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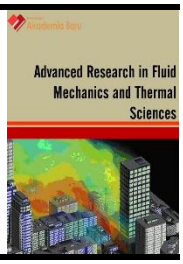

Field Dependent-Shear Stress Prediction of Magnetorheological Fluid Using an Optimum Extreme Learning Machine Model

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ABSTRACT

Extreme learning machine (ELM) application to model the shear stress of magnetorheological (MR) fluids has superiority over the existing methods, such as Herschel-Bulkley. Although the shear stress has been successfully predicted, the hidden node numbers are too high reaching up to 10,000 that will hinder the application of the models. Furthermore, the existing works have tried to determine the hidden node number only by trial and error method. Therefore, this paper aims to reduce the hidden node number by employing the particle swarm optimization (PSO) considering the accuracy and the hidden node numbers. The ELM based-shear stress model was firstly defined by treating the magnetic field and shear rate as the inputs and shear stress as output. The objective function optimization method was then formulated to minimize the normalized error and the hidden node numbers. Finally, the proposed methods were tested at various ELM activation functions and samples. The results have shown that the platform has successfully reduced the hidden node numbers from 10,000 to 571 while maintaining the error of less than 1%. In summary, the proposed objective function for PSO optimization has successfully built the optimum shear stress model automatically.

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1. Introduction

Magnetorheological (MR) fluids have been known for its controllable rheological properties. The control is carried out by applying magnetic fields caused by the magnetic particles within the fluid that make an alignment. Consequently, the yield stress and apparent viscosity values increase. The manipulate-able viscosity properties of the MR fluid have attracted the studies to apply the fluid in various energy dissipation devices, such as MR damper [1-2], MR brake [3-4], MR clutch [5], etc. In the process of applying the fluids, model is an important tool to design and calculate the devices performance before fabrication. The examples of the challenge of the model applications are the function complexity, accuracy, various important variables, and various compositions.

The modeling methods have been developed over time ranging from simple equation to the advanced models. The early works namely conventional models have various limitations, such as the acceptable accuracy at a narrow operating range and inflexible input numbers [6]. Some studies have proposed machine learning as the methods to overcome the limitations. For example, Rabbani *et al.,* [7] proposed artificial neural networks (ANN) and support vector regression as the solution. The ANN itself has carried the limitation of the high possibility to be trapped at local solution [8]. Extreme learning machine (ELM) application in MR fluids [9-10], elastomer [11], and grease [12] has been proposed to overcome the limitations. The results have shown that a single model can exceed the accuracy of the conventional models. However, the existing ELM methods show a high number of hidden neuron number (about 10,000). While the lower hidden number reduces the accuracy, the higher number means longer prediction and training time. An optimization method can overcome the problem by formulating the appropriate objective function to consider both criteria. There are many choices to select the optimization methods. One of the widely known methods is particle swarm optimization (PSO). PSO has also been known for its speed prediction and better generalizations [13-16].

Therefore, this work aims to use PSO method to reduce the hidden node number and maintain the accuracy. An objective function was proposed with the intention to reach an optimum condition considering both hidden node number and model error simultaneously. The paper firstly discussed about the proposed platform and the simulation setup including the model description, the optimization algorithm, data description, normalization, and simulation setup. Then, the results are discussed from point of view the accuracy while comparing with the experimental data and the ELM model without optimization.

2. The platform Description

2.1 Model Description

MR fluids can be modeled in various forms depending on the application, such as computational fluid dynamics [13], controls [7,14] and device designs [4], or the study of MR fluid rheology [5,15]. To model the rheological behavior of material, the model can be in the form of a type of neural network, known as a single-hidden layer feed forward neural network (SLFNs), which has been well-described in the previous work [16], and it was trained or solved using an ELM. An ELM is an algorithm that to determine the parameters of single-hidden layer feed forward neural networks without iterations [8, 17-18]. The ELM is known for its enhanced generalization and faster training time than the classic support vector machine and back propagation artificial neural network. The experimental data for training purposes comprised N datasets that included the measured shear stress (τ_{ex}) as a target, and the shear rate ($\dot{\gamma}_i$) and magnetic field ($\mathrm{B_i}$) as the inputs as shown in Figure 1. The model had a total of L hidden nodes. The j-th hidden node was calculated using Eq. (1), where $\mathrm{f_j}(.)$ is the

activation function, β_j is the bias, x_i is the i-th input from the total population of the training data, and a is the weighting input. The hard-limit function was used as the activation function, as expressed in Eq. (2). The i-th output (o_i) or shear stress (τ_i) was defined as in Eq. (3), where w_j is the j-th weighting output.

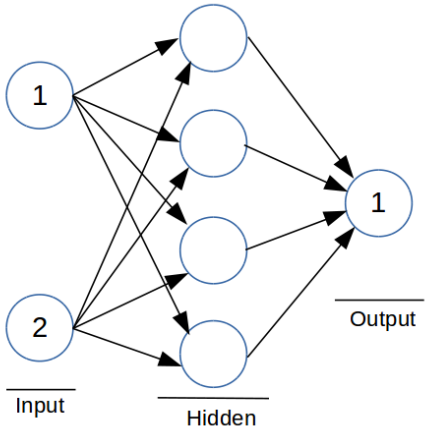

Fig 1. SLFNs with two inputs (magnetic field and shear rate) and one output

$$g_j(x_i) = f_j(\beta_j, x_i, a); x_i = \begin{bmatrix} \dot{\gamma}_i \\ B_i \end{bmatrix}^T ; a = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \tag{1}$$

$$f_j(\beta_j, x_i, a) = g(a, x_i, \beta_j) = \begin{cases} 1, & \text{if } a.x_i + \beta_j \geq 0 \\ 0, & \text{if } a.x_i + \beta_j < 0 \end{cases} \tag{2}$$

$$o_i = \sum_{i=j}^{L} w_j g_j(x_i) \tag{3}$$

The algorithm of ELM to build a model consists of three steps. Firstly, a random distribution continuous function (usually is Gaussian function) are utilized to give value to the inputs weighting or a and bias or β. Then, the matrix output of the hidden nodes is calculated and represented as H in Eq. (4). If the output of hidden nodes and target (T) or the measured data that will be predicted by the mode are known, then the output weighting w can be calculated as shown in Eq. (5) where $H^{\dagger}$is the Moore–Penrose generalized inverse of matrix H. The operation is treated as pseudo inverse case that can be solved by utilizing Singular value decomposition (SVD) [17-18].

$$H = \begin{bmatrix} f(\beta_1, x_1, a) & \dots & f(\beta_L, x_1, a) \\ \vdots & \cdots & \vdots \\ f(\beta_1, x_N, a) & \dots & f(\beta_L, x_N, a) \end{bmatrix}_{N \times L} \tag{4}$$

$$w = H^{\dagger}T \; ; \; T = \begin{bmatrix} T_1 \\ \dots \\ T_j \end{bmatrix} ; w = \begin{bmatrix} w_1 \\ \dots \\ w_L \end{bmatrix} \tag{5}$$

2.2 Optimization Algorithm

The employed optimization algorithm is particle swarm optimization (PSO). PSO is initially formulated based on the movement of a group of bird to search food at various locations. The algorithm of the PSO can be described as the following

i. Initialization of particle position and velocity.
ii. The initial position is calculated using Eq. (6).

$$\mathrm{X_p(t+1) = X_p(t) + V_p(t)} \tag{6}$$

Each particle contains three types of information, namely, position ($\mathrm{X_p}$), velocity ($\mathrm{V_p}$) and local best position (P). The best position to obtain the best group particles is represented by G.

iii. Calculate the output of the cost function. The output replaces the previous value as the best particle position, if the value is better than the previous position. If the output is better than group best output, then the particle is defined as the best group positions.
iv. Velocity is updated using the following equation

$$\mathrm{V_p(t+1) = w * V_p(t) + c_p * r_p * \Big(P(t) - X_p\,(t)\Big) + c_g * r_g * \Big(G(t) - X_p(t)\Big)} \tag{7}$$

The variables, c_p and c_g, are the weighting coefficients, known as the self and group confidence for the cognitive and social parts of Eq. **Error! Reference source not found.**, while r_p and r_g are uniform random variables in the range (0, 1) for the particles and groups, respectively. w is updated in every iteration using a method known as linearly decreased inertia weight PSO (LDWPSO) as formulated in Eq. (8) where $\mathrm{i_{max}}$ and i are the highest and present iteration value, respectively. w is changed from w_{end} to w_{start} along the iteration. According Shi and Eberhart [19], $\mathrm{c_p}$ and $\mathrm{c_g}$ as particle and group constant, respectively, are 2.0.

$$w_{p,v} = w_{end} - (w_{end} - w_{start})\frac{i}{i_{max}} \tag{8}$$

v. The calculation back to the point 2 until terminated according to the pre-determined accuracy or maximum iteration, which one come first.

The objective of the optimization is to get the least root mean square error (RMSE) of the training data and minimum hidden node numbers. Thus, the objective function is formulated using Eq. (9). $RMSE_{training}$ is defined by Eq. (10) where T, O, and K are the target or reference, output of the model, and the data number, respectively. The weighting of each objective is determined as a function of the training data range or the range of possible hidden node number to keep both objective values comparable as expressed in Eq. (11) and (12).

$$C = \frac{RMSE_{training}}{w_1} + \frac{L}{w_2} \tag{9}$$

$$RMSE_{training} = \sqrt{\frac{\sum_{h=1}^{K}(T_{training} - O_{training})^2}{K_{Training}}} \tag{10}$$

$$w_1 = \mathrm{f\big(R_{training\_data\_range}\big)} \tag{11}$$

$$w_2 = L_{max} - L_{min} \quad (12)$$

2.3 Materials and Simulation Setup

The model is built based on the empirical data from the characterization of MR fluids using parallel plate rheometer. The material type is MRF 132DG from Lord Corporation [20]. The rheometer is manufactured by Anton Paar, Physical, GmbH, Austria. The training data has the ranges as the following [20]

i. Shear rate : 0.0977-993.000 s^{-1}
ii. Magnetic field : 0, 0.090, 0.420, 0.610, 0.700, 0.783 Tesla
iii. Shear stress : 6-50627 Pa

Before feeding the data to the training algorithm, the training data need to be normalized first to get a standardized range. The normalization method is expressed in Eq. (13) for shear rate and Eq. (14) for magnetic field where $\dot{\gamma}_{n,i}$, $\dot{\gamma}_i$, $\dot{\gamma}_{min}$, and $\dot{\gamma}_{max}$ are the normalized shear rate, the current shear rate, minimum and maximum value of shear rate in the training data, respectively. B is the magnetic field with the similar meaning for the similar subscripted symbol in the shear rates.

$$\dot{\gamma}_{n,i} = \frac{log(\dot{\gamma}_i) - log(\dot{\gamma}_{min})}{log(\dot{\gamma}_{max}) - log(\dot{\gamma}_{min})} \quad (13)$$

$$B_{n,i} = \frac{B_i - B_{min}}{B_{max} - B_{min}} \quad (14)$$

The available data were divided into training and testing data group. The flow curve with applied magnetic field of 0.310 and 0.830 Tesla are selected as testing data representing the interpolation and extrapolation cases, respectively. The rest of the data is selected as training data. The activation function is varied from sinusoid, hard limit, and sigmoid activation functions. For the optimization, the number of particles is varied from 4 to 100. Initial velocity is set at 0. All particle and group bests are set at 10,000.

3. Results and Discussion

3.1 Materials and Simulation Setup

The simulation results of the platform with and without optimization are described in Table 1. As previously mentioned in section 2.2, the objective of the optimization process is to minimize the hidden node number while maintaining the training accuracy. In general, the results have shown that hidden node number can be significantly decreased with ELM with sinusoid activation is the best in term of training and testing cases. On the other hand, the training accuracy tends to decrease. It is understandable that the reducing of the hidden node number will affect the model accuracy. Nevertheless, the additional error after optimization process is still less than NRMSE of 1.5 %. The hidden node number reduction of ELM using sinusoid model is the highest among the others. On the other hand, the accuracy reduction is also the higher.

Meanwhile, ELM with sigmoid activation function shows the least reduction of hidden node number and accuracy. The optimization has the difficulty to reduce hidden node while maintaining the accuracy for sigmoid case. Hard limit is in the middle position in term of the accuracy decrease and hidden node reduction compared to other schemes. The visual representation of the

convergence of the optimization process was depicted in Figure 2. ELM with sigmoid (Sim Sig) and Hard limit (Sim HL) activation function has the less decrease compared to the Sinusoid (Sim Sin). This pattern is with agreement with Table 1 showing Sim Sin has a highest hidden node number decrease compared to others. In summary, the proposed platform has successfully decreased more than 80 % of the hidden node number with the slight increase of the error.

Table 1
The comparison before and after the application of optimization algorithm

Activation functions	Hidden Node	Training Accuracy		Testing Accuracy	
		RMSE	NRMSE (%)	RMSE	NRMSE (%)
Hard limit	314	406	0.80	3756	7.42
	10,000	14	0.03	3514	6.94
Sigmoid	1398	1331	2.63	1424	2.81
	10,000	1350	2.67	1328	2.62
Sinusoid	74	1310	2.59	1399	2.76
	10,000	770	1.52	1280	2.53

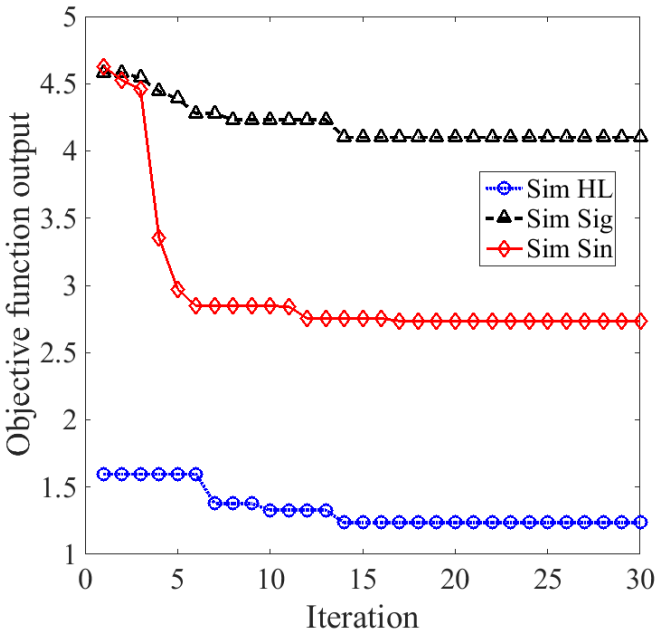

Fig. 2. Convergence graph of objective function output as a function of iteration

The platform still has space for further development. The possible improvements include the modification and investigation of the weighting effect, additional objective such as a set of validation data. Nevertheless, the platform has shown its importance in MR fluid modeling using ELM. Different with ANN that will show an over fitting phenomena if the hidden node number increase, ELM in some cases, especially in MR fluid modeling [16], shows a consistent acceptable or better generalization capability with the increasing hidden node number at both training and testing datasets.

4. Conclusions

A platform to optimize the ELM structure has been developed and evaluated. In general, the platform has successfully reduced the hidden node number while maintaining the model accuracy. The model hidden node number can be reduced from 10,000 to at most 1400 hidden node that results to a simpler model and a faster calculation when applied in a program or a device. The

algorithm can affect ELM based model using sinusoid activation function. However, the drawback of the proposed platform is the additional training time because the optimization algorithm. In the future, the proposed platform needs to be tested at various sample and more comprehensive investigation of each parameter.

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