MAGNETOSTRICTION BEHAVIOR MODELING OF MAGNETORHEOLOGICAL FOAM USING DATA-DRIVEN NEURAL NETWORK ALGORITHM

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DEDICATION

This thesis is dedicated to my family. I am incredibly grateful to my supportive parents, whose words of wisdom and insistence on perseverance still echo in my mind. My brother and younger sister have always been there for me, and they're both very important in my life.

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ABSTRACT

Magnetorheological (MR) foam is a magnetic polymer composite (MPC) that has the potential to be used for the application of soft sensors and actuators in robotics due to its tuneable mechanical properties and magnetostriction. Material development has recently become challenging since it is both time-consuming and costly. As such, it is crucial to model the mechanical properties and magnetostriction of MR foam to expedite the development of MR foam devices. As a consequence, extreme learning machine (ELM) and artificial neural network (ANN) machine learning models for predicting the magnetostriction behavior are performed. These models were developed to describe the non-linear relationship between different carbonyl iron particles (CIP) compositions and magnetic field as inputs, whereas strain and normal force as outputs. The model had variation hyperparameters, such as different learning algorithms and activation functions. For ANN, RMSProp and ADAM learning algorithms were applied with two different activation functions, sigmoid and ReLU. The ELM model, on the other hand, considered the Hard limit (HL), ReLU and sigmoid activation function. Then, the model was assessed for both training and testing datasets. Based on the results, RMSProp with activation function sigmoid of ANN model showed an agreeable accuracy with the experimental data compared to the other models. However, the correlation analysis and comparison between prediction and experimental data showed that ELM HL was more generalized in predicting strain and normal force with R2, 0.999 and root mean square error (RMSE) less than 0.002 respectively. In conclusion, the ELM HL model successfully predicts the magnetostriction behavior of MR foam at various compositions that could be applied in the development of MR foam devices in the near future.

ABSTRAK

Reologi magnet (MR) busa adalah komposit polimer magnetik (MPC) yang berpotensi digunakan untuk penggunaan sensor dan penggerak lembut dalam robotik kerana sifat mekaniknya dan *magnetostriction* yang dapat diselaraskan. Pembangunan bahan baru-baru ini menjadi cabaran kerana memakan masa dan kos yang tinggi. Oleh itu, adalah sangat penting untuk memodelkan sifat mekanikal dan magnetostriction MR busa untuk mempercepatkan pembangunan peranti MR busa. Disebabkan itu, mesin pembelajaran ekstrem (ELM) dan rangkaian neural buatan (ANN) model pembelajaran mesin untuk meramalkan tingkah laku *magnetostriction* dijalankan. Model-model ini dibangunkan untuk menerangkan hubungan tidak linear antara zarah besi karbonil (CIP) yang berbeza komposisi dan medan magnet sebagai input, sementara terikan dan daya normal sebagai output. Model ini mempunyai variasi *hyperparameters*, seperti algoritma pembelajaran dan fungsi pengaktifan yang berbeza. Untuk algoritma pembelajaran ANN, RMSProp dan ADAM digunakan dengan dua fungsi pengaktifan yang berbeza, sigmoid dan ReLU. Selain itu, model ELM mempertimbangkan fungsi pengaktifan had keras (HL), ReLU dan sigmoid. Kemudian, model itu dinilai untuk kedua-dua set data latihan dan ujian. Berdasarkan hasilnya, RMSProp dengan fungsi pengaktifan sigmoid model ANN mempunyai ketepatan yang dapat dipersetujui dengan data eksperimen berbanding model yang lain. Walau bagaimanapun, analisis korelasi dan perbandingan antara data ramalan dan eksperimen menunjukkan bahawa ELM HL lebih generalisasi dalam meramalkan terikan dan daya normal dengan masing-masing mendapat R2, 0.999 dan ralat *root mean square* (RMSE) yang kurang dari 0.002. Kesimpulannya, model ELM HL Berjaya meramalkan tingkah laku *magnetostriction* MR busa pada pelbagai komposisi yang dapat digunakan untuk penbangunan peranti MR busa dalam masa terdekat.

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LIST OF ABBREVIATIONS

ADAM	-	Adaptive Moment Estimation
ANN	-	Artificial Neural Network
BVP	-	Boundary Value Problems
CFD	-	Computational Fluid Dynamics
ELM	-	Extreme Learning Machine
MCR	-	Modular Compact Rheometer
MH	-	Magnetically Hard
MPC	-	Magnetic Polymer Composite
MR	-	Magnetorheological
MRE	-	Magnetorheological Elastomer
MS	-	Magnetically Soft
PU	-	Polyurethane
R2	-	R-Squared
ReLU	-	Rectified Linear Unit
RMSE	-	Root Mean Square Error
RMSProp	-	Root Mean Squared Propagation
SGD	-	Stochastic Gradient Descent
SLFN	-	Single hidden layers feedforward neural network
Tr	-	Training data
Ts	-	Testing data

LIST OF SYMBOLS

$\vec{\mu}_h$	-	Dipole Moment
B	-	Magnetic Field Density
b	-	Bias
d	-	Diameter
ε	-	Strain
δJ/δw	-	Cost Function Gradient to Weight
E	-	Young Modulus
$E[(J)^2]$	-	Moving Average of Square Gradients
F_N	-	Normal Force
g	-	Gram
H	-	Magnetic Field Strength
h	-	Hidden Node
$\mathbf{H}^{\dagger}$	-	Moore Penrose Inverse
Hc	-	Coercive Force
L	-	Length
m_i, v_i	-	First and second momentum
Mr	-	Remanence
T	-	Tesla
V_H	-	High Velocity
V_L	-	Low Velocity
w	-	Weight
wt%	-	Weight Percent
x	-	Input
y	-	Output
ΔL	-	Total Length
N	-	Newton

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CHAPTER 1

INTRODUCTION

1.1 Problem Background

One of the areas in robotic research that is now making a significant development is using magnetostrictive materials such as Magnetic Polymer Composites (MPC) to accomplish the soft robotic goals in applying in the fields of bio-medicine, bio-mimicry, and robotic grasping, as shown in Figure 1.1 [1]. It can also be seen that those studies have manipulated and controlled the movement of soft robotics through the presence of a magnetic field using MPC. In other words, MPC materials can be classified as smart materials because their properties can be varied by external stimuli, such as their responsiveness to external magnetic inducement [2]. Generally, MPC is fabricated from a soft polymer matrix with magnetic particles embedded in it. When the magnetic field is applied, the MPC material exhibits mechanical deformation either by contracting or expanding the length of the material due to the induced magnetic particles. The deformation of the material is generally referred to as magnetostriction. Magnetostriction has the ability to have reversible exchange energy between the mechanical form and the magnetic form. This shows that the magnetostriction has a transduction capability that allows the material to be used in actuator and sensor applications [3].

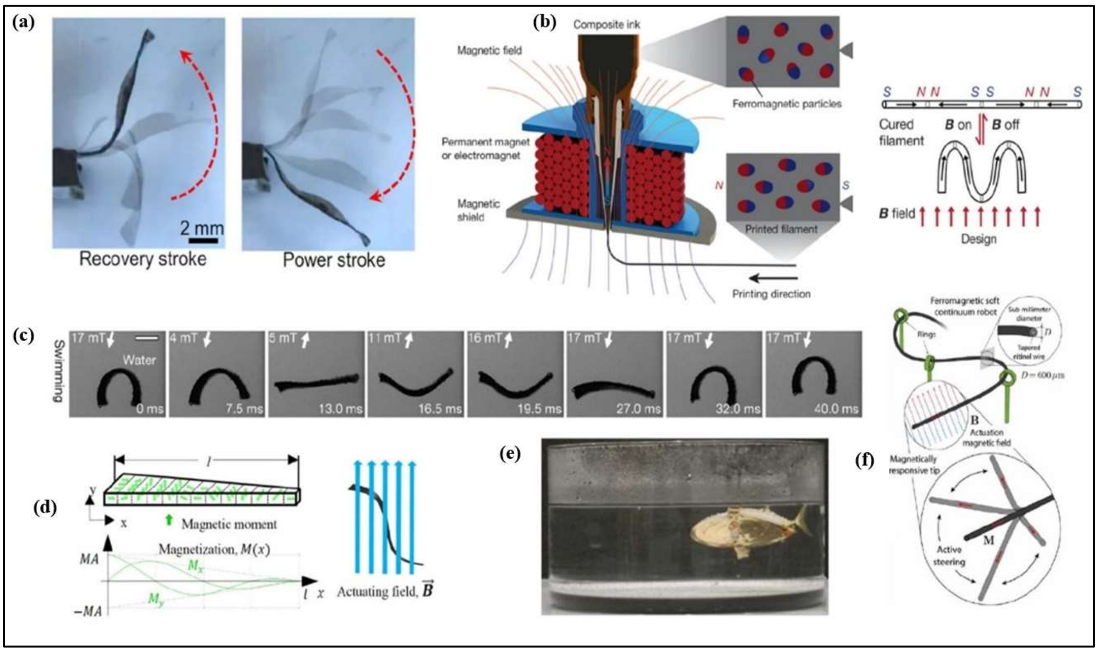

Figure 1.1 MPC soft robotic applications: (a) Shape- programmable magnetic soft matter, (b) Printing ferromagnetic domains (c) Small-scale soft-bodied robot, (d) Magnetic soft robot, (e) Self-folded soft robotic structures and (f) Ferromagnetic soft continuum robots. [1]

Recently, the main challenge faced by many researchers is the magnetostrictive materials development towards application. According to Bahiuddin et al. [4], material development is not only time-consuming but requires a large workforce and the cost of the materials. Thus, introducing a model to represent the material's properties can be used to speed up the development process. Furthermore, modeling may provide a theoretical definition of the material because models are substitute systems tested to gather information on their target systems, indirectly allowing them to exploit its capabilities and fully tailor their performance [4].

1.2 Motivation of study

Several authors have proposed a model to describe MPC material magnetostriction. Most of the approaches relied on parametric models. For instance, one known MPC material is MR material, such as MR elastomer (MRE). MRE typically represents a two-component system of micron-sized magnetizable particles embedded into a non-magnetizable polymer matrix. Due to particle-particle interactions on the microscopic scale, these materials can alter their macroscopic behavior reversibly when subjected to an external magnetic field. In terms of modeling, researchers have proposed mesoscopic models [5–7] to consider the magnetostriction effect by performing a numerical homogenization procedure. However, these models were suitable for a small deformation because they depended on the interaction of both the magneto-mechanical properties and the dimension of the material. In addition, Romeis et al. [8] modeled the magnetostriction effect by using the Hookean body under uniaxial deformation, but this model was also for a small deformation. In another study, Sanchez et al. [9] presented a twofold modeling strategy to analyse the magnetostriction behavior for MRE material with a mixture of magnetically soft and hard spherical microparticles. The model represented magnetostriction for an elementary material cell consisting of central magnetically hard particles surrounded by a cloud of magnetically soft particles, all mechanically bound by an elastic matrix. Nevertheless, these parametric models need to consider the microstructure of the material and their primary purpose is to classify different detailed information when designing devices [10]. Thus, applying these models might involve a complicated mathematical derivation that may inhibit incorrect identification of parameters that affect model efficiency [11]. Although these parametric models can accommodate the relationship between the applied magnetic field and strain, Sorokin et al. [12] found another important parameter, particularly normal force, because the normal force is directly related to magnetostriction. The reason is that normal force increases based on the applied magnetic field, which attempt the material to elongate itself in a homogenous magnetic field [13]. In addition, Liao et al. [14] stated that when a normal force was coupled with the magnetostrictive process, it could be highly effective in developing actuators and sensors.

On the other hand, machine learning has several advantages over parametric models in which the input-output relationship can be non-linear without parameter identification. Machine learning is considered artificial intelligence incorporating previous data experience to extrapolate future performances [15]. Implementing machine learning techniques can reduce the workload and accelerate discoveries in computational or experimental studies [16]. Besides that, machine learning has not only been shown to be an effective approach for learning and predicting the material properties of experimental data [17], but it is also frequently employed in studying MR materials [18]. Most of the machine learning techniques that are widely utilized are Artificial Neural Network (ANN) and Extreme Learning Machine (ELM) because of the model capabilities. ANN can control many variables for which the analytical models would be complicated to create. ANN provide a straightforward way to assess potential outcomes on a complicated problem and a compact approach to handling vast volumes of data [19]. Meanwhile, ELM advantages include improved scalability, good generalization performance for regression and classification, a more excellent approximation of any target continuous function, reduced computational complexity, and faster learning speed [20], [21]. In general, machine learning models have been implemented in MPC materials especially MRE, such as Zhao et al. [22] employed an ANN to forecast the dynamic properties of the MRE isolator and Saharuddin et al. [23] used an ELM to predict viscoelastic properties. As a result, both models gained a higher accuracy.

Recently, a new material, known as magnetorheological (MR) foam, has been introduced into MPC material. MR foam is made up of micron-sized magnetically permeable particles, such as carbonyl iron particles (CIP), which manifest themselves in the porous absorbent foam matrix during the foaming process [24]–[26]. The magnetostriction behavior of MR foam is controllable and reversible by altering the external magnetic field [27]. Because of its low density, soft matter, and tunable properties [28]–[30], this material has great promise for application in soft sensors and actuators for soft robotics.

1.3 Problem Statement

The MR magnetostriction models are crucial in the advancement of nonlinear materials, particularly in terms of device application. Although existing studies had proposed the magnetostriction model for MRE, most models have challenges in predicting the magnetostriction behavior, such as dependency on the microstructure of the materials, the use of complex mathematical derivation, and limited to a single prediction at a time. Recently, machine learning has not only been shown to be a practical approach for learning and predicting the material properties of experimental data, but it is also frequently employed in the study of MR materials, yet research related to magnetostriction has not been reported. Since MR foam is a potential candidate for soft robotic applications, the magnetostriction model of MR foam for various range predictions has to be undertaken to gain a fundamental understanding of the materials. In addition, strain and normal force are important in developing the actuators and sensors, especially when they depend on the magnetic particle's concentration and magnetic field intensity.

1.4 Research Objectives

The main objective of the research is to propose a new magnetostriction model of MR foam using machine learning. In order to achieve this goal, several objectives of the research have been identified:

(a) To develop a modeling platform of MR foam magnetostriction using ANN and ELM.

(b) To analyse the correlation between the dataset of different machine learning hyperparameters of ANN and ELM.

(c) To evaluate the prediction model accuracy of ANN and ELM by comparing with experimental data.

1.5 Research Scope

This research develops a new platform to predict the MR foam magnetostriction behavior using machine learning. The scope of this study includes:

(a) Fabrication of MR foam with five different compositions varying in weight of CIP, which are 35%, 45%, 55%, 65% and 75%.

(b) Magnetostriction and normal force of MR foam was obtained by using a rheometer under oscillatory mode.

(c) The magnetostriction model was developed using neural networks, particularly ANN and ELM, with different hyperparameters based on various inputs covering magnetic fields and CIP composition. Meanwhile, the output for the magnetostriction behavior is strain and normal force. The ANN model utilized RMSProp and the ADAM learning algorithm, each using sigmoid and ReLU activation functions. Meanwhile, ELM utilized sigmoid, ReLU and Hard limit (HL) activation functions.

1.6 Outlines of thesis

This thesis consists of five chapters and the main contents of each chapter are given below:

Chapter 1 provides a brief introduction to the background of the research followed by the motivation and the problem statement that clearly identifies the research gap, research objectives, and research scope.

Chapter 2 reviews the literature on MPC magnetostriction modeling and the recent issues of machine learning techniques in different fields. The review begins with a brief introduction to magnetostriction behavior and then focuses on MPC material, modeling, and machine learning methods in different fields. Research gaps have been identified due to assessing several fundamental studies on the research topics.

Chapter 3 describes the materials fabrication processes used to develop MR Foam. Furthermore, this chapter also describes the methodology for the proposed machine learning platform development to predict the MR Foam magnetostriction behavior and related experimental works.

Chapter 4 presents the results and discussion on the machine learning models for MR foam magnetostriction behavior prediction. The machine learning models were assessed and compared for the hyperparameter utilized statistical analysis.

Chapter 5 summarizes all previous chapters, concluding remarks, and key accomplishments related to the research objectives. This chapter also suggests future works as an extension of the existing research.

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