Gradient Boosting-Based Predictive Modeling and Interpolation of Force-Displacement Characteristics in Magnetorheological Damper

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ABSTRACT

Magnetorheological dampers are controllable fluid-based devices that use the rheological properties of magnetorheological fluids to achieve variable damping forces. The application of MR dampers in various engineering fields such as automotive, civil, and aerospace engineering has led to a significant interest in their study to optimize their performance and expand their applications. MR dampers exhibit complex, nonlinear force-displacement behavior under varying magnetic fields, posing challenges for accurate modelling and prediction. This study proposes a data-driven interpolation framework using the Gradient Boosting (GB) algorithm to predict damper behavior at unseen current levels. Experimental tests were conducted at five discrete current values (0–2 A) at 0.52 m/s. A GB regression model was trained on this data using current, velocity, and displacement as inputs to predict damper force. The model was validated by predicting force-displacement plots at intermediate currents (0.25, 0.75, 1.25, and 1.75 A), which showed strong agreement with experimental trends. Performance metrics confirmed the model accuracy and generalization capability. The approach reduces the need for extensive physical testing and supports real-time implementation in vehicle suspension systems. This work highlights the potential of machine learning techniques in modelling smart materials and enhancing automotive suspension design.

Keywords: Magnetorheological (MR) damper, Gradient Boosting Regression, Force-displacement interpolation, Data-driven modeling, Nonlinear Hysteresis.

1. Introduction

Several studies have focused on the accurate modelling of MR dampers to capture their nonlinear and hysteretic dynamics. Control methodologies for MR dampers have also evolved significantly. AlHamaydeh et al. (2017) leveraged genetic algorithm-optimized Quasi-Bang-Bang controllers for seismic structural control, highlighting the balance between computational simplicity and performance**.** Nguyen et al. (2018) developed a fuzzy disturbance observer-enhanced sliding mode controller, showcasing robustness under uncertainty and disturbance, tailored for train suspension systems. Savaia et al. (2021) utilized a Hammerstein–Wiener framework to model magnetization dynamics explicitly, a key feature often overlooked in traditional approaches, to enhance control-oriented modelling. Azar et al. (2020) proposed an inverse TSK model optimized with a modified grey wolf algorithm, demonstrating effectiveness in estimating control forces for complex structural applications. Saharuddin et al. (2021) introduced an Extreme Learning Machine (ELM) for predicting the hysteresis loop of MR dampers. This approaches provided faster computation and higher accuracy compared to traditional artificial neural networks, making it suitable for real-time applications in vibration control systems.

Tsang et al. (2006) introduced the Simplified Inverse Dynamics (SID) model for modelling the non-linear behavior of MR dampers, focusing on piston velocity feedback (PVF) and damper force feedback (DFF) algorithms. Numerical simulations using a 20-ton MR damper demonstrated that the SID model achieves force-tracking accuracy comparable to fully active control while maintaining simplicity. The study highlights the model's adaptability to various MR damper configurations and control algorithms. (e.g., bang-bang and Lyapunov). Chen et al. (2022) employed the Fireworks Algorithm (FWA) to optimize Bouc-Wen model parameters for MR dampers. The method demonstrated faster convergence and higher stability compared to Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). The average calculation accuracies under three harmonic excitations exceeded 80%, indicating effective parameter fitting for the Bouc-Wen model in semi-active suspension systems. Hu et al. (2017) used a hyperbolic tangent model to characterize MR damper hysteresis behavior in a semi-active suspension system. The study developed a hybrid fuzzy and fuzzy PID (HFFPID) controller to enhance suspension performance. Numerical simulations demonstrated significant reductions in body acceleration, suspension deflection, and tire displacement under various road excitations, validating the model and control system's effectiveness. Bai and Tang (2021) proposed a Dynamic Resistor-Capacitor Operator-based Model (dRCOM) to predict MR damper behavior. Incorporating graph neural networks, the model surpassed the basic RC operator and Bouc-Wen models in predicting hysteresis and non-linear damping characteristics. Experimental results showed that dRCOM achieved the lowest mean square errors among the models tested, emphasizing its accuracy and suitability for real-time applications. Negash et al. (2020) developed a novel GA with modified crossover and mutation processes for Bouc-Wen model parameter identification. Compared to standard GA, the proposed method improved accuracy by 46.67% while reducing the number of generations for convergence. The approach offers better applicability for real-time control in MR damper systems. Yarali et al. (2019) presented a prototype double-tube MR damper and used a neural network algorithm for damping force prediction. The study demonstrated that damping force in saturated current conditions increased fivefold compared to zero current. Neural network predictions closely matched experimental results, highlighting the feasibility of combining neural networks with parametric models for advanced damper applications. Zhang et al. (2021) used the Shuffled Frog-Leaping Algorithm (SFLA) for parameter identification in hyperbolic tangent models of MR dampers. Sensitivity analysis revealed critical parameters affecting hysteresis behavior. The modified model achieved high fitting accuracy across varying currents and excitation frequencies, showing its versatility for dynamic modelling and suspension control.

2. Methodology

2.1 Experimental Setup

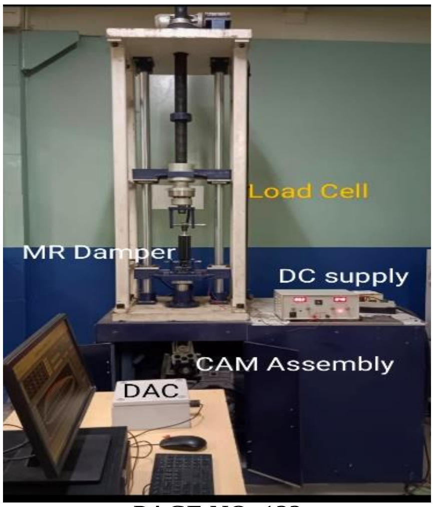


Figure 1: Damper Testing Machine.

The MR damper is securely mounted in the Damper testing machine to allow for controlled movement and measurement of damping forces. Inbuilt actuation system is used to apply controlled displacements or velocities to the damper. This can be achieved using a servo motor, Cam actuator. The constant current supply is provided by the external source to vary the magnetic fields to the MR damper. A load cell force sensor is integrated to measure the damping forces generated by the MR damper which is capable of measuring forces accurately. A computer based software is used to regulate actuation system, and data acquisition. The data acquisition system records the data from the sensors and control system. Figure 1 represents the experimental set up of the damper testing machine and its technical specification is listed in Table 1.

Table 1. Damper Testing Machine Specification

SN.	Damper testing parameter	Value
1	Force range	0 - 1000 kgf
2	Displacement range (stroke)	0 to 200 mm
3	Frequency range (Force input)	0 – 10 Hz
4	Velocity range	0 – 1 m/s

2.2 Testing of magnetorheological (MR) damper

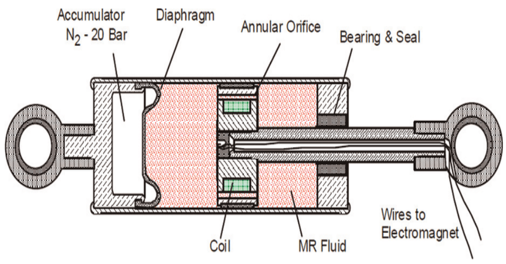


Figure 2: Cut section of MR Damper.

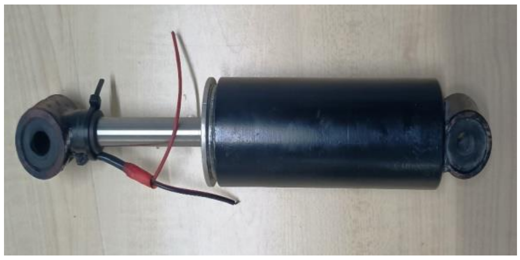


Figure 3: MR damper used for Experimentation

Table 2: MR damper Specification

SL.No	Design variable /Response Variable	(mm)
1	Total length (extended)	285
2	Total length (compressed)	215
3	Stroke length (maximum)	70
4	External tube diameter	48
5	Shaft rod diameter	14

In this test, the MR damper is subjected to dynamic loading by applying various current inputs and the damping force response is measured to evaluate the damper's performance under the velocity of 0.52 m/s. This test determines the damping force response of the MR damper at constant velocity with varying current helps in understanding the damper's ability to control vibrations over a range of frequencies the stroke test evaluates the damping force characteristics of the MR damper at stroke length of 60mm. It provides insights into the damper performance under different operating conditions. Experimental data from the tests are utilized to validate numerical models of the MR damper, ensuring that the models accurately predict the damper's behavior

2.3 Predictive Modelling

Predictive modelling plays a crucial role in estimating system behavior based on experimental data. In this study, predictive modelling is employed to estimate the force-displacement relationship of an automotive semi-active suspension system using a machine learning approach. This chapter discusses the methodology, algorithm selection, data preparation, model training, and evaluation techniques used in the predictive modelling process. Predictive modelling is a statistical technique that utilizes historical data to predict future outcomes. In the context of this study, predictive modelling is used to estimate force values at intermediate control current levels using experimental force-displacement data.

2.4 Selection of Algorithm for Predictive Modelling

In the domain of predictive modeling for MR dampers—particularly for forecasting force–displacement and force–velocity behavior—a range of data-driven techniques have been explored, each with distinct advantages depending on data availability and application complexity. Gradient boosting methods, including XGBoost, LightGBM, and CatBoost, are among the most powerful due to their ability to handle nonlinear relationships, manage outliers, and incorporate regularization techniques. These models are especially suited for predicting force response under varying current and velocity conditions, offering high accuracy and robustness. Random Forest, an ensemble of decision trees, is another effective method that reduces overfitting and provides interpretable feature importance. It performs well even when the experimental dataset is limited, making it a reliable choice for damping force modeling.

Support Vector Regression (SVR), using radial basis function (RBF) or polynomial kernels, excels in scenarios with small datasets and high-dimensional input features. It is particularly useful in modeling force–velocity characteristics where data quantity is a constraint. Artificial Neural Networks (ANNs), including feedforward networks and Long Short-Term Memory (LSTM) models, are capable of learning complex nonlinear dynamics. LSTM, in particular, is well-suited for capturing temporal dependencies in dynamic force prediction and modeling hysteresis behavior.

In more empirical approaches, polynomial regression (typically 2nd to 5th order) is frequently employed to fit nonlinear hysteresis loops observed in MR damper experiments. While easy to implement and interpret, its effectiveness is usually localized and lacks generalization beyond the training range. K-Nearest Neighbors (KNN), a non-parametric, instance-based learner, offers good interpolation performance within the known data space but struggles to generalize to unseen scenarios, making it suitable only for well-covered input ranges. Gaussian Process Regression (GPR) brings a Bayesian perspective to regression by not only offering high predictive accuracy on small datasets but also providing confidence intervals, thus quantifying the uncertainty in model predictions—an essential feature for safety-critical automotive applications. Lastly, Decision Tree models, such as CART, though simple and fast to train, serve best as baseline models or for early-stage exploratory analysis due to their interpretability and low computational demands.

Among the various predictive modeling techniques evaluated for MR damper systems, Gradient Boosting (GB) methods stand out as the most effective and reliable due to their unique combination of high prediction accuracy, robust handling of nonlinearities, and built-in regularization mechanisms. Unlike traditional models such as polynomial regression or decision trees, GB methods sequentially learn from the errors of prior models, thereby capturing complex force–displacement and force–velocity hysteresis behavior with remarkable precision. Their ability to handle large numbers of input features (e.g., current, velocity, derived velocity slopes, etc.) without overfitting makes them ideal for modeling the nonlinear and hysteretic nature of MR dampers. Furthermore, GB algorithms are less sensitive to noise and outliers, which is crucial in experimental damper data where irregularities or minor inconsistencies are common. Advanced implementations like XGBoost and LightGBM offer fast training speeds, parallel processing, and automatic feature importance ranking, enabling effective parameter tuning and model interpretability. Additionally, compared to black-box models like neural networks, GB models offer better explainability, making them more suitable for safety-critical automotive applications, where understanding model behavior is essential. The consistent outperformance of GB in cross-validation results and its generalization ability to predict unseen current levels (e.g., 0.25 A, 0.75 A, etc.) further reinforces its suitability for MR damper force prediction tasks. Gradient Boosting is selected for predictive modelling due to its ability to handle nonlinear relationships and improve prediction accuracy iteratively. Gradient Boosting builds an ensemble of weak learners (decision trees) sequentially, where each new tree corrects the errors of the previous ones. The dataset consists of force-displacement measurements for an MR damper obtained at different current levels (0, 0.5, 1, 1.5, and 2 A) and input velocity levels at 0.52 m/s. The dataset includes:

- Input variables: Displacement, Velocity, and Current.
- Output variable**:** Force

3. Results And Discussion

The Gradient Boosting (GB) machine learning approach can significantly enhance the comprehensive study of performance characteristics, nonlinear rheological behavior, and multi-model curve fitting. Mathematical models like Bingham, polynomial, or Tanh may struggle to fully capture the complex, nonlinear behavior of MR dampers under various operating conditions. GB excels in handling nonlinearities and interactions among variables. By learning from residuals iteratively, GB can model complex relationships between input parameters current, velocity, and output force more accurately. This results in improved prediction of force-displacement behavior across different operational scenarios. Thus, GB is used for validating the accuracy of mathematical models against experimental data especially when the models need to generalize well to unseen data. For model training, the dataset comprising force–displacement was prepared from experimental test cases at five input current levels. The dataset was then segmented into input features such as current, velocity, and displacement, while the corresponding damper force served as the target variable. Data normalization was applied to maintain numerical stability and enhance learning efficiency. The model training process involved an 80:20 train-test split, with 5-fold cross-validation employed to ensure generalization and prevent overfitting. Additionally, hyperparameters such as learning rate, number of estimators, maximum tree depth, and regularization terms were fine-tuned using grid search and early stopping.

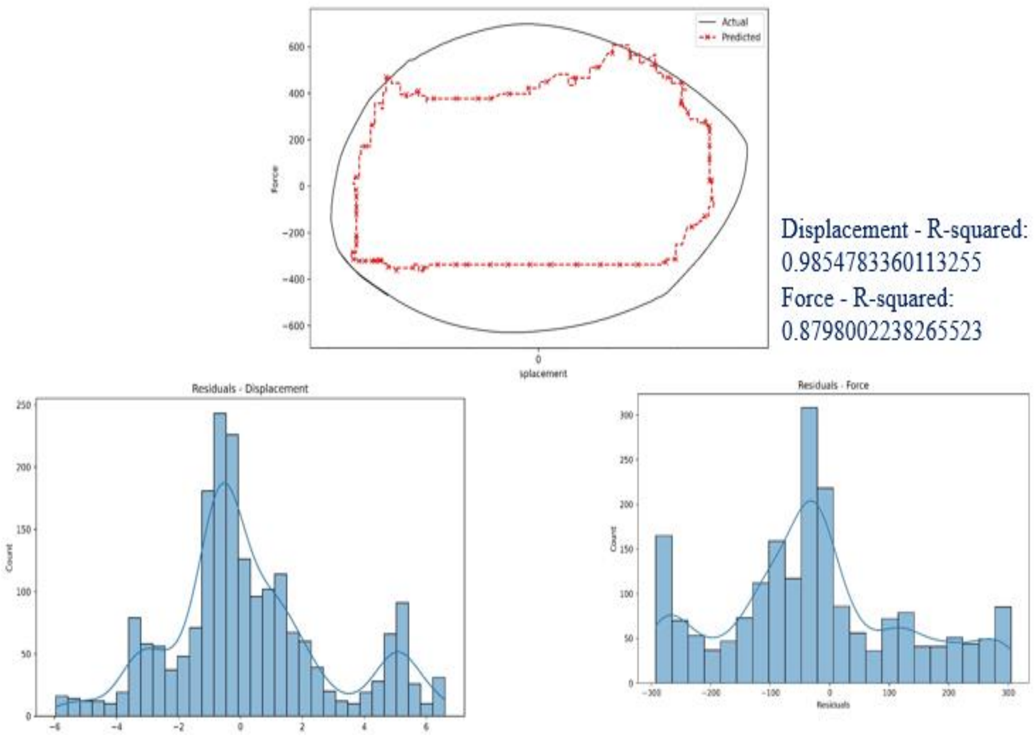


Figure 4 Force Displacement Plot for Data Trained at 0A 0.52 m/s

At zero current, Figure 4 the MR fluid exhibits minimal magnetic field influence. The damper behavior closely resembles that of a passive damper, characterized by a narrow hysteresis loop and relatively low force output. This serves as the baseline reference for evaluating active control capability. The force values here are predominantly due to mechanical friction and inherent fluid resistance.

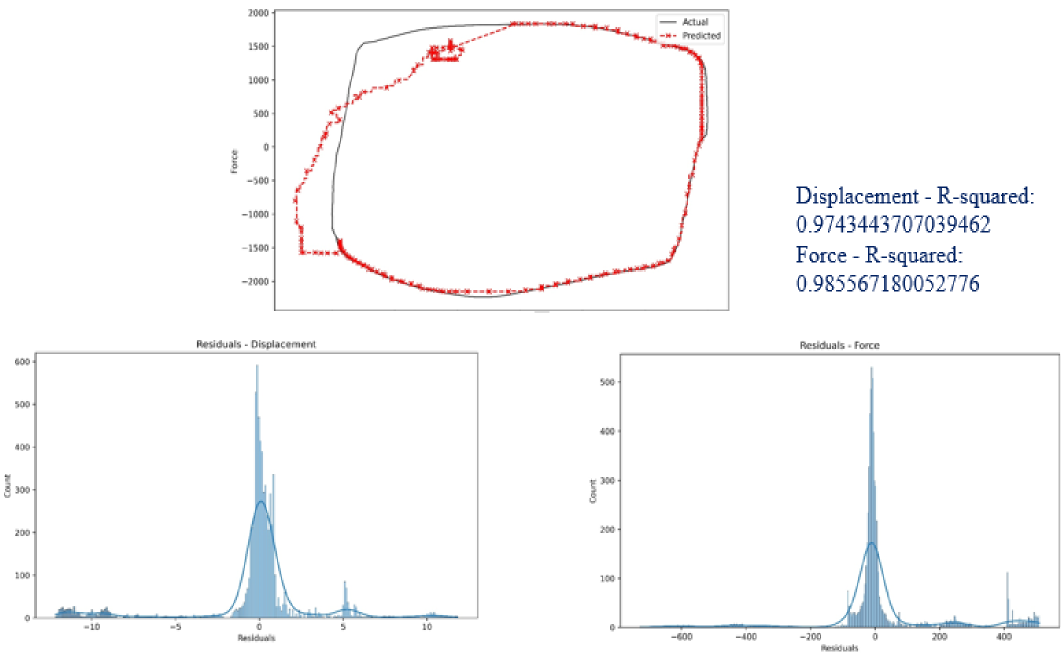


Figure 5 Force Displacement Plot for Data Trained at 0.5A 0.52 m/s

A noticeable increase in force amplitude is observed in Figure 5. The magnetic field begins to align the MR particles, increasing yield stress and contributing to greater energy dissipation. The area enclosed by the hysteresis loop (indicative of energy dissipation) increases, confirming enhanced damping performance

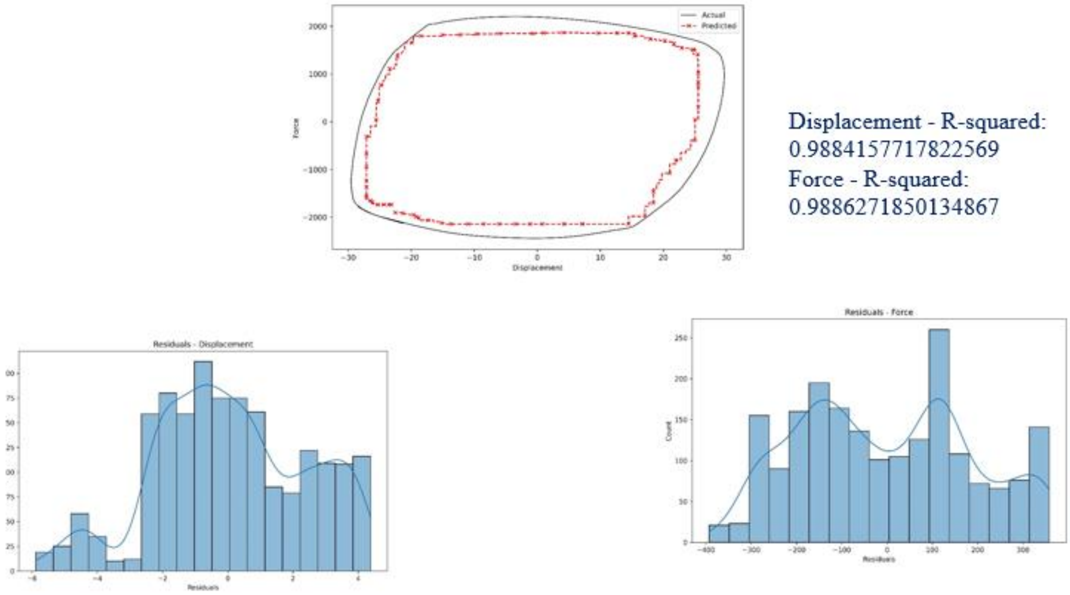


Figure 6 Force Displacement Plot for Data Trained at 1A 0.52 m/s

The force continues to rise with increasing current Figure 6. The loop becomes broader and more symmetric, reflecting the development of a fully formed yield surface in the MR fluid. The system transitions into a semi-active damping regime where the damper responds more strongly to external inputs

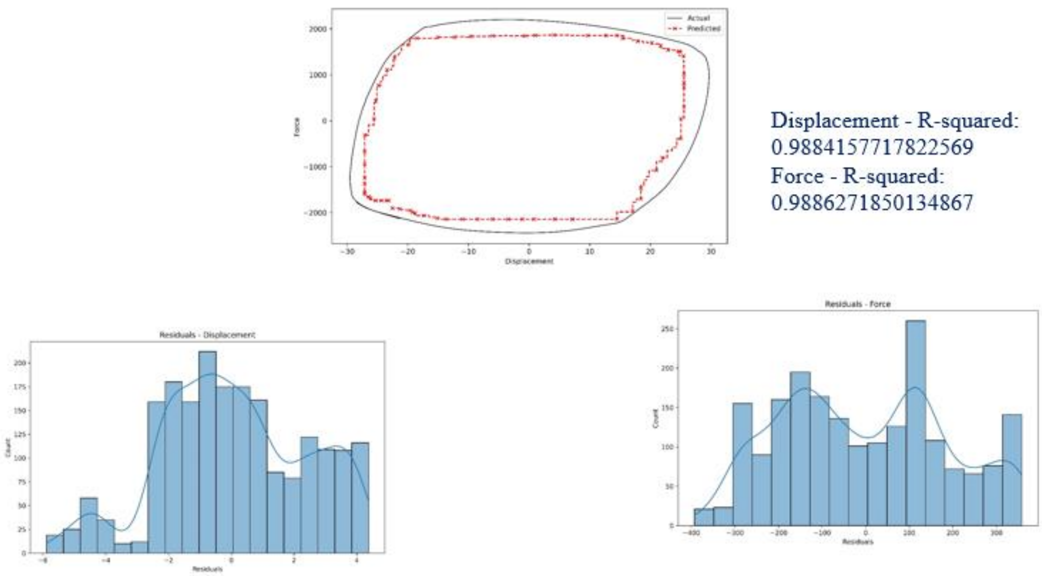


Figure 7 Force Displacement Plot for Data Trained at 2A 0.52 m/s

The maximum damping effect is achieved Figure 7. The hysteresis loop becomes the widest among the experimental cases, showing significant resistance in both compression and rebound strokes. The force-displacement curve demonstrates strong nonlinearity, especially near the displacement reversal zones. This nonlinearity is attributed to the combined viscoplastic behavior and magnetic saturation effects in the MR fluid.

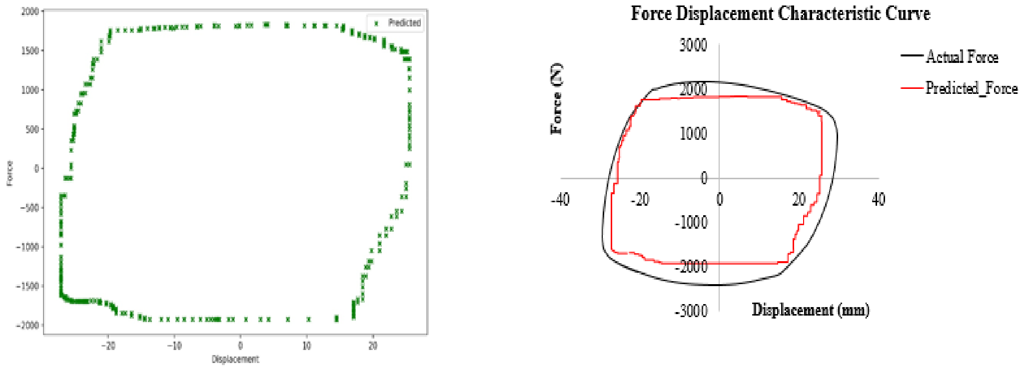
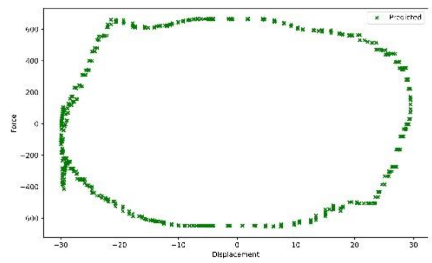


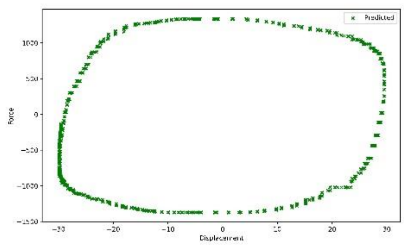
Figure 8 Force Displacement Plot for Data Trained at 1.5A 0.52 m/s

The response at 1.5 A Figure 8 shows intermediate behavior between 1 A and 2 A. The loop is broad and exhibits nonlinear stiffness, signifying the transitional regime between moderate and saturated magnetic field strength.

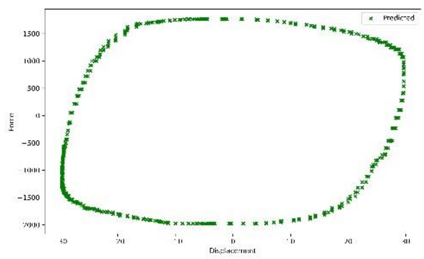
These plots validate the experimental consistency of the MR damper's performance across different magnetic field strengths and form the training basis for predictive modeling using



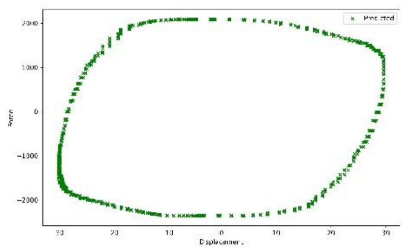
a Predicted Force Displacement Plot for 0.25 A



b Predicted Force Displacement Plot for 0.75 A



c Predicted Force Displacement Plot for 1.25 A



d Predicted Force Displacement Plot for 1.75 A

Figure 9 Illustration of Predicted Force Displacement Plot for Unseen data

The trained model was subsequently tested on unseen current levels (0.25 A, 0.75 A, 1.25 A, 1.75 A) to evaluate its ability to interpolate damper behavior between known data points. The prediction results showed strong agreement with the experimental trends, confirming the model's capability to simulate MR damper force response across varying operating conditions. Evaluation metrics R^2 score were used to select the optimal parameter configuration. This rigorous tuning approach enabled the model to accurately predict damper force response across a wide range of input currents and velocities, ensuring its reliability in capturing the nonlinear behavior of the MR damper system. The interpolation method is employed to estimate force-displacement data for intermediate current values (e.g., 0.25 A, 0.75 A, 1.25 A, and 1.75 A) that are not directly measured during the experiment. The method uses data from the experimentally recorded force-displacement datasets for current values 0 A, 0.5 A, 1 A, 1.5 A, and 2 A at 0.52 m/s. The Gradient-Based (GB) interpolation algorithm ensures accurate predictions by leveraging the trends and relationships inherent in the measured data that are illustrated in Figures 9a, 9b, 9c, and 9d.

The predicted loop shows a small but distinguishable increase in force compared to 0 A Figure 9.a. It captures the early onset of magnetorheological activity. The shape and size of the loop align well with expected physical behavior, confirming the model's ability to interpolate low-field responses. In figure 9.b the predicted force response displays smooth scaling from 0.5 A to 1 A behavior. The loop area is larger than 0.5 A, indicating more energy dissipation. The plot effectively preserves the curve symmetry and nonlinearity, demonstrating the model's sensitivity to moderate field strengths. The prediction at 1.25 A shows excellent transition between the responses at 1 A and 1.5 A Figure 9.c. the increase in force is more pronounced in the compression region than rebound, a trend consistent with experimental behavior. The prediction successfully reflects asymmetric hysteresis Figure 9.d. As the current approaches 2 A, the predicted plot begins to resemble the maximum damping response. The model maintains fidelity to experimental trends, with high force output and wide hysteresis. Higher R^2 value (0.98) for all interpolated cases, confirming strong correlation between predicted and experimental behavior that indicates the strength of GB model.

4. Conclusion

MR dampers exhibit complex, nonlinear behavior due to hysteresis and viscoplastic properties. Traditional models like Bingham or Herschel-Bulkley may not fully capture dynamic force-displacement variations. Gradient Boosting helps identify nonlinear patterns from experimental data. Instead of conducting physical experiments for every possible operating condition, the model predicts damper responses for new inputs and also helps to analyze the effects of different currents, displacements, and velocities without repeated prototyping. The model aids in designing MR dampers with optimal performance characteristics. The trained model can be integrated into semi-active suspension controllers. Real-time force estimation improves adaptive control strategies, enhancing vehicle ride comfort and handling.

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