Modeling of magnetorheological elastomer rheological properties using artificial neural network

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Abstract. One of the important issues of Magnetorheological (MR) elastomer characteristic is to determine the linear viscoelastic region (LVE). This lead to the number of prediction models to predict the characteristic of MR elastomer based on its rheological properties. Based on the previous research, it is found that the availability of prediction model is regarded as one of the concerned issue in the development of MR elastomer material and devices. Therefore in this work, Artificial Neural Network (ANN) is proposed as prediction model due to its advantages particularly in terms of non-parametric modeling approach flexibility. Here, the shear strain and magnetic flux density are adopted as the inputs of the prediction model. Meanwhile the predicted outputs were the storage and loss modulus. The prediction model performance index was analyzed based on its generalization performance. Comparison between simulation result and experiment data shows good agreement where prediction on 0.80T of output storage modulus produced 0.0086MPa and 0.998 for Root Mean Square Error (RMSE) and Coefficient of Determination (R²) respectively.

1. Introduction

Application of MR elastomer can be seen through medical devices such as prosthetic leg [1] and vibration absorber [2]. MR elastomer is embedded by micron size magnetic particle along with non-magnetic elastomer matrix either silicon rubber or natural rubber which can change its rheological properties with the presence of external magnetic field [3][4]. In microstructure study of MR elastomer, it is crucial to determine the rheological properties such as storage modulus and loss modulus of the material. These properties were used to examine the amount of energy being stored and dissipated into heat during material deformation, which is can speed up the development process of MR-based devices implementation. Research on microstructure of MR elastomer may lead in determining the varieties of material characterizations such as Payne affect, MR effect and linear viscoelastic region (LVE) [5][6]. LVE is a region that determine through relationship between storage modulus and shear strain which shows the ability of MR elastomer to store its energy on the application of magnetic field. Development
and fabrication of MR elastomer may lead to time consuming and high cost. Thus, a prediction model is need as the solution for such issue. Parametric model such as Kelvin Voight model [7], Four parameters viscoelastic model [8], Lugre model [9], and Dahl model [10] are the available prediction model for material characterization and device development. However, these models involved with high order differential equation, which lead to the issue such as adding new input parameter because of its complex mathematical structure. In addition, the model performance is too depend on model parameters. Therefore, this paper aim to develop a prediction model of MR elastomer rheological properties to determine the material characterizations using machine learning approach that is Artificial Neural Network (ANN).

2. Material fabrication and data collection
The preparation of MR elastomer and fabrication method was based on the published works in [11]. Rubber matrix used for this work is natural rubber (NR). Carbonyl Iron Particle (CIP) used as magnetic particle filler which average size in 6µm. Moreover, epoxidised palm oil (EPO) was used as medium to disperse the CIP. Zinc Oxide (ZnO) and stearic acid were used as activator. In addition, Sulphur and N-Cyclohexylbenzothiazole-2-sulphenamide (CBS) was used to act as vulcanizing agent and accelerator respectively. Santoflex-13 and synthetic polymer used for antiozonant and stabilizer correspondingly. The fabricated sample of MR elastomer materials were in size of 20mm for the diameter and 1mm of the thickness. To investigate the rheological properties of MR elastomer, the oscillatory testing was done on the sample using a rotational rheometer (Physica MCR 302, Anton Paar, Germany) by applying various magnetic fluxes via the variation of current from 0A to 5A. Moreover, sweep strain test was done to investigate the linear viscoelastic region by shear strain variation from 0.001% to 25% for 20 points with constant frequency of 1 Hz on six different magnetic flux densities.

3. Simulation using Artificial Neural Network
A feed-forward network using multilayer perceptron as network architecture along with Levernberg Marquardt as training algorithm was adopted to develop the MR elastomer rheological properties prediction model. Here, three layers including the input, hidden and output layers were developed where a back-propagation learning algorithm was used to update weight applied as the connection between layers. Selections of network parameters were crucial in order to obtain best response accuracy during training process. The optimized network parameters obtained from the trial and error tuning process based on the evaluation of RMSE and R² shown in the equation (1) and (2) respectively. The ANN prediction model produces two outputs which were storage modulus and loss modulus.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}
\]
\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y}_{output})^2}
\]

Where \(n\), \(Y_i\), \(\hat{Y}_i\), and \(\bar{Y}_{output}\) are the total number of data set, experimental output, simulation output and mean of experimental output respectively. The selected network parameters and the distribution of data for training and testing of the model are as described in Table 1.
Table 1. Network parameters for the ANN model.

| Network parameter               | Types and Value   |
|---------------------------------|-------------------|
| Training algorithm              | Levenberg Marquardt |
| Number of hidden neuron         | 5                 |
| Hidden layer activation function | Logarithm sigmoid |
| Output layer activation function | Pure-linear       |
| Training data ratio (Learned data) | 70%              |
| Testing ratio (Learned data)    | 30%               |

In this work, data sets from six different values of external magnetic flux density which are 0.007T, 0.18T, 0.36T, 0.53T, 0.69T, and 0.80T were collected. Here, the shear strain range was varied from 0.001% to 25% on each value of magnetic flux density. In order to validate the developed prediction model, 0.53T and 0.80T were adopted as interpolation and extrapolation data respectively. These two data were kept aside to evaluate the generalization of the prediction model. Table 2 shows the adopted data set for training and validation phase.

Table 2. Data set for training and validation.

| Data set               | Magnetic flux density (T) |
|------------------------|---------------------------|
| Training set (Learned data) | 0.007          |
|                        | 0.18                      |
|                        | 0.36                      |
|                        | 0.69                      |
| Validation set (Unlearned data) | 0.53 (interpolation data) |
|                        | 0.80 (extrapolation data) |

Table 1 present the learned data with ratio 70:30 where 70% used for data train while 30% used for data test that representing the training set tabulated in Table 2. While validation set representing the validation data which out of modelling data. Thus, generally there were three sets of data which is training data, testing data and validation data.

4. Results and discussions

Figure 1(a) and Figure 1(b) shows the testing results for interpolation and extrapolation data (i.e. unlearned data) respectively. Graphical representation in Figure 1(a) shows that the proposed prediction model successfully replicate the response of experimental data at the linear part of the storage modulus response with a small response magnitude error. Meanwhile, at the non-linear part of the storage modulus, the prediction model response capable to follow the response trend. In contrast, prediction model on extrapolation data shows favourable prediction response especially in predict non-linear as depict in Figure 1(b).

Table 3 summaries the tangible value of the prediction performance on statistical analysis based on RMSE and $R^2$ of the validation interpolation and extrapolation data on both storage and loss modulus response. For storage modulus, extrapolation data gives better performance compared to interpolation data in terms of RMSE with the recorded narrow difference of 0.0062MPa. On the other hand, the $R^2$ of interpolation data were approximately identical with the extrapolation data. This means that the prediction model was also good in predicting moderate value of magnetic field (i.e. 0.53 T). Meanwhile, prediction output of loss modulus of both interpolation and extrapolation data shows promising regression performance with the variation of prediction model data was approximately 90% around its mean. Nevertheless, extrapolation data still gives better performance compared to interpolation data. This shows that the model capable in predicting the rheological properties for higher...
magnetic field which can avoid material scientist from doing the fabrication process on higher magnetic field which may lead to high cost and time consuming.

**Figure 1(a).** Comparison between experiment and simulation result of interpolation data

**Figure 1(b).** Comparison between experiment and simulation result of extrapolation data

| Performance index | Storage modulus | Loss modulus |
|-------------------|-----------------|--------------|
|                   | 0.53T (interpolation) | 0.80T (extrapolation) | 0.53T (interpolation) | 0.80T (extrapolation) |
| RMSE (MPa)        | 0.0148           | 0.0086       | 0.0050         | 0.0037         |
| R²                | 0.996            | 0.998        | 0.898          | 0.940          |

5. **Conclusion**
A prediction model of MR elastomer rheological properties has been developed by using machine learning approach which is artificial neural network. The prediction model has been done via feed-forward network using multilayer perceptron architecture consist of logarithm sigmoid activation function with five hidden neurons. In general, the prediction model is successful to predict the rheological properties of MR elastomer through storage and loss modulus. The prediction of LVE region via shear strain-storage modulus relationship is achieve successfully. However, this prediction model can be improved to accomplish better prediction accuracy. The optimization through data normalization, inclusion of additional input parameters and varies number of hidden neuron will be considered in future work to improve the prediction performance.
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