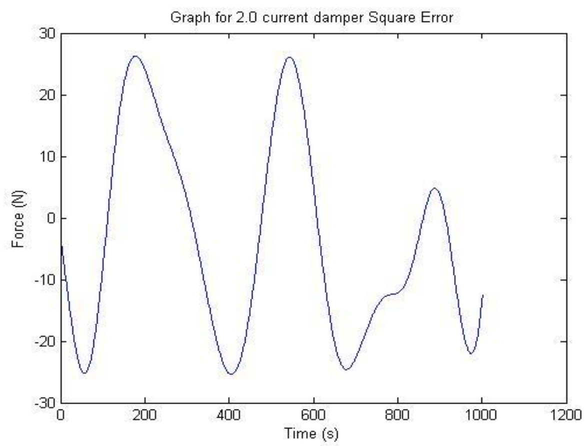

Figure 4.30: Square error graph for 2.0 Ampere damper

(e) Results for RMSE for 2.0 Ampere damper:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Frnn - Fact)^2}{N}}$$

Square error for 2.0 Ampere damper: 3956.94

No of data, N: 1001

$$RMSE = \sqrt{\frac{(3956.94)}{1001}}$$

$$RMSE = 1.9882$$

Table 4.1: Result for RMSE

Parameter value	**RMSE**
$\boldsymbol{f_0}, \boldsymbol{V_{0,}} \boldsymbol{d_0}$	0.8659
$\boldsymbol{f_{0.5,}} \boldsymbol{V_{0.5,}} \boldsymbol{d_{0.5}}$	1.6895
$\boldsymbol{f_{1.0,}} \boldsymbol{V_{1.0,}} \boldsymbol{d_{1.0}}$	0.4008
$\boldsymbol{f_{1.5,}} \boldsymbol{V_{1.5,}} \boldsymbol{d_{1.5}}$	1.1880
$\boldsymbol{f_{2.0,}} \boldsymbol{v_{2.0}}, \boldsymbol{d_{2.0}}$	1.9882

Table above shows the R.M.S.E for the MR damper. The smallest value of the R.M.S.E is 1.0 Ampere damper with a value of 0.4008. While, the highest value of the R.M.S.E is 2.0 Ampere, with a value of 1.9882. The smallest value for the RMSE will indicated that the MR damper can be used to model using RNN method. For these results, the better way to modeling the MR damper is using the average current. As can see the 1.0 Ampere damper has the lowest RMSE value. This is because the MR damper is type of semi- active damper, this type of damper have the advantage of the requirement for low power requirement. While for 2.0 Ampere damper, the RMSE is higher because of the high power supply to the MR damper. The better parameter for modeling the MR damper using RNN method is using 1.0 Ampere current.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

Modeling the MR damper can be done using variation of methods, and one of the methods is Recurrent Neural Network method. To modeling the MR damper using Recurrent Neural Network, the comparison is needed in order to determine whether the method can be used to model it as a real damper. The comparison between the experimental damper and simulation damper were made to modeling the MR damper. The comparison in this project is measure using the Root Mean Square Error of the simulation damper. The RMSE frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled. From the results, the lowest RMSE is the 1.0 Ampere damper which is 0.4008. The RMSE value is quite low, and it shows that the difference between the experimental damper and the simulation damper using RNN method is small. If the differences are small it indicates that the RNN method can be used to modeling the MR damper.

5.2 RECOMMENDATION

The Recurrent Neural Network method can be use to modeling the complex or bigger model than MR damper. In order to do that, the data from the experimental model need to be collected, so that the RMSE of the simulation model can be obtained and the model can be determine either it can be model using this method or not.

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