MODELING FOR VISCOELASTIC BEHAVIORS OF MAGNETORHEOLOGICAL ELASTOMER USING SINGLE HIDDEN LAYER FEED-FORWARD NEURAL NETWORK APPROACHES

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DEDICATION

This thesis is dedicated to my father Saharuddin bin Mokhtar, and my mother, Wan Meriam binti Wan Mohd. This thesis is also dedicated to all my family members, Nasfu, Norasida, Shafie, Sufian, Saufiq, Ibrahim and Iqlyma.

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ABSTRACT

The prediction of magnetorheological elastomer (MRE) dynamic modulus behavior is a challenging process because of the material's highly nonlinear nature. This problem becomes apparent while considering various possible material's fabrication parameters selection. Previously, parametric modeling techniques such as Kelvin Voigt and Maxwell's models were applied to simulate the viscoelastic behavior. Nevertheless, it required parameter identification or data fitting for each applied magnetic field which is less efficient and becomes more complex when considering various material responses. In other words, parametric modeling method's performance was limited in the change of input-output data, especially for larger-scale cases involving vast databases. Consequently, prediction model construction using a non-parametric approach such as machine learning has gained much attention in recent years. The advantages of machine learning techniques, such as to identify complex patterns or trends, and the ability to handle multi-variety of data, allow its potential to be utilized in material science study. Therefore, this research presents a data-driven approach prediction model using machine learning techniques for predicting the dynamic viscoelastic modulus of MRE. The multiple input multiple output-dependent dynamic modulus models were formulated using two feedforward neural network approaches called backpropagation artificial neural network (BP-ANN) and extreme learning machine (ELM). In this research, the MRE samples were synthesised under various compositions to undergo dynamic testing using a rheometer for data collection purposes. For the basic model design, three inputs variables were considered which were the shear strain, magnetic flux density, and input frequency. On the output side, storage and loss modulus were the targeted material dynamic properties. Meanwhile, for extended model design, fabrication effects such as filler concentration and distribution were also considered as additional input to predict dynamic modulus. To optimize the model configuration, sensitivity analysis was conducted. Here, the hyperparameters such as a number of hidden nodes and types of activation functions were varied in the training process. Thereafter, hyperparameters for optimized model configuration were selected based on the training accuracy performance. Next, the models were evaluated by utilizing the testing data sets for generalization purposes. Evaluation results showed that the ELM model had produced higher prediction accuracy, particularly at the linear viscoelastic (LVE) region where the achieved root mean square error (RMSE) and coefficient of determination (R^2) were 0.0021 MPa and 0.994 respectively. Moreover, in terms of material's fabrication effect, the ELM model also had demonstrated promising performance in forecasting the unlearned filler concentration where a relatively small RMSE of 0.0096 MPa was recorded. It is concluded that the ELM model had shown its potential to be as an accurate, flexible, and fast prediction modeling platform. The establishment of this non-parametric approach to replace the parametric model in predicting material dynamic properties is expected to contribute towards a time-efficient and cost-effective strategy for the MRE-based device development process.

ABSTRAK

Meramal kelakuan modulus dinamik elastomer reologi magnet (MR) adalah proses yang mencabar kerana sifat bahan yang tak lelurus. Masalah ini menjadi semakin jelas dengan adanya pelbagai kemungkinan pemilihan parameter untuk pembikinan bahan. Sebelum ini, teknik pemodelan berparameter seperti model Kelvin Voigt dan Maxwell telah digunakan untuk selaku kelakuan likat-anjal. Namun begitu, ia memerlukan pengenalpastian parameter atau pemasangan data untuk setiap medan magnet yang digunakan di mana ianya kurang cekap dan menjadi lebih kompleks jika kepelbagaian tindak balas bahan diambil kira. Dalam erti kata lain, prestasi kaedah pemodelan berparameter adalah terhad kepada perubahan data masukan-keluaran, terutamanya untuk kes berskala besar yang melibatkan pangkalan data yang luas. Disebabkan itu, pembinaan model ramalan tak-berparameter seperti pembelajaran mesin telah mendapat banyak perhatian dalam beberapa tahun kebelakangan ini. Kelebihan teknik pembelajaran mesin, seperti mengenal pasti corak atau arah aliran yang kompleks, dan keupayaan untuk mengendalikan data pelbagai jenis, membolehkan potensinya digunakan dalam kajian sains bahan. Oleh itu, kajian ini mempersembahkan model ramalan melalui pendekatan didorong oleh data menggunakan teknik pembelajaran mesin untuk meramal modulus dinamik likat-anjal elastomer MR. Model modulus dinamik berbilang masukan berbilang keluaran dirumus menggunakan pendekatan dua rangkaian saraf suap depan iaitu rangkaian neural tiruan perambatan balik (BP-ANN) dan pembelajaran mesin lampau (ELM). Dalam kajian ini, sampel MRE telah disintesis dalam pelbagai komposisi untuk menjalani ujian dinamik menggunakan reometer bagi tujuan pengumpulan data. Untuk rekabentul model asas, tiga pembolehubah masukan telah diambil kira iaitu, terikan ricih, ketumpatan fluks magnet dan frekuensi. Di bahagian keluaran, sifat dinamik bahan yang disasarkan adalah modulus storan dan modulus kehilangan. Sementara itu, untuk rekabentuk model lanjutan, kesan pembikinan seperti kepekatan dan agihan zarah pengisi juga diambil sebagai masukan tambahan untuk meramal modulus dinamik. Untuk mengoptimumkan tatarajah model, analisis sensitiviti telah dijalankan. Di sini, hiperparameter seperti bilangan nod terlindung dan jenis-jenis fungsi pengaktifan telah dipelbagaikan dalam proses latihan. Kemudian, hiperparameter yang sesuai untuk tatarajah model yang dioptimumkan telah dipilih berdasarkan prestasi kejituan latihan. Seterusnya, model telah dinilai menggunakan set data ujian untuk tujuan pengitlakan. Dapatan penilaian menunjukkan bahawa model ELM telah menghasilkan ketepatan ramalan yang lebih tinggi terutamanya di rantau likat-anjal linear (LVE) dimana ralat purata kuasa dua akar (RMSE) dan pekali penentuan (R^2) masing-masing mencapai nilai 0.0021 MPa dan 0.994. Selain itu, dari segi kesan pembikinan bahan, model ELM juga telah menunjukkan prestasi yang memberangsangkan dalam meramalkan data kepekatan zarah yang tidak dipelajari oleh model sebelum ini dimana RMSE yang kecil secara perbandingannya telah direkodkan iaitu sebanyak 0.0096 MPa. Dapat disimpulkan bahawa model ELM telah menunjukkan potensinya sebagai platform pemodelan ramalan yang tepat, boleh suai, dan pantas. Pengenalan kepada pendekatan tak-berparameter bagi menggantikan model berparameter dalam meramal sifat dinamik bahan ini dijangka dapat menyumbang ke arah strategi meningkatkan kecekapan masa dan penjimatan kos untuk proses pembangunan peranti berasaskan MRE.

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LIST OF ABBREVIATIONS

LVE	-	Linear Viscoelastic
NLVE	-	Nonlinear Viscoelastic
FFNN	-	Feedforward Neural Network
MRE	-	Magnetorheological Elastomer
MRF	-	Magnetorheological Fluid
RMSE	-	Root Mean Square Error
CIP	-	Carbonyl Iron Particle
BP-ANN	-	Backpropagation Artificial Neural network
ELM	-	Extreme Learning Machine
DMA	-	Dynamic Mechanical Analysis
FEM	-	Finite Element Method
LAOS	-	Large Amplitude Oscillatory Shear
SAOS	-	Small Amplitude Oscillatory Shear
RNN	-	Recurrent Neural Network
SVR	-	Support Vector Regression
RL	-	Reinforcement Learning
FNNC	-	Fuzzy Neural Network Controller
ANFIS	-	Adaptive Neural Fuzzy Inference System
ADNN	-	Adaptive Neural Network
PSO	-	Particle Swarm Optimization
GA	-	Genetic Algorithm
RF	-	Random Forest
XGBoost	-	Extreme Gradient Boosting
K-NN	-	K Nearest Neighbour
SLFN	-	Single Layer Feedforward Neural Network
LM	-	Levenberg Marquardt
RTV-SR	-	Room Temperature Vulcanization Silicon Rubber
FDM	-	Fractional Derivative Model
GPR	-	Gaussian Process Regression
MAE	-	Mean Absolute Error

LIST OF SYMBOLS

G'	-	Storage modulus
G''	-	Loss modulus
G^*	-	Complex Modulus
R^2	-	Coefficient of Determination
ε	-	epsilon
β	-	Output weight of ELM
$\mathbf{H}^\dagger$	-	Moore Penrose generalized Inverse matrix
w_i	-	Input weight
b_i	-	Input bias
γ_i	-	Shear strain
f_i	-	Frequency
B_i	-	Magnetic field
Wp_i	-	Weight percentage of CIP
Bc_i	-	Curing magnetic flux density
x_i	-	Input model
o_i	-	Predicted output
t_i	-	Experimental data
G_0	-	Static elastic modulus
C	-	Elastic part of viscoelastic branch
τ	-	Relaxation time
α	-	Fractional parameter
δ	-	Phase shift
η	-	Learning rate
$\mathbf{H}$	-	Hidden layer output matrix
g	-	Activation function
W_{k+1}	-	Updated matrix
W_k	-	Current matrix
J	-	Jacobian matrix
e	-	Vector error
μ	-	Scalar
$\mathbf{I}$	-	Identity matrix
f_{norm}	-	Normalized frequency

B_{norm}	-	Normalized magnetic flux density
$\log \gamma_{norm}$	-	Normalized logarithm shear strain
Wp_{norm}	-	Normalized weight percentage of CIP
Bc_{norm}	-	Normalized curing magnetic flux density
x_{norm}	-	Normalized input of FFNN
x_{exp}	-	Experimental input of FFNN
x_{min}	-	Minimum input of FFNN
x_{max}	-	Maximum input of FFNN
σ	-	Standard deviation

CHAPTER 1

INTRODUCTION

1.1 Research background

Magnetorheological (MR) material is an intelligent materials with tuneable properties exposed to external magnetic fields [1] in which MR fluid (MRF) was the first established of MR material having controllable viscosity. Nowadays, researchers have focused on MR elastomer (MRE) due to drawbacks on MRF such as undergo sedimentation and agglomeration [2]. In addition, MRE having the advantages of locking up the magnetic particle commonly used micron-sized such as carbonyl iron particles (CIPs) [3,4] as the filler in the matrix element (e.g., silicone rubber, natural rubber) [5–10]. Moreover, the viscoelastic behavior in which the properties of elastic and viscous can be changed in the presence of magnetic fields [6,11].

The changes of dynamic viscoelastic properties such as storage and loss modulus on effect of magnetic field is called MR effect. The storage modulus indicates the ability to store energy elastically while loss modulus indicates the energy dissipated as heat. In the meantime, the loss factor represents the damping capability of the MRE. The properties of MRE have two primary responses, which are linear response (commonly used to measure the MR effect) and non-linear response known as linear viscoelastic (LVE) and nonlinear viscoelastic (NLVE) region, respectively. These regions can be observed from the storage modulus-shear strain relationship. Furthermore, the LVE region can be shortern and NLVE region can be wider as increased the magnetic field, occurred due to Payne effect [12].

Many studies have proposed various methods to improve MR effect, particularly the essential fabrication process-parameters, such as the variations of filler concentration [9,13–17] magnetic field [15,18–20] and the particle shapes and sizes [18,21,22]. As discussed in recent works [19,23], different curing conditions can affect material properties by changing the dispersion or distribution condition and distance between magnetic particles during curing process. The curing condition classification can be anisotropic and isotropic with chain like-alignment in existence and arbitrary alignment in the absence of magnetic fields, respectively [24].

While the effect of each fabrication process-related parameter is quite predictable, the pattern exhibits by MRE dynamic behavior becomes more challenging to be modelled if two or more parameters are considered [25]. Moreover, in terms of predicting the dynamic viscoelastic properties in LVE and NLVE region, the pattern along the LVE region can be considered easy to predict. However, on NLVE region, the storage modulus, is overlapping at the various magnetic fields (e.g. B1 and B2) which is difficult to predict, as illustrated in Figure 1.1. Therefore, it is quite a challenge to duplicate the behavior of MRE at LVE and NLVE region. Hence, a thorough studies should be done to find a proper approach to replicate the complex and nonlinear MRE dynamic viscoelastic behavior.

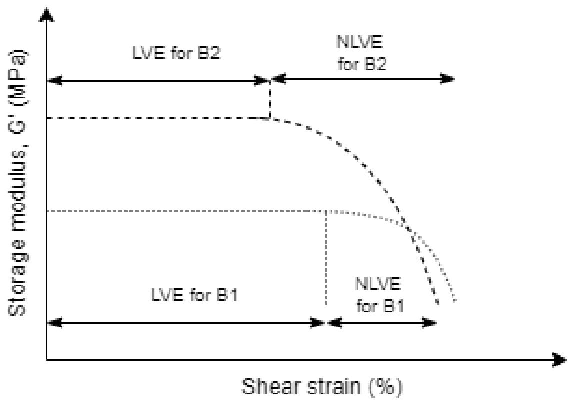

Figure 1.1 Illustration of the viscoelastic behavior on NLVE region

1.2 Motivation of study

Various MRE viscoelastic models were developed to fulfill the demands of researches [26–30]. The continuum mechanics-based model is one of the MRE based-model where it theoretically coupled the elasticity and magnetism response which numerically structured based on the principle of strain energy function and thermodynamics [31]. Several studies have developed continuum mechanics-based MRE models [32–34]. Nevertheless, one of the disadvantages was it cannot distinguish the spatial particle distribution such as isotropic, anisotropic, and plane-like structures [35] due to the continuum assuming homogeneity of the media [36]. Aforementioned, the influence of spatial particle distribution was very significant on the MRE behavior [19,23].

Then, the microscale-based model was introduced that able to distinguish between isotropic and anisotropic distribution. This model was developed by using a lattice network model in which the mechanism of microstructural was presented in detailed [29,33,37]. Furthermore, the model able to relate microstructural concept, such as dipole interaction towards the magnetic field interaction in which became the main cause of modulus changes [29]. Even so, it can only be applied to the quasi-static properties, not for dynamic properties. Limited studies on this issue might be due to difficulty of finding the best lattice network model. Therefore, microscale and continuum mechanics-based models were unable to predict the MRE material dynamic properties in which the MRE devices such as isolator is applicable in dynamic mode rather than quasi-static mode.

Another model that is appropriate in predicting the dynamic behavior is called phenomenological-based parametric model [7,10,11,13,17,38,39]. This kind of model is more suitable for the use of MRE dynamic behavior prediction where the dynamic behavior is more relatable to the MRE device behavior compared to continuum-mechanics and microscale-based model which focus on static behavior prediction. Used of elements such as spring, dashpot, and slider coulomb friction in phenomenological-based parametric model allowed the modelling structure explicitly explained for dynamic behavior. These elements allowed the inclusion of crucial responses such as strain amplitude, frequency, and magnetic field in predicting the dynamic behavior [7,10,13,40–42] where the physics law such as Hooke’s law and Newton’s law were utilized in the model development structure.

Nevertheless, the parametric models were too dependent on a specific magnetic field. The parameter identification needs to be done on each value of magnetic field intensity through a data fitting process which is acknowledged as a tedious procedure. Otherwise, the prediction accuracy would drop if a single model parameter was utilized for various magnetic fields. This led to less efficient, and the issue becomes aggravated when considering other variables related to material fabrication, such as the filler concentration effect. According to Vatandoost et al. [43], parameter identification from the measured data only valid in the vicinity of the condition used for experimental characterization. In addition, Leng et al. [44] described the parametric models could have too many parameters need to be identified which lead to unrealistic values (e.g. negative stiffness and damping).

Hence, an approach that able to predict the MRE dynamic behavior without involving complex parameter identification while able to cover various magnetic fields in a simple model structure is needed and favorable. Rather than parametric approach, the nonparametric approach is more preferable because no prior assumptions with regards the functional relationship between inputs and targets are required [45]. Moreover, it is good at handling complex behavior [46] which suitable for MRE dynamic behavior as its exhibit nonlinear characteristics with respect to different magnetic field strength.

Several studies have applied the nonparametric approaches using machine learning model to predict the rheological properties such as shear strength of soil [47] and tensile properties of rubber [48] with good prediction accuracy. There were also studies on the prediction of shear force on MRE isolator. Yu et al. [49] proposed an adaptive neuro-fuzzy inference system (ANFIS) model having displacement at current and previous time, and also applied current as model inputs. The same author also in a different publication [50], had adopted support vector regression (SVR) model to predict the shear force. Here, the rate of change of the displacement (i.e. velocity) was added as model input along with input variables used in [49]. Meanwhile, neural network have been applied by Zhou et al. [51] and Vatandoost [43] to predict the MRE isolator in shear-squeeze mode and forecast the MRE tensile strength, respectively.

The advantages of neural network in solving multiple regression problem allowed its widespread utilization especially in viscoelastic material [52–54]. In addition, neural network had demonstrated an acceptable capability in interpolation and extrapolation estimation, in the case where generalization data were either within or beyond the training data range, respectively [55]. Apparently, neural network-based model can be one of nonparametric approach potential solution for MRE dynamic viscoelastic behavior prediction.

1.3 Problem statement

Various MRE parametric models have been exploited since it is important to represent the dynamic properties which affected by numerous magnetic field intensities in real application. Nonetheless, the MRE parametric models are currently dependent on a specific magnetic field, resulting in inaccurate prediction accuracy once the single model parameter is applied at different magnetic field. Repetition in parameter identification process is needed to determine the model parameters at different magnetic fields which is deemed as pivotal. Furthermore, the parametric model development involved higher order differential equations, which are complex. Therefore, an approach that can simplify the MRE dynamic viscoelastic model development and able to predict at various magnetic field should be explored.

1.4 Research objectives

This research was embarked based on the following objectives:

1. To design the MRE dynamic viscoelastic model for predicting the field-dependent modulus using the machine learning approach.
2. To develop the MRE prediction model with the influence of fabrication effect by considering filler concentration and distribution as extended input.
3. To analyze the model generalization through RMSE and R^2 performance index.

1.5 Research scope

- MRE fabrication process involves two main components: matrix element and magnetic particle used as a filler. The silicon rubber and CIP were utilized as matrix element and magnetic particle, respectively.

- The MRE were fabricated on two different distributions based on curing conditions which is isotropic distribution with the absence of magnetic field was applied to make it as homogenous. Then, anisotropic distribution was fabricated with the presence of 300 mT to make it in aligned chain.

- The fabricated MRE has five different concentrations that vary by weight percentages of CIP, among which are 30%, 40%, 50%, 60% and 70%. These concentration ranges were selected because if the CIP concentrations less than 30%, it brings forth to a narrow range of shear modulus with respect to magnetic field variation. Moreover, most works used 70% as their maximum concentration due to stability in the microstructure.

- The oscillation testing (i.e. dynamic testing) of the samples was conducted using parallel plate rheometer to investigate the viscoelastic properties of MRE. Three sweep tests were performed: 1) Strain sweep, 3) Frequency sweep and 3) current sweep.

- In this study, two MRE's dynamic viscoelastic properties which were the storage modulus (MPa) and loss modulus (MPa) were considered as the prediction model.

- All modeling, simulations and analysis were performed using MATLAB R2018b platform.

1.6 Significance of research

This research offered a flexible, intelligent, simple, and high performances solution of prediction the MRE viscoelastic behavior. The details of the contribution for this study can be found as follow.

1. A new model for characterize the Payne effect phenomenon

The Payne effect can be observed by plotting the storage modulus versus shear strain. This effect can be seen when the storage modulus is maintained until it drops at critical strain, along with the increase of strain amplitude. By this, the observation of LVE and NLVE can be determined. The LVE is a region where the microstructure is strong. Meanwhile, the microstructure in the NLVE region is weak. To be specific, at the large deformations which occur at NLVE region, the stress induced MRE has broken down the filler network due to unstable particle bonding resulted to the decreasing of storage modulus. In the meantime, the particle interaction are much stronger at small deformation which is in LVE region [56]. Differentiating these two regions with the given shear strain can be essential, especially for material characterization and device development. Considering different magnetic fields will become arduous because the LVE and NVLE region will keep changing. Hence, a model that can mitigate this behavior is a need. However, only a few commercially available finite element algorithms take into account the effect of amplitude dependency when incorporating a magnetic field response. Furthermore, developing such an algorithm is a complex endeavor that requires the incorporation of actual material features with mathematical formulation. Hence, machine learning models offer an easy way to model the behavior and may solve issues such as nonlinear SAOS and LAOS analysis.

2. A new composition and filler distribution dependent linear viscoelastic MRE model.

In the case of the linear viscoelastic model, many constitutive MRE models have been developed, including the fabrication effect such as CIP concentration as input response. It is a challenging task for the previous works to provide a model that can accommodate magnetic flux density, filler concentration, and filler distribution as a function of frequency as the input in one model. Thus, this study offers a machine learning model for predicting the linear viscoelastic behavior as a function of frequency which can predict the dynamic viscoelastic properties at the desired magnetic field, with the desired composition for either isotropic or anisotropic distribution flexibly. Therefore, this model helps optimize or tune the magnetic field and composition for isotropic and anisotropic distribution according to the application requirement.

1.7 Thesis outline

This thesis is organized in five chapters that can be shortly described as follow:

Chapter 1: This chapter describes the introduction of the thesis, starting with the research background and motivation of study to gain the reader's understanding related to the topic and then followed by the problem statement and research objective. After that, this thesis's scope is briefly explained, followed by the significance of the research.

Chapter 2: This chapter presents the literature review conducted in this work. It started with introducing MRE, including the components of matrix rubber, magnetic particle, and its dynamic viscoelastic properties. Furthermore, the existing linear viscoelastic models is described. Then, the available machine learning model for MRE and its shortage is explained.

Chapter 3: This chapter starts with a flowchart presentation of the proposed model's process to gain understanding. After that, the fabrication process of MRE by explaining the raw material used and rheological testing of MRE is described. Then, this chapter presents the modeling platform of MRE via the machine learning approach by proposed backpropagation artificial neural network (BP-ANN) and extreme learning machine (ELM) method by describing the network structure of the model. The data sets of the model are introduced and followed by the data division for training and validation purposes.

Chapter 4: This chapter describes the performance of the proposed modeling method in predicting the viscoelastic properties of MRE, particularly the storage modulus and loss modulus. The training performance is discussed on the basic viscoelastic model and extended input case. Then, the model generalization performance is presented, followed by the effect of the model hyperparameter, which is the number of hidden nodes and type of activation function.

Chapter 5: This chapter concludes with research outcomes reflecting this thesis's objective. Also, the contribution of research is declared, and lastly, the recommendation and future work is stated at the last of the chapter.

REFERENCES

1. Perales-Martínez IA, Palacios-Pineda LM, Lozano-Sánchez LM, Martínez-Romero O, Puente-Cordova JG, Elías-Zúñiga A. Enhancement of a Magnetorheological PDMS Elastomer with Carbonyl Iron Particles. *Polymer Testing*, 2017 **57**: 78–86.
2. Kumar JS, Paul PS, Raghunathan G, Alex DG. A Review of Challenges and Solutions in the Preparation and Use of Magnetorheological Fluids. *International Journal of Mechanical and Materials Engineering*, 2019 **14**(1): 13.
3. Aziz SAA, Mazlan SA, Nordin NA, Rahman NANA, Ubaidillah U, Choi SB, *et al.* Material Characterization of Magnetorheological Elastomers with Corroded Carbonyl Iron Particles: Morphological Images and Field-Dependent Viscoelastic Properties. *International Journal of Molecular Sciences*, 2019 **20**(13): 3311.
4. Yu M, Ju B, Fu J, Liu X, Yang Q. Influence of Composition of Carbonyl Iron Particles on Dynamic Mechanical Properties of Magnetorheological Elastomers. *Journal of Magnetism and Magnetic Materials*, 2012 **324**(13): 2147–2152.
5. Yu M, Qi S, Fu J, Zhu M, Chen D. Understanding the Reinforcing Behaviors of Polyaniline-Modified Carbonyl Iron Particles in Magnetorheological Elastomer Based on Polyurethane/Epoxy Resin IPNs Matrix. *Composites Science and Technology*, 2017 **139**: 36–46.
6. Liu T, Xu Y. Magnetorheological Elastomers: Materials and Applications. *Smart and Functional Soft Materials*, IntechOpen; 2019.
7. Kang S, Choi K, Nam JD, Choi H. Magnetorheological Elastomers: Fabrication, Characteristics, and Applications. *Materials*, 2020 **13**(20): 4597.
8. Chen L, Gong XL, Jiang WQ, Yao JJ, Deng HX, Li WH. Investigation on Magnetorheological Elastomers Based on Natural Rubber. *Journal of Materials Science*, 2007 **42**(14): 5483–5489.
9. Berasategi J, Salazar D, Gomez A, Gutierrez J, Sebastián MS, Bou-Ali M, *et al.* Anisotropic Behaviour Analysis of Silicone/Carbonyl Iron Particles

Magnetorheological Elastomers. *Rheologica Acta*, 2020 **59**(7): 469–476.

10. Bastola AK, Hossain M. A Review on Magneto-Mechanical Characterizations of Magnetorheological Elastomers. *Composites Part B: Engineering*, 2020 **200**(May): 108348.
11. Boczkowska A, Awietj S. Microstructure and Properties of Magnetorheological Elastomers. *Advanced Elastomers - Technology, Properties and Applications*, InTech; 2012.
12. Agirre-Olabide I, Elejabarrieta MJ, Bou-Ali MM. Matrix Dependence of the Linear Viscoelastic Region in Magnetorheological Elastomers. *Journal of Intelligent Material Systems and Structures*, 2015 **26**(14): 1880–1886.
13. Dargahi A, Sedaghati R, Rakheja S. On the Properties of Magnetorheological Elastomers in Shear Mode: Design, Fabrication and Characterization. *Composites Part B: Engineering*, 2019 **159**: 269–283.
14. Wu C, Cheng C, El-Aty AA, Li T, Qin Y, Yang Q, *et al.* Influence of Particles Size and Concentration of Carbonyl Iron Powder on Magnetorheological Properties of Silicone Rubber-Based Magnetorheological Elastomer. *Materials Research Express*, 2020 **7**(8): 86101.
15. Puente-Córdova J, Reyes-Melo M, Palacios-Pineda L, Martínez-Perales I, Martínez-Romero O, Elías-Zúñiga A. Fabrication and Characterization of Isotropic and Anisotropic Magnetorheological Elastomers, Based on Silicone Rubber and Carbonyl Iron Microparticles. *Polymers*, 2018 **10**(12): 1343.
16. Vatandoost H, Rakheja S, Sedaghati R. Effects of Iron Particles' Volume Fraction on Compression Mode Properties of Magnetorheological Elastomers. *Journal of Magnetism and Magnetic Materials*, 2021 **522**(August 2020): 167552.
17. Agirre-Olabide I, Lion A, Elejabarrieta MJ. A New Three-Dimensional Magneto-Viscoelastic Model for Isotropic Magnetorheological Elastomers. *Smart Materials and Structures*, 2017 **26**(3): 035021.
18. Hapipi N, Aziz SAA, Mazlan SA, Ubaidillah, Choi SB, Mohamad N, *et al.* The Field-Dependent Rheological Properties of Plate-like Carbonyl Iron Particle-Based Magnetorheological Elastomers. *Results in Physics*, 2019 **12**(December 2018): 2146–2154.
19. Li T, Abd El-Aty A, Cheng C, Shen Y, Wu C, Yang Q, *et al.* Investigate the Effect of the Magnetic Field on the Mechanical Properties of Silicone Rubber-

Based Anisotropic Magnetorheological Elastomer during Curing Process. *Journal of Renewable Materials*, 2020 **8**(11): 1411–1427.

20. Samal S, Škodová M, Blanco I. Effects of Filler Distribution on Magnetorheological Silicon-Based Composites. *Materials (Basel, Switzerland)*, 2019 **12**(18): 3017.
21. Gan R, Li Y, Qi S, Zhu M, Yu M. Study on the Effect of Particle Size on Viscoelastic Properties of Magnetorheological Elastomers. *Current Smart Materials*, 2019 **4**(1): 59–67.
22. Winger J, Schümann M, Kupka A, Odenbach S. Influence of the Particle Size on the Magnetorheological Effect of Magnetorheological Elastomers. *Journal of Magnetism and Magnetic Materials,* 2019 **481**: 176–182.
23. Vatandoost H, Hemmatian M, Sedaghati R, Rakheja S. Dynamic Characterization of Isotropic and Anisotropic Magnetorheological Elastomers in the Oscillatory Squeeze Mode Superimposed on Large Static Pre-Strain. *Composites Part B: Engineering*, 2020 **182**: 107648.
24. Khairi MHA, Mazlan SA, Ubaidillah, Choi SB, Aziz SAA, Mohamad N, *et al.* Role of Additives in Enhancing the Rheological Properties of Magnetorheological Solids: A Review. *Advanced Engineering Materials*, 2019 **21**(3): 1800696.
25. Abedi V, Hontecillas R, Carbo A, Philipson C, Hoops S, Bassaganya-Riera J. Multiscale Modeling. In: Bassaganya-Riera JBTCI, editor. *Computational Immunology*, Elsevier; 2016.
26. Guo F, Du C bin, Li R pu. Viscoelastic Parameter Model of Magnetorheological Elastomers Based on Abel Dashpot. *Advances in Mechanical Engineering*, 2014 **6**: 629386.
27. Eem SH, Jung HJ, Koo JH. Modeling of Magneto-Rheological Elastomers for Harmonic Shear Deformation. *IEEE Transactions on Magnetics*, 2012 **48**(11): 3080–3083.
28. Cantera MA, Behrooz M, Gibson RF, Gordaninejad F. Modeling of Magneto-Mechanical Response of Magnetorheological Elastomers ({MRE}) and {MRE}-Based Systems: A Review. *Smart Materials and Structures*, 2017 **26**(2): 23001.
29. Khanouki MA, Sedaghati R, Hemmatian M. Experimental Characterization and Microscale Modeling of Isotropic and Anisotropic Magnetorheological

Elastomers. *Composites Part B: Engineering*, 2019 **176**(July): 107311.

30. Nam TH, Petríková I, Marvalová B. Experimental and Numerical Research of Stress Relaxation Behavior of Magnetorheological Elastomer. *Polymer Testing*, 2021 **93**: 106886.
31. Beheshti A, Sedaghati R, Rakheja S. Finite Deformation Analysis of Isotropic Magnetoactive Elastomers. *Continuum Mechanics and Thermodynamics*, 2021 **33**(1): 163–178.
32. Yarali E, Farajzadeh MA, Noroozi R, Dabbagh A, Khoshgoftar MJ, Mirzaali MJ. Magnetorheological Elastomer Composites: Modeling and Dynamic Finite Element Analysis. *Composite Structures*, 2020 **254**: 112881.
33. Danas K, Kankanala S V, Triantafyllidis N. Experiments and Modeling of Iron-Particle-Filled Magnetorheological Elastomers. *Journal of the Mechanics and Physics of Solids*, 2012 **60**(1): 120–138.
34. Wang B, Kari L. Constitutive Model of Isotropic Magneto-Sensitive Rubber with Amplitude, Frequency, Magnetic and Temperature Dependence under a Continuum Mechanics Basis. *Polymers*, 2021 **13**(3): 472.
35. Ivaneyko D, Toshchevikov VP, Saphiannikova M, Heinrich G. Magneto-Sensitive Elastomers in a Homogeneous Magnetic Field: A Regular Rectangular Lattice Model. *Macromolecular Theory and Simulations*, 2011 **20**(6): 411–424.
36. Ivaneyko D, Toshchevikov VP, Saphiannikova M, Heinrich G. Effects of Particle Distribution on Mechanical Properties of Magneto-Sensitive Elastomers in a Homogeneous Magnetic Field. *Condensed Matter Physics*, 2012 **15**(3): 33601.
37. Khanouki MA, Sedaghati R, Hemmatian M. Adaptive Dynamic Moduli of Magnetorheological Elastomers: From Experimental Identification to Microstructure-Based Modeling. *Materials Science and Engineering: B*, 2021 **267**: 115083.
38. Yunus NA, Mazlan SA, Ubaidillah, Choi SB, Imaduddin F, Aziz SAA, *et al.* Rheological Properties of Isotropic Magnetorheological Elastomers Featuring an Epoxidized Natural Rubber. *Smart Materials and Structures*, 2016 **25**(10): 107001.
39. Chen L, Jerrams S. A Rheological Model of the Dynamic Behavior of Magnetorheological Elastomers. *Journal of Applied Physics*, 2011 **110**(1):

013513.

40. Ulmer JD. Strain Dependence of Dynamic Mechanical Properties of Carbon Black-Filled Rubber Compounds. *Rubber Chemistry and Technology*, 1996 **69**(1): 15–47.

41. Lion A, Kardelky C, Haupt P. On the Frequency and Amplitude Dependence of the Payne Effect: Theory and Experiments. *Rubber Chemistry and Technology*, 2003 **76**(2): 533–547.

42. Kraus G. Mechanical Losses in Carbon-Black-Filled Rubbers. *Journal of Applied Polymer Science: Applied Polymer Symposium*, 1984 **39**: 75–92.

43. Vatandoost H, Alehashem SMS, Norouzi M, Taghavifar H, Ni YQ. A Supervised Artificial Neural Network-Assisted Modeling of Magnetorheological Elastomers in Tension–Compression Mode. *IEEE Transactions on Magnetics*, 2019 **55**(12): 1–8.

44. Leng D, Xu K, Ma Y, Liu G, Sun L. Modeling the Behaviors of Magnetorheological Elastomer Isolator in Shear-Compression Mixed Mode Utilizing Artificial Neural Network Optimized by Fuzzy Algorithm (ANNOFA). *Smart Materials and Structures*, 2018 **27**(11): 115026.

45. Razi MM, Kelessidis VC, Maglione R, Ghiass M, Ghayyem MA. Experimental Study and Numerical Modeling of Rheological and Flow Behavior of Xanthan Gum Solutions Using Artificial Neural Network. *Journal of Dispersion Science and Technology*, 2014 **35**(12): 1793–1800.

46. Xu X, Gupta N. Artificial Neural Network: Artificial Neural Network Approach to Predict the Elastic Modulus from Dynamic Mechanical Analysis Results (Adv. Theory Simul. 4/2019). *Advanced Theory and Simulations,* 2019 **2**(4): 1970011.

47. Pham BT, Nguyen-Thoi T, Ly HB, Nguyen MD, Al-Ansari N, Tran VQ, *et al.* Extreme Learning Machine Based Prediction of Soil Shear Strength: A Sensitivity Analysis Using Monte Carlo Simulations and Feature Backward Elimination. *Sustainability*, 2020 **12**(6): 2339.

48. Zhang J, Xu J, Liu C, Zheng J. Prediction of Rubber Fiber Concrete Strength Using Extreme Learning Machine. *Frontiers in Materials*, 2021 **7**: 465.

49. Yu Y, Li YC, Li JC, Gu XY, Royel S, Pokhrel A. Nonlinear and Hysteretic Modelling of Magnetorheological Elastomer Base Isolator Using Adaptive Neuro-Fuzzy Inference System. *Applied Mechanics and Materials,* 2016 **846**:

258–263.

50. Yu Y, Li Y, Li J, Gu X. Self-Adaptive Step Fruit Fly Algorithm Optimized Support Vector Regression Model for Dynamic Response Prediction of Magnetorheological Elastomer Base Isolator. *Neurocomputing*, 2016 **211**: 41–52.
51. Zhao S, Ma Y, Leng D. An Intelligent Artificial Neural Network Modeling of a Magnetorheological Elastomer Isolator. *Algorithms*, 2019 **12**(9): 195.
52. Omari MA, Almagableh A, Sevostianov I, Ashhab MS, Yaseen AB. Modeling of the Viscoelastic Properties of Thermoset Vinyl Ester Nanocomposite Using Artificial Neural Network. *International Journal of Engineering Science*, 2020 **150**: 103242.
53. Kianfar E, Shirshahi M, Kianfar F, Kianfar F. Simultaneous Prediction of the Density, Viscosity and Electrical Conductivity of Pyridinium-Based Hydrophobic Ionic Liquids Using Artificial Neural Network. *Silicon*, 2018 **10**(6): 2617–2625.
54. Yusoff NIM, Alhamali DI, Ibrahim ANH, Rosyidi SAP, Hassan NA. Engineering Characteristics of Nanosilica/Polymer-Modified Bitumen and Predicting Their Rheological Properties Using Multilayer Perceptron Neural Network Model. *Construction and Building Materials*, 2019 **204**: 781–799.
55. Zhang P, Yin ZY, Jin YF, Liu XF. Modelling the Mechanical Behaviour of Soils Using Machine Learning Algorithms with Explicit Formulations. *Acta Geotechnica*, 2022 **17**(4): 1403–1422.
56. Khairi MHA, Fatah AYA, Mazlan SA, Ubaidillah U, Nordin NA, Ismail NIN, *et al.* Enhancement of Particle Alignment Using Silicone Oil Plasticizer and Its Effects on the Field-Dependent Properties of Magnetorheological Elastomers. *International Journal of Molecular Sciences*, 2019 **20**(17): 4085.
57. Dassisti M, Brunetti G. Introduction to Magnetorheological Fluids. In: Olabi AGBTE of SM, editor. *Encyclopedia of Smart Materials*, Oxford: Elsevier; 2022.
58. Lopez-Lopez MT, Duran JDG, Zubarev AY. Rheological Analysis of Magnetorheological Fluids. In: Olabi AGBTE of SM, editor. *Ecyclopedia of Smart Materials*, Oxford: Elsevier; 2022.
59. Wang X, Gordaninejad F. Study of Magnetorheological Fluids at High Shear Rates. *Rheologica Acta*, 2006 **45**(6): 899–908.

60. Li Y, Li J. A Highly Adjustable Base Isolator Utilizing Magnetorheological Elastomer: Experimental Testing and Modeling. *Journal of Vibration and Acoustics*, 2015 **137**(1): 011009.
61. Zhao L, Yu M, Fu J, Zhu M, Li B. A Miniature MRE Isolator for Lateral Vibration Suppression of Bridge Monitoring Equipment: Design and Verification. *Smart Materials and Structures*, 2017 **26**(4): 047001.
62. Mohamad N, Ubaidillah, Mazlan SA, Imaduddin F, Choi SB, Yazid IIM. A Comparative Work on the Magnetic Field-Dependent Properties of Plate-like and Spherical Iron Particle-Based Magnetorheological Grease. *PLOS ONE*, 2018 **13**(4): e0191795.
63. Muhazeli NS, Nordin NA, Ubaidillah U, Mazlan SA, Aziz SAA, Nazmi N, *et al.* Magnetic and Tunable Sound Absorption Properties of an In-Situ Prepared Magnetorheological Foam. *Materials*, 2020 **13**(24): 5637.
64. Pang H, Xuan S, Liu T, Gong X. Magnetic Field Dependent Electro-Conductivity of the Graphite Doped Magnetorheological Plastomers. *Soft Matter*, 2015 **11**(34): 6893–6902.
65. Bunoiu M, Bica I. Magnetorheological Elastomer Based on Silicone Rubber, Carbonyl Iron and Rochelle Salt: Effects of Alternating Electric and Static Magnetic Fields Intensities. *Journal of Industrial and Engineering Chemistry*, 2016 **37**: 312–318.
66. Zhang Y, Fang F, Huang W, Chen Y, Qi S, Yu M. Dynamic Mechanical Hysteresis of Magnetorheological Elastomers Subjected to the Cyclic Loading and Periodic Magnetic Field. *Frontiers in Materials*, 2019 **6**: 262.
67. Ubaidillah, Imaduddin F, Li Y, Mazlan SA, Sutrisno J, Koga T, *et al.* A New Class of Magnetorheological Elastomers Based on Waste Tire Rubber and the Characterization of Their Properties. *Smart Materials and Structures*, 2016 **25**(11): 115002.
68. Bose H. Viscoelastic Properties of Silicone-Based Magnetorheological Elastomers. *International Journal of Modern Physics B*, 2007 **21**: 4790–4797.
69. Lokander M, Stenberg B. Improving the Magnetorheological Effect in Isotropic Magnetorheological Rubber Materials. *Polymer Testing*, 2003 **22**(6): 677–680.
70. Sorokin V V., Ecker E, Stepanov G V., Shamonin M, Monkman GJ, Kramarenko EY, *et al.* Experimental Study of the Magnetic Field Enhanced Payne Effect in Magnetorheological Elastomers. *Soft Matter*, 2014 **10**(43):

8765–8776.

71. Li WH, Zhang XZ, Du H. Magnetorheological Elastomers and Their Applications. In: Visakh PM, Thomas S, Chandra AK, Mathew AP, editors. *Advances in Elastomers I: Blends and Interpenetrating Networks*, Berlin, Heidelberg: Springer Berlin Heidelberg; 2013.
72. Stepanov G, Borin D, Odenbach S. Magnetorheological Effect of Magneto-Active Elastomers Containing Large Particles. *Journal of Physics: Conference Series*, 2009 **149**: 012098.
73. Chen L, Gong XL, Li WH. Effect of Carbon Black on the Mechanical Performances of Magnetorheological Elastomers. *Polymer Testing*, 2008 **27**(3): 340–345.
74. Ivaneyko D, Toshchevikov V, Saphiannikova M. Dynamic Moduli of Magneto-Sensitive Elastomers: A Coarse-Grained Network Model. *Soft Matter*, 2015 **11**(38): 7627–7638.
75. Han Y, Hong W, Faidley LE. Field-Stiffening Effect of Magneto-Rheological Elastomers. *International Journal of Solids and Structures*, 2013 **50**(14–15): 2281–2288.
76. Jolly MR, Carlson JD, Muñoz BC. A Model of the Behaviour of Magnetorheological Materials. *Smart Materials and Structures*, 1996 **5**(5): 607–614.
77. Akbari E, Khajehsaeid H. A Continuum Magneto-Mechanical Model for Magnetorheological Elastomers. *Smart Materials and Structures*, 2021 **30**(1): 015008.
78. Ivaneyko D, Toshchevikov V, Saphiannikova M. Dynamic-Mechanical Behaviour of Anisotropic Magneto-Sensitive Elastomers. *Polymer*, 2018 **147**: 95–107.
79. Khanouki MA, Sedaghati R, Hemmatian M. Experimental Characterization and Microscale Modeling of Isotropic and Anisotropic Magnetorheological Elastomers. *Composites Part B: Engineering*, 2019 **176**: 107311.
80. Li WH, Zhou Y, Tian TF. Viscoelastic Properties of MR Elastomers under Harmonic Loading. *Rheologica Acta*, 2010 **49**(7): 733–740.
81. Blom P, Kari L. A Nonlinear Constitutive Audio Frequency Magneto-Sensitive Rubber Model Including Amplitude, Frequency and Magnetic Field Dependence. *Journal of Sound and Vibration*, 2011 **330**(5): 947–954.

82. Norouzi M, Alehashem SMS, Vatandoost H, Ni YQ, Shahmardan MM. A New Approach for Modeling of Magnetorheological Elastomers. *Journal of Intelligent Material Systems and Structures*, 2015 **27**(8): 1121–1135.
83. Poojary UR, Gangadharan K V. Integer and Fractional Order-Based Viscoelastic Constitutive Modeling to Predict the Frequency and Magnetic Field-Induced Properties of Magnetorheological Elastomer. *Journal of Vibration and Acoustics*, 2018 **140**(4): 041007.
84. Poojary UR, Gangadharan K V. Material Modeling of Frequency, Magnetic Field and Strain Dependent Response of Magnetorheological Elastomer. *Journal of Materials Science*, 2021 **56**(28): 15752–15766.
85. Zhu G, Xiong Y, Li Z, Li M, Bai X `Frank'. A Fractional-Order Model on the Dynamic Mechanical Behavior of Magnetorheological Elastomers. *Smart Materials and Structures*, 2020 **29**(2): 25020.
86. Zhu G, Xiong Y, Li Z, Xiao L, Li M, Bai X 'Frank.' A Nonlinear Dynamic Model of Magnetorheological Elastomers in Magnetic Fields Based on Fractional Viscoelasticity. *Journal of Intelligent Material Systems and Structures*, 2021 **32**(2): 228–239.
87. Nadzharyan TA, Sorokin V V., Stepanov G V., Bogolyubov AN, Kramarenko EY. A Fractional Calculus Approach to Modeling Rheological Behavior of Soft Magnetic Elastomers. *Polymer*, 2016 **92**: 179–188.
88. Agirre-Olabide I, Kuzhir P, Elejabarrieta MJ. Linear Magneto-Viscoelastic Model Based on Magnetic Permeability Components for Anisotropic Magnetorheological Elastomers. *Journal of Magnetism and Magnetic Materials*, 2018 **446**: 155–161.
89. Nam TH, Petríková I, Marvalová B. Experimental Characterization and Viscoelastic Modeling of Isotropic and Anisotropic Magnetorheological Elastomers. *Polymer Testing*, 2020 **81**: 106272.
90. Qiao Y, Zhang J, Zhang M, Liu L, Zhai P. A Magnetic Field- and Frequency-Dependent Dynamic Shear Modulus Model for Isotropic Silicone Rubber-Based Magnetorheological Elastomers. *Composites Science and Technology*, 2021 **204**: 108637.
91. Sorokin V V, Ecker E, Stepanov G V, Shamonin M, Monkman GJ, Kramarenko EY, *et al.* Experimental Study of the Magnetic Field Enhanced Payne Effect in Magnetorheological Elastomers. *Soft Matter*, 2014 **10**(43): 8765–8776.

92. Cho JH, Youn SK. A Viscoelastic Constitutive Model of Rubber under Small Oscillatory Load Superimposed on Large Static Deformation Considering the Payne Effect. *Archive of Applied Mechanics*, 2006 **75**(4–5): 275–288.
93. Wu J, Chen L, Su BL, Wang YS. Evolution of Payne Effect of Silica-Filled Natural Rubber in Curing Process. *Journal of Rubber Research*, 2019 **22**(3): 127–132.
94. Walter BL, Pelteret JP, Kaschta J, Schubert DW, Steinmann P. Preparation of Magnetorheological Elastomers and Their Slip-Free Characterization by Means of Parallel-Plate Rotational Rheometry. *Smart Materials and Structures*, 2017 **26**(8): 85004.
95. Suo S, Xu Z, Li W, Gan Y. Improved Mathematical Model for Analysis of the Payne Effect of Magnetorheological Elastomers. *Journal of Aerospace Engineering*, 2018 **31**(5): 04018046.
96. Bahiuddin I. A Modeling Platform of Magnetorheological Fluids Using An Extreme Learning Machine Method. 2019.
97. Kopal I, Harničárová M, Valíček J, Kušnerová M. Modeling the Temperature Dependence of Dynamic Mechanical Properties and Visco-Elastic Behavior of Thermoplastic Polyurethane Using Artificial Neural Network. *Polymers*, 2017 **9**(10): 519.
98. Xu X, Gupta N. Artificial Neural Network Approach to Determine Elastic Modulus of Carbon Fiber-Reinforced Laminates. *JOM*, 2019 **71**(11): 4015–4023.
99. Kopal I, Harničárová M, Valíček J, Krmela J, Lukáč O. Radial Basis Function Neural Network-Based Modeling of the Dynamic Thermo-Mechanical Response and Damping Behavior of Thermoplastic Elastomer Systems. *Polymers*, 2019 **11**(6): 1074.
100. Guo Q, Wang S. Free Vibration Analysis and Optimal Design of Adhesively Bonded Double-Strap Joints by Using Artificial Neural Networks. *Latin American Journal of Solids and Structures*, 2020 **17**(4): e271.
101. Chen Q, Wang C, Song L. Prediction of Low-Temperature Rheological Properties of SBS Modified Asphalt. *Advances in Civil Engineering*, 2020 **2020**: 8864766.
102. Uwanuakwa ID, Ali SI, Hasan MR, Akpinar P, Sani A, Shariff KA. Artificial Intelligence Prediction of Rutting and Fatigue Parameters in Modified Asphalt

Binders. *Applied Sciences*, 2020 **10**(21): 7764.

103. Lin T, Wang Z, Wang W, Sui Y. A Neural Network-Based Algorithm for High-Throughput Characterisation of Viscoelastic Properties of Flowing Microcapsules. *Soft Matter*, 2021 **17**(15): 4027–4039.

104. Alsabaa A, Elkatatny S. Improved Tracking of the Rheological Properties of Max-Bridge Oil-Based Mud Using Artificial Neural Networks. *ACS Omega*, 2021 **6**(24): 15816–15826.

105. Yang C, Ma W, Zhong J, Zhang Z. Comparative Study of Machine Learning Approaches for Predicting Creep Behavior of Polyurethane Elastomer. *Polymers*, 2021 **13**(11): 1768.

106. Ali Y, Hussain F, Irfan M, Buller AS. An EXtreme Gradient Boosting Model for Predicting Dynamic Modulus of Asphalt Concrete Mixtures. *Construction and Building Materials*, 2021 **295**: 123642.

107. Imaduddin F, Mazlan SA, Ubaidillah, Idris MH, Bahiuddin I. Characterization and Modeling of a New Magnetorheological Damper with Meandering Type Valve Using Neuro-Fuzzy. *Journal of King Saud University - Science*, 2017 **29**(4): 468–477.

108. Bahiuddin I, Imaduddin F, Mazlan SA, Ariff MHM, Mohmad KB, Ubaidillah, *et al.* Accurate and Fast Estimation for Field-Dependent Nonlinear Damping Force of Meandering Valve-Based Magnetorheological Damper Using Extreme Learning Machine Method. *Sensors and Actuators A: Physical*, 2021 **318**: 112479.

109. Bahiuddin I, Mazlan SA, Shapiai MI, Choi SB, Imaduddin F, Rahman MAA, *et al.* A New Constitutive Model of a Magneto-Rheological Fluid Actuator Using an Extreme Learning Machine Method. *Sensors and Actuators A: Physical*, 2018 **281**: 209–221.

110. Agrawal AK, Amjadian M. 22 - Seismic component devices. In: Pipinato ABTIBDH (Second E, editor. *Innovation Brigde Design Handbook (Second Edition)*, Butterworth-Heinemann; 2022.

111. Bahiuddin I, Mazlan SA, Shapiai I, Imaduddin F, Ubaidillah, Choi SB. Constitutive Models of Magnetorheological Fluids Having Temperature-Dependent Prediction Parameter. *Smart Materials and Structures*, 2018 **27**(9): 95001.

112. Bahiuddin I, Mazlan SA, Shapiai MI, Imaduddin F, Ubaidillah, Choi SB. A

New Platform for the Prediction of Field-Dependent Yield Stress and Plastic Viscosity of Magnetorheological Fluids Using Particle Swarm Optimization. *Applied Soft Computing Journal*, 2019 **76**: 615–628.

113. Bahiuddin I, Wahab NAA, Shapiai MI, Mazlan SA, Mohamad N, Imaduddin F, *et al.* Prediction of Field-Dependent Rheological Properties of Magnetorheological Grease Using Extreme Learning Machine Method. *Journal of Intelligent Material Systems and Structures*, 2019 **30**(11): 1727–1742.

114. Li S, Tian T, Wang H, Li Y, Li J, Zhou Y, *et al.* Development of a Four-Parameter Phenomenological Model for the Nonlinear Viscoelastic Behaviour of Magnetorheological Gels. *Materials & Design*, 2020 **194**: 108935.

115. Liao G, Fu J, Lai J, Bai J, Yu M. Inverse Modelling of Magnetorheological Elastomer Isolator with Recurrent Neural Network and Genetic Algorithms for Real-time Control. *8th Conference on Smart Structures and Materials SMART 2017 and 6th International Conference on Smart Materials and Nanotechnology in Engineering, SMN 2017*, 2017.

116. Yu Y, Li Y, Li J, Gu X, Royel S. Dynamic modeling of magnetorheological elastomer base isolator based on extreme learning machine. *Mechanics of Structures and Materials: Advancements and Challenges - Proceedings of the 24th Australasian Conference on the Mechanics of Structures and Materials, ACMSM24 2016*, 2017.

117. Yu Y, Li Y, Li J, Gu X, Royel S. Nonlinear Characterization of the MRE Isolator Using Binary-Coded Discrete CSO and ELM. *International Journal of Structural Stability and Dynamics*, 2017 **18**(08): 1840007.

118. Park JE, Lee J, Kim YK. Design of Model-Free Reinforcement Learning Control for Tunable Vibration Absorber System Based on Magnetorheological Elastomer. *Smart Materials and Structures*, 2021 **30**(5): 55016.

119. Fu J, Lai J, Yang Z, Bai J, Yu M. Fuzzy-Neural Network Control for a Magnetorheological Elastomer Vibration Isolation System. *Smart Materials and Structures*, 2020 **29**(7): 74001.

120. Gu X, Yu Y, Li Y, Li J, Askari M, Samali B. Experimental Study of Semi-Active Magnetorheological Elastomer Base Isolation System Using Optimal Neuro Fuzzy Logic Control. *Mechanical Systems and Signal Processing*, 2019 **119**: 380–398.

121. Nguyen XB, Komatsuzaki T, Truong HT. Novel Semiactive Suspension Using

a Magnetorheological Elastomer (MRE)-Based Absorber and Adaptive Neural Network Controller for Systems with Input Constraints. *Mechanical Sciences*, 2020 **11**(2): 465–479.

122. Liu C, Hemmatian M, Sedaghati R, Wen G. Development and Control of Magnetorheological Elastomer-Based Semi-Active Seat Suspension Isolator Using Adaptive Neural Network. *Frontiers in Materials*, 2020 **7**: 171.

123. Maulud D, Abdulazeez AM. A Review on Linear Regression Comprehensive in Machine Learning. *Journal of Applied Science and Technology Trends*, 2020 **1**(4): 140–147.

124. Awad M, Khanna R. Support Vector Regression BT - Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers. In: Awad M, Khanna R, editors. *Efficient Learning Machines*, Berkeley, CA: Apress; 2015.

125. Wu X, Tang W, Wu X. Support Vector Machine Based on Hybrid Kernel Function. In: Zhu R, Ma Y, editors. *Information Engineering and Applications*, London: Springer London; 2012.

126. Krishnan NMA, Mangalathu S, Smedskjaer MM, Tandia A, Burton H, Bauchy M. Predicting the Dissolution Kinetics of Silicate Glasses Using Machine Learning. *Journal of Non-Crystalline Solids*, 2018 **487**: 37–45.

127. Shangguan W, Hengl T, Jesus JM de, Yuan H, Dai Y. Mapping the Global Depth to Bedrock for Land Surface Modeling. *Journal of Advances in Modeling Earth Systems*, 2017 **9**(1): 65–88.

128. Zhang L, Gao T, Cai G, Hai KL. Research on Electric Vehicle Charging Safety Warning Model Based on Back Propagation Neural Network Optimized by Improved Gray Wolf Algorithm. *Journal of Energy Storage*, 2022 **49**: 104092.

129. Choromanska A, Henaff M, Mathieu M, Arous G Ben, LeCun Y. The Loss Surfaces of Multilayer Networks. *Journal of Machine Learning Research*, 2014 **38**: 192–204.

130. Shen L, Qian Q. A Virtual Sample Generation Algorithm Supporting Machine Learning with a Small-Sample Dataset: A Case Study for Rubber Materials. *Computational Materials Science*, 2022 **211**: 111475.

131. Huang GB, Zhu QY, Siew CK. Extreme Learning Machine: Theory and Applications. *Neurocomputing*, 2006 **70**(1–3): 489–501.

132. Zhao Z, Zhang X. Theory and Numerical Analysis of Extreme Learning

Machine and Its Application for Different Degrees of Defect Recognition of Hoisting Wire Rope. *Shock and Vibration*, 2018 **2018**: 1–13.
133. Huang Y wei, Lai D hu. Hidden Node Optimization for Extreme Learning Machine. *AASRI Procedia*, 2012 **3**: 375–380.
134. Schneider A, Hommel G, Blettner M. Linear Regression Analysis: Part 14 of a Series on Evaluation of Scientific Publications. *Deutsches Arzteblatt International*, 2010 **107**(44): 776–782.
135. Uddin S, Haque I, Lu H, Moni MA, Gide E. Comparative Performance Analysis of K-Nearest Neighbour (KNN) Algorithm and Its Different Variants for Disease Prediction. *Scientific Reports*, 2022 **12**(1): 6256.
136. Kim M. The Generalized Extreme Learning Machines: Tuning Hyperparameters and Limiting Approach for the Moore–Penrose Generalized Inverse. *Neural Networks*, 2021 **144**: 591–602.
137. N.Koivo H. NEURAL NETWORKS : Basics Using MATLAB Neural Network Toolbox By. *Neural Networks*, 2008: 1–59.
138. Bahiuddin I, Mazlan SA, Shapiai MI, Imaduddin F, Ubaidillah, Choi SB. Constitutive Models of Magnetorheological Fluids Having Temperature-Dependent Prediction Parameter. *Smart Materials and Structures*, 2018 **27**(9): 095001.
139. Wei S, Wang J, Ou J. Method for Improving the Neural Network Model of the Magnetorheological Damper. *Mechanical Systems and Signal Processing*, 2021 **149**: 107316.
140. Yang G, Pan J, Ye D, Ye K, Gao H. Prediction and Analysis of Thermal Aging Behavior of Magnetorheological Grease. *Materials Research Express*, 2021 **8**(12): 125701.
141. Karsoliya S. Approximating Number of Hidden Layer Neurons in Multiple Hidden Layer BPNN Architecture. *International Journal of Engineering Trends and Technology*, 2012 **3**(6): 714–717.
142. Panchal FS, Panchal M. International Journal of Computer Science and Mobile Computing Review on Methods of Selecting Number of Hidden Nodes in Artificial Neural Network. *International Journal of Computer Science and Mobile Computing*, 2014 **3**(11): 455–464.
143. Cao W, Gao J, Ming Z, Cai S. Some Tricks in Parameter Selection for Extreme Learning Machine. *IOP Conference Series: Materials Science and Engineering*,

vol. 261, IOP Publishing; 2017.

144. Choudhary K, DeCost B, Chen C, Jain A, Tavazza F, Cohn R, *et al.* Recent Advances and Applications of Deep Learning Methods in Materials Science. *Npj Computational Materials*, 2022 **8**(1): 59.

145. Cao Z, Dan Y, Xiong Z, Niu C, Li X, Qian S, *et al.* Convolutional Neural Networks for Crystal Material Property Prediction Using Hybrid Orbital-Field Matrix and Magpie Descriptors. *Crystals*, 2019 **9**(4): 191.

146. Duchanoy CA, Moreno-Armendáriz MA, Moreno-Torres JC, Cruz-Villar CA. A Deep Neural Network Based Model for a Kind of Magnetorheological Dampers. *Sensors (Basel, Switzerland)*, 2019 **19**(6): 1333.

147. Ubaidillah, Purnomo ED, Ismail H, Choi SB, Aziz SAA, Mazlan SA. Swelling, Thermal, and Shear Properties of a Waste Tire Rubber Based Magnetorheological Elastomer. *Frontiers in Materials*, 2019 **6**: 47.

148. Norén-Cosgriff KM, Ramstad N, Neby A, Madshus C. Building Damage Due to Vibration from Rock Blasting. *Soil Dynamics and Earthquake Engineering*, 2020 **138**: 106331.

149. Fakhree MAM, Nordin NA, Nazmi N, Mazlan SA, Aziz SAA, Ubaidillah U, *et al.* Field-Dependent Rheological Properties of Magnetorheological Elastomer with Fountain-Like Particle Chain Alignment. *Micromachines*, 2022 **13**(4): 492.

150. Yunus NA, Mazlan SA, Ubaidillah, Aziz SAA, Shilan ST, Wahab NAA. Thermal Stability and Rheological Properties of Epoxidized Natural Rubber-Based Magnetorheological Elastomer. *International Journal of Molecular Sciences*, 2019 **20**(3): 746.

151. Fan Y, Gong X, Xuan S, Zhang W, Zheng J, Jiang W. Interfacial Friction Damping Properties in Magnetorheological Elastomers. *Smart Materials and Structures*, 2011 **20**(3): 035007.

152. Chen L, Gong X long, Li W hua. Damping of Magnetorheological Elastomers. *Chinese Journal of Chemical Physics*, 2008 **21**(6): 581–585.

153. Paturi UMR, Cheruku S, Reddy NS. The Role of Artificial Neural Networks in Prediction of Mechanical and Tribological Properties of Composites—A Comprehensive Review. *Archives of Computational Methods in Engineering*, 2022.

154. Sherif EB, Ragaa AEH, Ahmed A. Comparing Artificial Neural Networks with

Regression Models for Hot-Mix Asphalt Dynamic Modulus Prediction. *Journal of Materials in Civil Engineering*, 2018 **30**(7): 4018128.

155. S.J.Elliott. Active Control of Nonlinear System. *Signal Processing for Active Control*, Elsevier; 2001.

156. Kopal I, Labaj I, Harničárová M, Valíček J, Hrubý D. Prediction of the Tensile Response of Carbon Black Filled Rubber Blends by Artificial Neural Network. *Polymers*, 2018 **10**(6): 644.

157. Rodríguez-Sánchez AE. An Artificial Neural Networks Approach to Predict Low-Velocity Impact Forces in an Elastomer Material. *SIMULATION*, 2020 **96**(6): 551–563.

158. Aziz SAA, Mazlan SA, Ubaidillah U, Mohamad N, Sedlacik M, Nordin NA, *et al.* Loss Factor Behavior of Thermally Aged Magnetorheological Elastomers. *Materials*, 2021 **14**(17): 4874.

159. Baldo N, Manthos E, Miani M. Stiffness Modulus and Marshall Parameters of Hot Mix Asphalts: Laboratory Data Modeling by Artificial Neural Networks Characterized by Cross-Validation. *Applied Sciences*, 2019 **9**(17): 3502.

160. Lyu Z, Yu Y, Samali B, Rashidi M, Mohammadi M, Nguyen TN, *et al.* Back-Propagation Neural Network Optimized by K-Fold Cross-Validation for Prediction of Torsional Strength of Reinforced Concrete Beam. *Materials*, 2022 **15**(4): 1477.

161. García-Laencina PJ, Roca-Gonzáles JL, Bueno-Crespo A, Sancho-Gómez JL. Exploiting Diversity of Nueral Network Ensembles Based on Extreme Learning Machine. *Neural Network World*, 2013 **23**(5): 395–409.

162. Xu K, Zhang M, Li J, Du SS, Kawarabayashi K ichi, Jegelka S. How Neural Networks Extrapolate: From Feedforward to Graph Neural Networks. *ArXiv Preprint*, 2020 **Sep 24**: 11848.

163. Szandała T. Review and Comparison of Commonly Used Activation Functions for Deep Neural Networks. *Studies in Computational Intelligence*, 2020 **903**: 203–224.

164. Jalal M, Grasley Z, Gurganus C, Bullard JW. RETRACTED: Experimental Investigation and Comparative Machine-Learning Prediction of Strength Behavior of Optimized Recycled Rubber Concrete. *Construction and Building Materials*, 2020 **256**: 119478.

165. Rabbani Y, Shirvani M, Hashemabadi SH, Keshavarz M. Application of

Artificial Neural Networks and Support Vector Regression Modeling in Prediction of Magnetorheological Fluid Rheometery. *Colloids and Surfaces A: Physicochemical and Engineering Aspects*, 2017 **520**: 268–278.

166. Aziz SAA, Mazlan SA, Ismail NIN, Ubaidillah, Choi SB, Nordin NA, *et al.* A Comparative Assessment of Different Dispersing Aids in Enhancing Magnetorheological Elastomer Properties. *Smart Materials and Structures*, 2018 **27**(11): 15.

167. Tong Y, Dong X, Qi M. Improved Tunable Range of the Field-Induced Storage Modulus by Using Flower-like Particles as the Active Phase of Magnetorheological Elastomers. *Soft Matter*, 2018 **14**(18): 3504–3509.

168. Ying X. An Overview of Overfitting and its Solutions. *Journal of Physics: Conference Series*, vol. 1168, {IOP} Publishing; 2019.

169. Dou T, Zhou X. The Fast Computation Methods for Extreme Learning Machine. *Proceedings of the 2nd International Conference on Intelligent Computing and Cognitive Informatics*, Atlantis Press; 2015.

LIST OF PUBLICATIONS

Journal With Impact Factor

1. Saharuddin, K,D., Ariff, M.H.M., Bahiuddin, I., Mazlan, S.A., Aziz, S.A.A., Nazmi, N., and Fatah, A.Y.A., Constitutive model for prediction field-dependent viscoelastic behavior of magnetorheological elastomer using machine learning. *Smart Mater. Struct.* (**Q1, 4.131**) **29**, 087001 (2020). https://iopscience.iop.org/article/10.1088/1361-665X/ab972d

2. Saharuddin, K.D., Ariff, M.H.M., Bahiuddin, I., Ubaidillah, U., Mazlan, S.A., Aziz, S.A.A., Nazmi, N., Fatah, A.Y.A., and Shapiai, M.I., Non-parametric multiple inputs prediction model for magnetic field dependent complex modulus of magnetorheological elastomer. *Sci Rep* (**Q2, 4.996**) **12,** 2657 (2022). https://doi.org/10.1038/s41598-022-06643-4

Indexed Journal (WOS)

1. Saharuddin, K. D., Ariff, M. H. M., Mohmad, K., Bahiuddin, I., Ubaidillah,, Mazlan, S. A., Nazmi, N. and Fatah, A. Y. A.. "Prediction Model of Magnetorheological (MR) Fluid Damper Hysteresis Loop using Extreme Learning Machine Algorithm" *Open Engineering*, vol. 11, no. 1, 2021, pp. 584-591. https://doi.org/10.1515/eng-2021-0053

Conference Proceeding

1. Saharuddin, K,D., Ariff, M.H.M., Bahiuddin, I., Mazlan, S.A., Aziz, S.A.A., Nazmi, N., and Fatah, A.Y.A.,. *IOP Conf. Ser.: Mater. Sci. Eng.* **1051** 012094. https://iopscience.iop.org/article/10.1088/1757-899X/1051/1/012094