Parameter Identification in Magnetorheological Dampers via Physics-Informed Neural Networks

Yuandi Wu, Brett Sicard, Patrick Kosierb, and S. Andrew Gadsden

Abstract This paper presents an investigation into the utilization of physics-informed neural networks for parameter identification in the domain of magnetorheological dampers. MR dampers are known for their controllable rheological properties, making them integral components in various engineering applications such as vibration control and structural dynamics. Efficient utilization of MR dampers relies on accurate characterization of their material properties, necessitating robust parameter identification techniques. The proposed methodology integrates physics-informed neural networks, a class of neural networks that embed physical principles into their architecture, enabling the incorporation of governing equations and boundary conditions during the training process. This fusion of physics-based constraints with machine learning facilitates the extraction of meaningful parameters from experimental data, enhancing the accuracy of the identification process. Through a series of simulations and experiments, this study assesses the efficacy of physics-informed neural networks in capturing the complex nonlinear behaviour exhibited by MR dampers. The neural network is trained on a dataset comprising experimental observations of the damper's response under varying conditions. The results demonstrate the capability of physics-informed neural networks to discern and infer key material parameters. The findings presented herein contribute to the growing body of research on the application of machine learning techniques in structural dynamics and control. The demonstrated results of physics-informed neural networks in parameter identification for MR dampers showcase their potential as a valuable tool for engineers and researchers seeking to optimize the design and control of these adaptive devices in real-world engineering applications.

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1 Introduction

Magnetorheological (MR) dampers are pivotal in engineering systems requiring dynamic response control due to their adaptive and tunable properties. However, accurately determining the material characteristics of MR dampers poses challenges due to their inherent complexity and nonlinearity [33]. Traditional methods for identifying parameters often struggle to manage these complexities, resorting to iterative techniques or local search algorithms that may necessitate substantial prior assumptions or system simplifications [7].

In addressing these challenges, this study investigates the integration of Physics-Informed Neural Networks (PINNs) as a potential approach to improve parameter identification accuracy in the context of MR dampers. PINNs utilize deep neural networks as solvers for differential equations, enabling relatively precise predictions for unknown terms even with limited data [25]. Their capacity as universal function approximators allows them to handle nonlinear problems without the need for predefined assumptions or system simplifications [11, 22, 26]. Additionally, PINNs leverage automatic differentiation to effectively explore parameter spaces and enhance model performance [2, 5, 21].

For MR dampers, characterized by significant nonlinearity in their rheological processes and the simultaneous estimation of multiple parameters, PINNs offer several compatible characteristics for the estimation process. The commonly used modified Bouc-Wen model [27], describing MR damper behaviour with a set of differential equations and multiple parameters, often poses challenges for traditional approaches in identifying satisfactory parameters due to initial value setting difficulties and high-dimensional parameter spaces [14, 32, 36]. PINNs present a promising solution by integrating physical principles and experimental data into the learning process, enabling accurate parameter estimation for MR dampers [26]. Results indicate strong alignment between PINN predictions and experimental data, although inherent noise in the data introduces some discrepancies. Factors contributing to this noise include the composite loss function used during training, the complexity of the model, and variations in voltage inputs. Further refinement of network architecture, loss weighting schemes, and consideration of system dynamics are crucial for improving the prediction accuracy of parameters, especially in capturing hysteresis behaviours and responses to low voltage inputs.

The paper is organized as follows: Sect. 2 provides an overview of current methodologies used for mathematically modelling MR dampers. Following this, Sect. 3 explores background information related to PINNs, which have shown promise in solving complex physics-based problems. The proposed parameter estimation scheme is then explained in Sect. 4, detailing how the model parameters are estimated using the PINNs framework. Subsequently, Sect. 5 presents the results of the parameter estimation scheme and discusses these findings. Finally, the paper is concluded in Sect. 6, summarizing the key points discussed and suggesting directions for future research in this area.

2 Parametric Modelling for Magnetorheological Dampers

Magnetorheological dampers are devices designed to provide variable damping in response to changes in an applied magnetic field, relying on the unique rheological properties exhibited by MR fluids. Beyond their fundamental contributions to the understanding of controllable damping systems, MR dampers have found widespread applications in civil engineering for structural vibration control [23, 44], seismic mitigation [6, 8], and adaptive suspension systems in automotive engineering [9, 37, 39]. Moreover, MR dampers have found their way into robotics, offering precise control over the damping characteristics in robotic joints and limbs [3, 34, 40]. This adaptability contributes to improved stability and maneuverability in various robotic applications. Key to their operation is the MR fluid itself, which is composed of a suspension of micron-sized ferrous particles within a liquid carrier. The dynamic behaviour may be actively controlled by adjusting the alignment of the aforementioned ferrous particles through the application of an external magnetic field, typically induced through an externally applied voltage [10]. The responsiveness of MR dampers to changes in voltage stems from the magnetic flux-induced alignment of ferrous particles along the field lines. As the applied voltage increases or decreases, corresponding adjustments in the magnetic field strength occur, leading to alterations in the alignment of particles and, consequently, changes in the rheological properties of the MR fluid [8]. Through this property, the damper may be adjusted to provide varying levels of resistance to motion, thereby influencing the damping characteristics of the overall system.

The mathematical modelling of MR dampers poses considerable challenges, primarily attributed to the intricate dynamics arising from force–velocity hysteresis and history dependency [37, 41, 46]. The nonlinearity inherent in these dampers results from complex interactions involving magnetic field strength, particle distribution, and rheological properties of the fluid. Force–velocity hysteresis, a key characteristic of MR dampers, brings in a complicated connection between the loading and unloading phases, making it challenging to develop a precise mathematical representation. Moreover, the history-dependent nature of these dampers implies that their response is influenced not only by the current state but also by preceding loading conditions [28]. To address these complexities, researchers have turned to phenomenological approaches, employing parametric models to capture the intricate nonlinear dynamics. Phenomenological models are empirical or semi-empirical models that are developed based on observed phenomena and experimental data, rather than being derived from underlying physical principles. These models aim to capture the essential features of a system's behaviour without necessarily delving into the detailed internal mechanisms or physics governing the phenomena. Various authors have proposed models based on empirical observations and experimental data, aiming to characterize the system's behaviour using parameters that encompass the interplay of magnetic, fluid, and structural elements [15, 27, 43]. However, the identification of these parameters remains challenging, involving navigation through a high-dimensional parameter space and necessitating comprehensive experimental data to ensure the accuracy of model predictions.

Prominent among the various mathematical models proposed for describing the behaviour of MR dampers is the modified Bouc-Wen model introduced by Spencer and colleagues [27]. This model has gained recognition for its effectiveness in capturing the intricate dynamics, especially in addressing the roll-off region, an aspect that posed challenges in the original Bouc-Wen model [12, 27]. The modified Bouc-Wen model is a phenomenological mathematical model extensively utilized to describe the behaviour of MR dampers. An illustration of the model is provided in Fig. 1 [27]. Spencer's modification has demonstrated improved accuracy in predicting the damping force over a wide range of velocities. However, it is essential to acknowledge that the modified Bouc-Wen model comes with a notable degree of complexity. The model involves a system of differential equations, necessitating a comprehensive understanding of the underlying physics and intricate interactions within the damper system [12]. Furthermore, the model demands the identification and tuning of 14 parameters, adding a layer of complexity to the calibration process. While the modified Bouc-Wen model has proven its efficacy in capturing the nonlinearity of MR dampers, its complexity raises challenges regarding computational implementation and the requirement for extensive experimental data to accurately identify and finetune the numerous model parameters [28, 35]. The modified Bouc-Wen model is characterized by the following equation:

$$F = \alpha z + c_0(\dot{x} - \dot{y}) + k_0(x - y) + k_1(x - x_0). \tag{1}$$

Equation (1) may also be simplified as

$$F = c_1\dot{y} + k_1(x - x_0), \tag{2}$$

where the evolutionary variable z (also denoted as the hysteretic displacement in certain publications), and the intermediary displacement y is represented in the following differential equations:

$$\dot{z} = -\gamma|\dot{x} - \dot{y}|z|z|^{n-1} - \beta(\dot{x} - \dot{y})|z|^n + A(\dot{x} - \dot{y}), \tag{3}$$

$$\dot{y} = \frac{1}{c_0 + c_1}(\alpha z + k_0(x - y) + c_0\dot{x}). \tag{4}$$

whereas the model outlined above is static for a set magnetic field strength within the damper, the model may be extended to incorporate the changes in magnetic field strength through varying applied voltage. Parameters α, c_0, and c_1 were shown to be

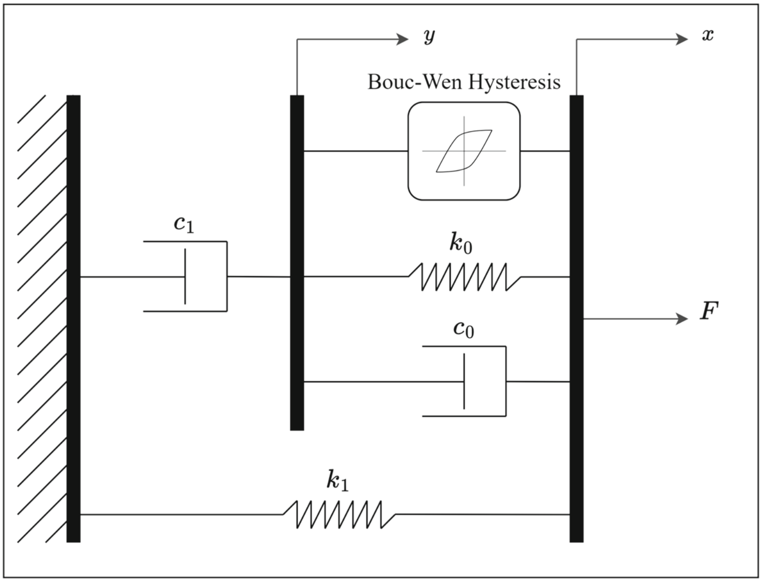

Fig. 1 The modified Bouc-Wen model. Adapted from [27]

changing linearly with an efficient voltage u, whereby u represents the filtered input voltage v [1, 16, 42]. The relations are given as follows:

$$\alpha = \alpha_a + \alpha_b u, \tag{5}$$

$$c_0 = c_{0,a} + c_{0,b}\, u, \tag{6}$$

$$c_1 = c_{1,a} + c_{1,b} u, \tag{7}$$

$$\dot{u} = \eta(u - v), \tag{8}$$

whereby parameters $\left[\alpha_a, \alpha_b, \beta, \gamma, \eta, A, c_{0a}, c_{0b}, c_{1a}, c_{1b}, k_0, k_1, n, x_0\right]$ are system parameters to be identified prior to simulations with the modified Bouc-Wen model.

3 Physics-Informed Neural Network for Parameter Estimation

In recent years, PINNs have emerged as a powerful paradigm for solving partial differential equations and elucidating complex physical phenomena. This section delves into the application of PINNs within the context of identifying solutions to partial differential equations, building upon the foundational work conducted by Raissi [26]. PINNs seamlessly integrate neural network architectures with the governing physics of a system, offering a data-driven approach to characterize latent solutions. Specifically, we explore the methodology employed in prior works of various authors, which involves utilizing PINNs to discern optimal parameters λ that effectively describe observed data [4, 13, 25, 26].

In the initial study conducted, the investigation primarily centred on the utilization of data-driven methodologies for the identification of the solution $u(t, x)$ to partial differential equations in a generalized form [26]. The considered equations are expressed concerning spatial and temporal variables, denoted as $x \in \Omega$ and $t \in [0, T]$, respectively.

$$0 = \frac{\delta u}{\delta t} - \mathcal{N}[u; \lambda]. \tag{9}$$

Here, the variable u symbolizes the latent solution of the differential equation, while $\mathcal{N}$ signifies the nonlinear operator parameterized by λ. In the context of a system with a hidden state $u(t, x)$, characterized by a sparse and potentially noisy set of observations, the authors employed the PINN to discern the optimal parameters λ that effectively characterize the observed data. This endeavour involved determining the parameters λ through the PINN methodology, which is designed to efficiently handle scattered and potentially noisy observations of the hidden state $u(t, x)$.

In the subsequent section, the framework established by Raissi, which was originally designed for the solution of partial differential equations, undergoes adaptation to address a system of ordinary differential equations (ODEs). The adaptability of the methodology becomes apparent as we extend its application from partial to ordinary differential equations, catering to a broader range of dynamical systems.

4 Parameter Estimation Framework Utilizing PINNs

To address the challenges associated with the complexity of the modified Bouc-Wen model, we propose to integrate this model into a PINN framework for parameter estimation. PINNs leverage the power of neural networks to learn the underlying physics of a system while simultaneously incorporating physical principles in the form of partial differential equations. By integrating the modified Bouc-Wen model into a PINN, we aim to harness the modelling accuracy of the former while benefiting from the data-driven capabilities of neural networks for parameter identification. It is worth noting that various authors have recognized the potential of PINNs for parameter estimation in diverse engineering applications [24, 29, 31, 38, 45]. The capability of PINNs to seamlessly integrate physical laws with data-driven approaches has been harnessed to identify and tune parameters in complex dynamical systems efficiently [26]. In the context of MR dampers, the application of PINNs for parameter estimation has gained traction due to the inherent challenges associated with the complexity of models such as the modified Bouc-Wen model. Leveraging the strengths of PINNs, we aim to contribute to this growing body of work by employing the network architecture to accurately estimate and fine-tune the 14 parameters of the modified Bouc-Wen model.

The challenge of parameter estimation is commonly formulated as an inverse problem, wherein the objective is to infer the parameters of a given model based on observed data [30]. In the context of parameter estimation, the utilization of NNs is particularly advantageous due to their inherent ability to be configured as inverse models [20]. In many real-world scenarios, the physical parameters of a system are often challenging to directly measure or quantify [45]. However, by casting these parameters as neural network parameters, the neural network can efficiently learn and approximate their values through the optimization of weights and biases. This approach aligns with the inherent capability of neural networks to adapt and generalize complex patterns from data. The neural network, equipped with the task of minimizing discrepancies between its predictions and the training dataset, naturally extends its ability to handle additional parameters. By incorporating the physical parameters into the architecture, the neural network explores various combinations to achieve the best fit with observed data.

Neural networks have emerged as powerful tools for approximating complex functions in various fields, owing to their universal approximation capabilities. The universal approximation theorem states that a neural network may approximate any continuous function to arbitrary precision, given a sufficiently large number of neurons in its hidden layers [22]. In the context of dynamical systems, ordinary differential equations (ODEs) represent a ubiquitous framework for describing the evolution of physical systems over time. The ability of neural networks to approximate functions renders them suitable candidates for approximating the solutions to systems of ODEs, as illustrated in the work of Lagrais and colleagues, who initially conceptualized the idea [17]. A specific implementation considered in this investigation involves employing a PINN to tackle the parameter estimation task, integrating ODEs governing the behaviour of the modified Bouc-Wen model, as illustrated in Eqs. (1), (2), (3), (4), (5), (6), (7) and (8). A visualization of the workflow adhered to herein is presented in Fig. 2.

For a neural network denoted as $N\left(x, \frac{dx}{dt}, v, t\right)$, where $x, \frac{dx}{dt}, v, t$ represents the input variables. Leveraging the universal approximation property, it is possible to express the neural network function as a suitable approximation for the solution to a system of ODEs. In this study, we focus on a specific scenario where the universal approximative capabilities of a neural network are employed to obtain the solution

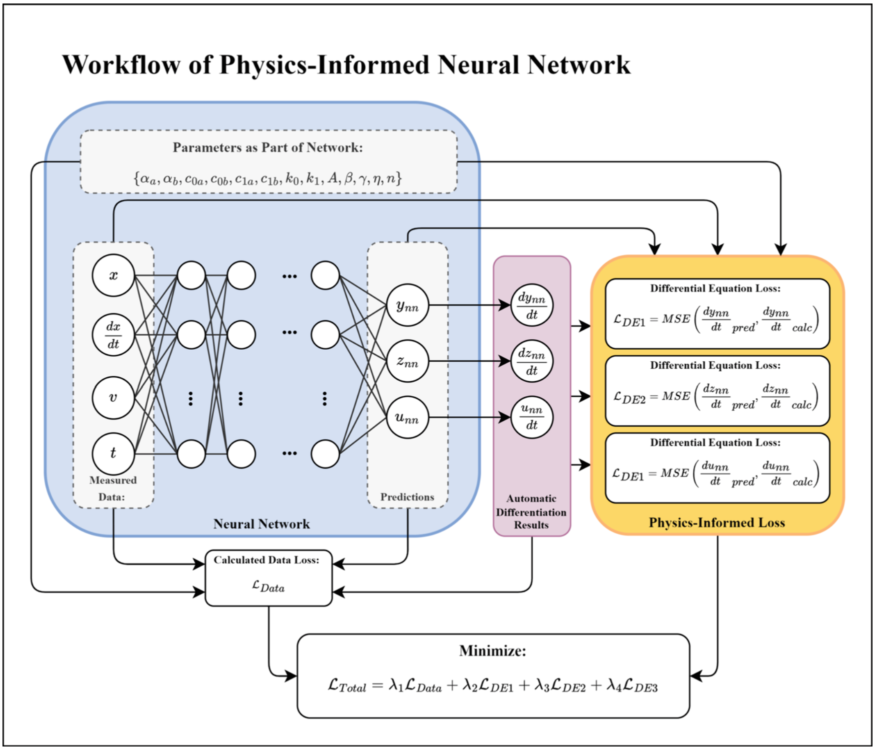

Fig. 2 Workflow of proposed physics-informed neural network for estimation of parameters

vector $\left[u_{NN}, y_{NN}, z_{NN}\right]^T$, representing the dependent variables of the system:

$$N\left(x, \frac{\mathrm{d}x}{\mathrm{d}t}, v, t\right) \approx [u, y, z]^T \tag{10}$$

where the subscript *NN* denotes predictions via the neural network. To facilitate the analysis of the dynamical system, it becomes necessary to determine the derivatives of the neural network function with respect to the independent variable t, such that variables $\frac{\mathrm{d}u_{NN}}{\mathrm{d}t}$, $\frac{\mathrm{d}y_{NN}}{\mathrm{d}t}$, and $\frac{\mathrm{d}z_{NN}}{\mathrm{d}t}$ are available for computation of Eqs. (3), (4), and (8). This differentiation process is accomplished through automatic differentiation, a technique that efficiently computes the derivatives of a function with respect to its input variable.

Thus, Eqs. (3), (4), and (8) may be reformulated in this context as

$$0 = \frac{\mathrm{d}u_{NN}}{\mathrm{d}t} - (\eta(u_{NN} - v)) \tag{11}$$

$$0 = \frac{\mathrm{d}y_{NN}}{\mathrm{d}t} - \left(\frac{1}{c_0 + c_1}\left(\alpha z_{NN} + k_0(x - y_{NN}) + c_0\frac{\mathrm{d}x}{\mathrm{d}t}\right)\right) \tag{12}$$

$$0 = \frac{\mathrm{d}z_{NN}}{\mathrm{d}t} - \left(-\gamma\left|\frac{\mathrm{d}x}{\mathrm{d}t} + \frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right| z_{NN}|z_{NN}|^{n-1} - \beta\left(\frac{\mathrm{d}x}{\mathrm{d}t} + \frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right)|z_{NN}|^n + A\left(\frac{\mathrm{d}x}{\mathrm{d}t} - \frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right)\right) \tag{13}$$

Thus, for a set of parameters to be identified:

$$\lambda = \left[\alpha_a, \alpha_b, \beta, \gamma, \eta, A, c_{0a}, c_{0b}, c_{1a}, c_{1b}, k_0, k_1, n\right], \tag{14}$$

the above equations outlined are in alignment with the original formulation by Raissi, whereby the network is trained to minimize discrepancies between predicted time derivatives of solution space, with the calculated value of time derivatives utilizing governing differential equations:

$$0 = \frac{\delta N}{\delta t} - \mathcal{N}[N; \lambda] \tag{15}$$

From the above, the physics-based mean squared error (MSE) loss functions are defined, and subsequently minimized by the network. The loss function is defined for each sample point i of total samples taken N for the sequence parsed:

$$\mathcal{L}_u = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{\mathrm{d}u_{NN}^{(i)}}{\mathrm{d}t}\right) - \left(\eta\left(u_{NN}^{(i)} - v^{(i)}\right)\right)\right]^2 \tag{16}$$

$$\mathcal{L}_y = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\frac{\mathrm{d}y_{NN}^{(i)}}{\mathrm{d}t}\right) - \left(\frac{1}{c_0^{(i)} + c_1^{(i)}}\left(\alpha^{(i)} z_{NN}^{(i)} + k_0\left(x^{(i)} - y_{NN}^{(i)}\right) + c_0^{(i)}\frac{\mathrm{d}x^{(i)}}{\mathrm{d}t}\right)\right)\right]^2 \tag{17}$$

$$\mathcal{L}_z = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\mathrm{d}z_{NN}}{\mathrm{d}t} + \gamma\left|\frac{\mathrm{d}x}{\mathrm{d}t} - \frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right| z_{NN}|z_{NN}|^{n-1} + \beta\left(\frac{\mathrm{d}x}{\mathrm{d}t} - \frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right)|z_{NN}|^n - A\left(\frac{\mathrm{d}x}{\mathrm{d}t}\frac{\mathrm{d}y_{NN}}{\mathrm{d}t}\right)\right]^2 \tag{18}$$

As direct observations of y and z are difficult, the data-driven section of the network will be reformulated such that the object of comparison is the force instead. From Eqs. (1) and (2), force may be represented as a function of variables from both the prediction and input space. The data-driven loss may then be derived as the MSE between observed force at each time point $F^{(i)}$, and the function of predicted and input variables. The new physics-informed data-driven loss is given as follows:

$$\mathcal{L}_{\text{data},1} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(F^{(i)}\right) - \left(\alpha^{(i)} z_{NN}^{(i)} + c_0^{(i)}\left(\frac{\mathrm{d}x^{(i)}}{\mathrm{d}t} - \frac{\mathrm{d}y_{NN}^{(i)}}{\mathrm{d}t}\right)\right.\right.$$
$$\left.\left. + k_0\left(x^{(i)} - y_{NN}^{(i)}\right) + k_1\left(x^{(i)} - x_0\right)\right)\right]^2 \tag{19}$$

$$\mathcal{L}_{\text{data},2} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(F^{(i)}\right) - \left(c_1^{(i)}\dot{y}_{NN}^{(i)} + k\left(x^{(i)} - x_0\right)\right)\right]^2 \tag{20}$$

The total loss by which the network is trained is thus a composite loss comprising the aforementioned component losses. The loss is given as

$$\mathcal{L} = \phi_{\text{data}}\mathcal{L}_{\text{data},1} + \phi_{\text{data}}\mathcal{L}_{\text{data},2} + \phi_{\text{phys}}\mathcal{L}_u + \phi_{\text{phys}}\mathcal{L}_y + \phi_{\text{phys}}\mathcal{L}_z \tag{21}$$

The learning process incorporates weights, denoted as $\phi = \left[\phi_{\text{data}}, \phi_{\text{phys}}\right]$, to achieve a balanced optimization between adherence to physically derived differential equations and alignment with observed measurements, specifically pertaining to force. The training process for the PINN involves the minimization of the overall loss function, which encompasses both the physical loss and data loss components. To ensure the model's robustness, a training and validation process was conducted with an 80–20 data split for training and validation data. Subsequently, the model was evaluated on a novel dataset that had not been seen during training. A Bayesian optimization strategy was employed to tune the hyperparameters of the PINN developed. Bayesian optimization was chosen over its counterparts such as grid and random search for its pragmatic utility in validation and hyperparameter optimization. This approach systematically explores the parameter space by leveraging probabilistic models, efficiently balancing the trade-off between exploration and exploitation. This approach allows for the navigation of high-dimensional parameter space efficiently, facilitating the convergence of our neural network model.

5 Results and Discussion

In this section, we present and discuss the results obtained from employing the PINN, as discussed in Sect. 4 for the estimation of key parameters within a modified Bouc-Wen model for MR dampers. Employing a Python environment with PyTorch, we constructed and tested the neural network framework to ascertain key parameters. Table 1 presents the parameters determined through the aforementioned processes.

Force–time, force–velocity, and force–displacement curves were plotted to compare the estimated values obtained from the neural network against the measured data from physical experimental setups. Notably, the curves generated by parameters identified by the neural network were found to be in agreement with the observed data. A sample of the predicted results, with varying voltage applied to the MR

Table 1 List of parameters and their corresponding values, as determined by the PINN parameter estimation algorithm outlined in Sect. 4

Parameter	Value	Units
α_a	1.92114100e+03	$\frac{\mathrm{N}}{\mathrm{m}}$
α_b	5.88251000e+03	$\frac{\mathrm{N}}{\mathrm{m}}$ V
β	3.63320700e+04	m^{-2}
γ	3.63320700e+04	m^{-2}
η	6.00043108e+01	s^{-1}
A	1.55320000e+02	–
c_{0a}	1.65073317e+05	$\frac{\mathrm{N\,s}}{\mathrm{m}}$
c_{0b}	− 3.33399584e+05	$\frac{\mathrm{N\,s}}{\mathrm{m}}$ V
c_{1a}	7.73465300e+01	$\frac{\mathrm{N\,s}}{\mathrm{m}}$
c_{1b}	2.40504070e+04	$\frac{\mathrm{N\,s}}{\mathrm{m}}$ V
k_0	2.60786039e+04	$\frac{\mathrm{N}}{\mathrm{m}}$
k_1	1.72270067e+02	$\frac{\mathrm{N}}{\mathrm{m}}$
n	1.99999659e+00	–
x_0	0	m

damper, are illustrated in Figs. 3, 4 and 5 for force–time, force–displacement, and force–velocity plots, respectively.

Upon examining the outcomes, it is apparent that the PINN has shown promising performance in estimating the parameters of the modified Bouc-Wen model. Figures 3, 4 and 5 illustrating the results reveal a significant correspondence between

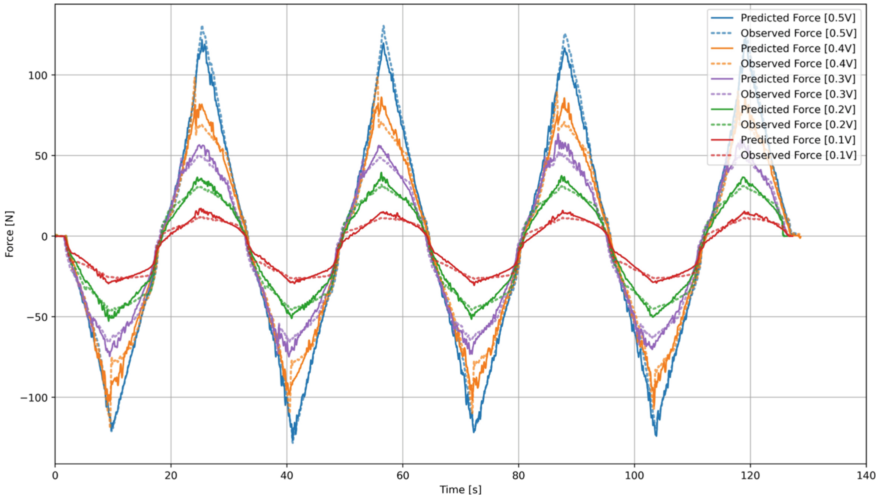

Fig. 3 Sample of predicted and observed force over time, with varying voltages applied to the MR damper

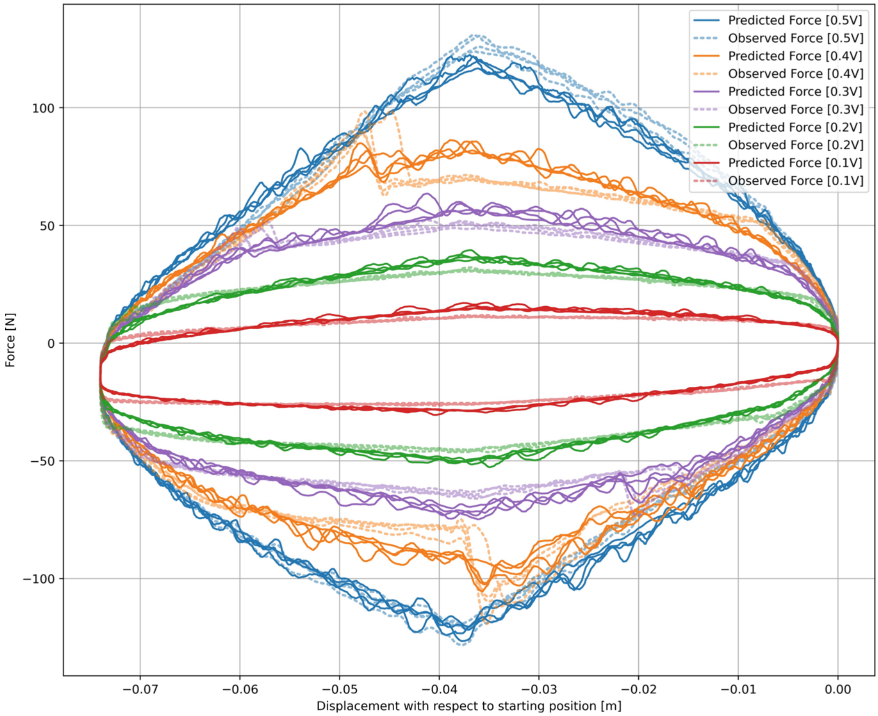

Fig. 4 Sample of predicted and observed force plotted with damper displacement, with varying voltages applied to the MR damper

the PINN predictions and experimental data, indicating the effectiveness of the physics-informed data-driven approach. However, it is important to note the presence of inherent noise in the experimental data used to train the PINN, which contributes to some level of noise in the obtained results.

The predictions obtained from the PINN exhibit some level of noise, which may be attributed to several factors. One potential reason for the noise in the predictions could be the composite loss function utilized during the training process. Since the PINN aims to simultaneously satisfy the governing equations of the physical system and match the observed data, tuning the weights of the loss function becomes crucial. However, achieving an optimal balance between these objectives is inherently challenging. The composite loss function's weighting scheme may inadvertently prioritize one aspect over the other, leading to discrepancies between the predicted and observed outputs. Moreover, the inherent complexity of the modified Bouc-Wen model for MR dampers introduces nonlinearities and uncertainties that further contribute to the noise in the predictions. Despite these challenges, efforts to fine-tune the network architecture and training parameters could potentially mitigate the noise and improve the accuracy of the predictions. Further investigation into the network's sensitivity to different loss weighting schemes and regularization techniques may

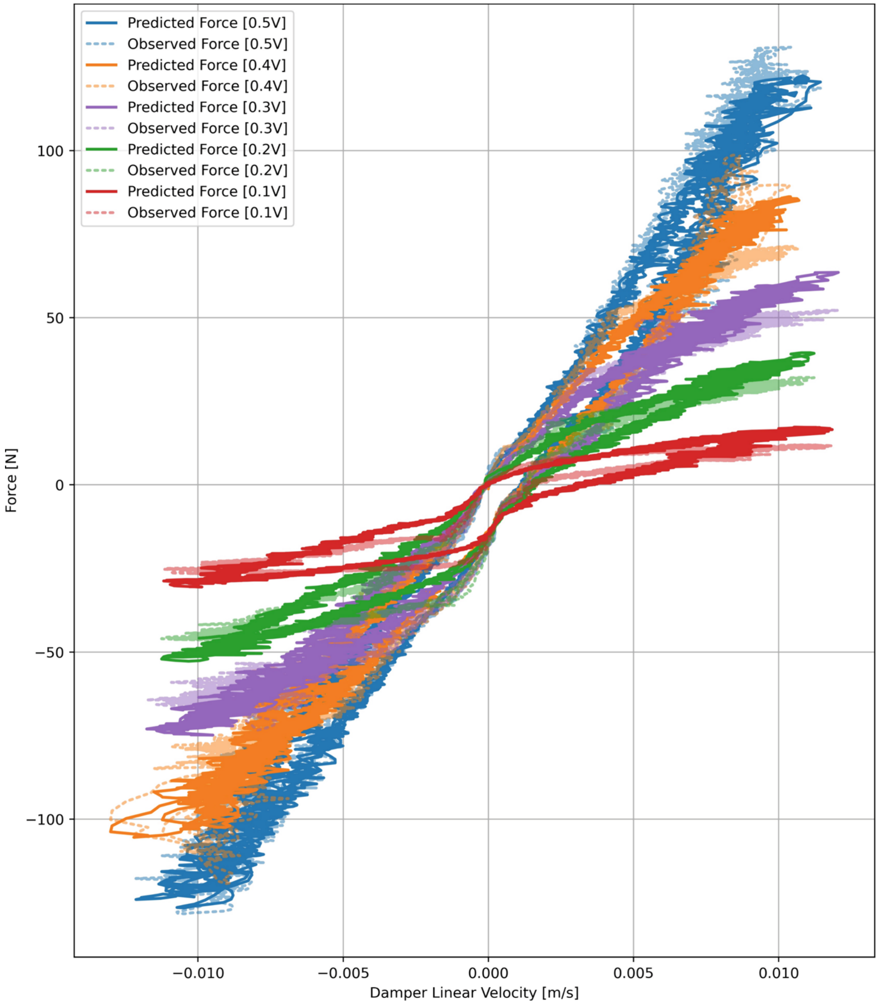

Fig. 5 Sample of predicted and observed force over time, with varying voltages applied to the MR damper

also offer insights into enhancing the predictive capabilities of the PINN in complex physical systems.

The observed discrepancy in the accuracy of predictions at different voltage inputs, particularly the notable deviation in capturing aspects of hysteresis at low voltage inputs, can be attributed to several factors inherent to both the physics of the system and the limitations of the machine learning approach employed. Root mean Squared Error (RMSE) of force predictions for a set sampling period of 100 s may be seen in Table 2. At higher voltage inputs, where the predictions demonstrate greater accuracy, the increased voltage likely induces a more pronounced response within the MR

Table 2 Root mean squared error obtained at various voltages

Applied voltage (V)	RMSE of force prediction
0	18.7936
0.1	17.7621
0.2	13.8159
0.3	11.8298
0.4	16.8806
0.5	10.0988

damper, leading to clearer and more distinguishable patterns in the force–displacement, force–velocity, and force–time curves. This heightened response facilitates the learning process of the PINN, resulting in more accurate parameter estimations. Conversely, at lower voltage inputs, the response of the MR damper is relatively weaker, potentially leading to smaller signal-to-noise ratios and increased susceptibility to measurement inaccuracies. One potential explanation for these discrepancies could be attributed to the effect of the accumulator within the MR damper. Additionally, considering the low velocities and extended stroke lengths examined in our study, it is important to acknowledge that the force exerted by the diaphragm and compressed nitrogen gas becomes non-negligible, potentially influencing the observed discrepancies in predictions, as explored in other publications on the subject [18, 19].

These observations underscore the importance of considering various factors, such as voltage inputs and the physical characteristics of the MR damper components when interpreting and refining the performance of machine learning models for parameter estimation in complex systems. Further investigation into these nuances is warranted to enhance the accuracy and robustness of future predictions. Additionally, it is essential to consider the inherent limitations of the machine learning approach itself. Despite its capabilities in learning complex relationships from data, the PINN relies on the quality and representativeness of the training dataset. If the dataset does not encompass a diverse range of operating conditions, including scenarios with low voltage inputs and intricate hysteresis behaviours, the network may struggle to generalize effectively to such conditions during inference. As a result, the discrepancies observed in the predictions at low voltage inputs may reflect the inherent challenges in training machine learning models to accurately capture the full range of dynamics exhibited by MR dampers, particularly under conditions of low excitation.

6 Conclusion

This study explored the application of PINNs for parameter identification in MR dampers, crucial components in engineering applications like vibration control and structural dynamics. Through the integration of physical principles into the neural network architecture, PINNs enabled the incorporation of governing equations during the hybrid physics-informed data-driven training process, enhancing the accuracy of parameter identification. The study assessed the efficacy of PINNs in capturing the complex nonlinear behaviour exhibited by MR dampers. The results illustrated the ability of PINNs to discern and infer key physical parameters from experimental data, providing insights into the underlying physics governing MR damper behaviour. Notably, the PINN framework demonstrated promising performance in estimating parameters within the modified Bouc-Wen model, as evidenced by the alignment between PINN predictions and experimental observations. In addition, results reveal that PINNs exhibit promising performance in discerning and inferring key material parameters from experimental data, despite encountering challenges such as the representation of hysteresis at low voltage inputs. Notably, there was greater accuracy in predictions at higher voltage inputs, indicating the network's proficiency in capturing pronounced system responses. However, the limitations in capturing subtle nuances of hysteresis underscore the need for further refinement in both network architecture and dataset representation.

References

1. Azar BF, Rahbari NM, Talatahari S (2011) Seismic mitigation of tall buildings using magnetorheological dampers. Asian J Civ Eng (Build Hous) 12(5):637–649
2. Baydin AG, Pearlmutter BA, Radul AA, Siskind JM (2018) Automatic differentiation in machine learning: a survey. J Mar Learn Res 18:1–43
3. Case D, Taheri B, Richer E (2011) Design and characterization of a small-scale magnetorheological damper for tremor suppression. IEEE/ASME Trans Mechatron 18(1):96–103
4. Chen Y, Lu L, Karniadakis GE, Dal Negro L (2020) Physics-informed neural networks for inverse problems in nano-optics and metamaterials. Opt Express 28(8):11618–11633
5. Chiu PH, Wong JC, Ooi C, Dao MH, Ong YS (2022) CAN-PINN: a fast physics-informed neural network based on coupled-automatic–numerical differentiation method. Comput Methods Appl Mech Eng 395:114909
6. Cruze D, Hemalatha G, Jebadurai SVS, Sarala L, Tensing D, Christy SJE (2018) A review on the magnetorheological fluid, damper and its applications for seismic mitigation. Civ Eng J 4(12):3058–3074
7. Dréo J, Pétrowski A, Siarry P, Taillard E (2006) Metaheuristics for hard optimization: methods and case studies. Springer Science & Business Media
8. Dyke S, Spencer B Jr, Sain M, Carlson J (1998) An experimental study of MR dampers for seismic protection. Smart Mater Struct 7(5):693
9. El Majdoub K, Giri F, Chaoui FZ (2020) Adaptive backstepping control design for semi-active suspension of half-vehicle with magnetorheological damper. IEEE/CAA J Automat Sin 8(3):582–596
10. Goncalves FD, Koo JH, Ahmadian M (2006) A review of the state of the art in magnetorheological fluid technologies–part i: MR fluid and MR fluid models. Shock Vibr Dig 38(3):203–220
11. Hornik K, Stinchcombe M, White H (1990) Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks. Neural Netw 3(5):551–560
12. Ikhouane F, Rodellar J (2007) Systems with hysteresis: analysis, identification and control using the Bouc-Wen model. Wiley

13. Jagtap AD, Mao Z, Adams N, Karniadakis GE (2022) Physics-informed neural networks for inverse problems in supersonic flows. J Comput Phys 466:111402
14. Jiang M, Rui X, Zhu W, Yang F, Zhu H, Jiang R (2021) Parameter sensitivity analysis and optimum model of the magnetorheological damper's Bouc–Wen model. J Vib Control 27(19–20):2291–2302
15. Jiang R, Rui X, Wei M, Yang F, Zhu H, Gu L (2023) A phenomenological model of magnetorheological damper considering fluid deficiency. J Sound Vibr 117851
16. Jung HJ, Spencer BF Jr, Lee IW (2003) Control of seismically excited cable-stayed bridge employing magnetorheological fluid dampers. J Struct Eng 129(7):873–883
17. Lagaris IE, Likas A, Fotiadis DI (1998) Artificial neural networks for solving ordinary and partial differential equations. IEEE Trans Neural Netw 9(5):987–1000
18. Lee AS (2021) Sliding innovation filtering: theory and applications. Ph.D. thesis. University of Guelph
19. Lee AS, Wu Y, Gadsden SA, AlShabi M (2023) Interacting multiple model estimators for fault detection in a magnetorheological damper. Sensors 24(1):251
20. Li H, Schwab J, Antholzer S, Haltmeier M (2020) Nett: solving inverse problems with deep neural networks. Inverse Prob 36(6):065005
21. Li Z, Zheng H, Kovachki N, Jin D, Chen H, Liu B, Azizzadenesheli K, Anandkumar A (2021) Physics-informed neural operator for learning partial differential equations. arXiv preprint arXiv:2111.03794
22. Lu L, Jin P, Pang G, Zhang Z, Karniadakis GE (2021) Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators. Nature Mach Intell 3(3):218–229
23. Or SW, Duan Y, Ni Y, Chen Z, Lam KH (2008) Development of magnetorheological dampers with embedded piezoelectric force sensors for structural vibration control. J Intell Mater Syst Struct 19(11):1327–1338
24. Pagnier L, Chertkov M (2021) Physics-informed graphical neural network for parameter & state estimations in power systems. arXiv preprint arXiv:2102.06349
25. Raissi M, Perdikaris P, Karniadakis GE (2019) Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys 378:686–707
26. Raissi M, Perdikaris P, Karniadakis GE (2017) Physics informed deep learning (part i): data-driven solutions of nonlinear partial differential equations. arXiv preprint arXiv:1711.10561
27. Spencer B Jr, Dyke S, Sain M, Carlson J (1997) Phenomenological model for magnetorheological dampers. J Eng Mech 123(3):230–238
28. Talatahari S, Kaveh A, Mohajer Rahbari N (2012) Parameter identification of Bouc-Wen model for MR fluid dampers using adaptive charged system search optimization. J Mech Sci Technol 26:2523–2534
29. Tanyu DN, Ning J, Freudenberg T, Heilenkötter N, Rademacher A, Iben U, Maass P (2023) Deep learning methods for partial differential equations and related parameter identification problems. Inverse Prob 39(10):103001
30. Tarantola A (2005) Inverse problem theory and methods for model parameter estimation. SIAM
31. Tartakovsky AM, Marrero CO, Perdikaris P, Tartakovsky GD, Barajas-Solano D (2020) Physics-informed deep neural networks for learning parameters and constitutive relationships in subsurface flow problems. Water Resourc Res 56(5):e2019WR026731
32. Tsang H, Su R, Chandler A (2006) Simplified inverse dynamics models for MR fluid dampers. Eng Struct 28(3):327–341
33. Xiaomin X, Qing S, Ling Z, Bin Z (2009) Parameter estimation and its sensitivity analysis of the MR damper hysteresis model using a modified genetic algorithm. J Intell Mater Syst Struct 20(17):2089–2100
34. Xu J, Xu, L, Li, Y, Liu, J, Li, X, Lu, L (2018) Design of lower extremity rehabilitation robots with magnetorheological dampers and wire-driven system. In: 2018 IEEE international conference on information and automation (ICIA). IEEE, pp 395–400

35. Yamin, AHM, Ab Talib MH, Zaurah I, Darus M, Nor NSM, Magneto-rheological (MR) damper–parametric modelling and experimental validation for lord RD 8040-1
36. Yang G, Spencer B Jr, Carlson J, Sain M (2002) Large-scale MR fluid dampers: modeling and dynamic performance considerations. Eng Struct 24(3):309–323
37. Yang J, Ning D, Sun S, Zheng J, Lu H, Nakano M, Zhang S, Du H, Li W (2021) A semi-active suspension using a magnetorheological damper with nonlinear negative-stiffness component. Mech Syst Signal Process 147:107071
38. Yang L, Meng X, Karniadakis GE (2021) B-PINNs: Bayesian physics-informed neural networks for forward and inverse pde problems with noisy data. J Comput Phys 425:109913
39. Yao G, Yap F, Chen G, Li W, Yeo S (2002) MR damper and its application for semi-active control of vehicle suspension system. Mechatronics 12(7):963–973
40. Yun D, Park C, Park D, Kim HS (2022) Magnetorheological damper for vibration reduction in a robot arm. Intell Serv Robot 15(5):671–678
41. Zambare H, Khoje A, Patil S, Razban A (2021) MR damper modeling performance comparison including hysteresis and damper optimization. IEEE Access 9:24560–24569
42. Zapateiro M, Karimi HR, Luo N, Phillips BM, Spencer BF Jr (2009) Semiactive backstepping control for vibration reduction in a structure with magnetorheological damper subject to seismic motions. J Intell Mater Syst Struct 20(17):2037–2053
43. Zeinali M, Mazlan SA, Abd Fatah AY, Zamzuri H (2013) A phenomenological dynamic model of a magnetorheological damper using a neuro-fuzzy system. Smart Mater Struct 22(12):125013
44. Zemp R, de la Llera JC, Almazan JL (2011) Tall building vibration control using a TM-MR damper assembly. Earthq Eng Struct Dynam 40(3):339–354
45. Zhai W, Tao D, Bao Y (2023) Parameter estimation and modeling of nonlinear dynamical systems based on Runge–Kutta physics-informed neural network. Nonlinear Dyn 111(22):21117–21130
46. Zhang S, Shi W, Chen Z (2021) Modeling and parameter identification of MR damper considering excitation characteristics and current. Shock Vib 2021:1–17