BTP MID TERM REPORT

PROBLEM STATEMENT: Applications of MR Fluid Actuators with Machine Learning for Vehicle Optimization

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Problem Statement: Applications of MR Fluid Actuators with Machine Learning for Vehicle Optimization

Background:
The project aims to integrate Magnetorheological (MR) Fluid Actuators into vehicle systems, utilizing Machine Learning (ML) techniques to optimize their performance. The foundation for this endeavor is based on the research outlined in the paper titled "Exact Physical Model of Magnetorheological Damper" by Cezary Graczykowski and Piotr Pawłowski.

Objectives: The primary objectives of this project are as follows:

- Integration of MR Fluid Actuators: Incorporate Magnetorheological (MR) fluid-based actuators within a vehicle's mechanical system to influence damping characteristics.
- Data Extraction and Analysis: Extract relevant data from the MR fluid actuators to comprehensively understand their behavior and responses in varying conditions.
- Machine Learning Optimization: Utilize Machine Learning algorithms and techniques to process the extracted data and optimize the control strategies for the MR fluid actuators.

Challenges and Focus Areas:

- Nonlinearity and Complex Behavior: MR fluid actuators exhibit highly nonlinear and complex behavior, making modeling and control challenging.
- Data Extraction and Preprocessing: Extracting meaningful data from the MR fluid actuators while dealing with noise and non-uniformity poses a significant challenge.
- Optimization Algorithms: Selecting appropriate optimization algorithms within Machine Learning that can effectively optimize the behavior of MR fluid actuators for vehicle dynamics.

Proposed Approach:
To address the outlined objectives and challenges, the project will adopt the following approach:

- Experimental Setup: Establish a comprehensive experimental setup to capture relevant data from the MR fluid actuators under various conditions.
- Data Processing and Feature Selection: Apply advanced data processing techniques and feature selection to preprocess the raw data, ensuring its suitability for Machine Learning applications.
- Machine Learning Model Development: Develop machine learning models and algorithms that can effectively analyze the processed data and optimize the control strategies for MR fluid actuators in a vehicle.
- Performance Evaluation and Validation: Evaluate the performance of the optimized MR fluid actuators through simulations and real-world testing, validating the effectiveness of the proposed approach.

Expected Outcome:

Upon successful completion of this project, we aim to achieve:

- Optimized MR Fluid Actuators: Enhanced control strategies for MR fluid actuators in vehicles, leading to improved vehicle performance, safety, and comfort.
- Insights into MR Fluid Behavior: In-depth understanding of the behavior of MR fluid actuators through data analysis, aiding in the development of future applications and advancements in the field.

Deliverables of the project and timeline

Deliverables:

(i). Machine Learning Model for Predicting Unknown Values: Utilizing advanced machine learning techniques to create a predictive model capable of estimating unknown values without the need for extensive experimentation.

(ii). Data Extraction and Segregation Process: Develop a systematic process for extracting and segregating data from MR fluid actuators, ensuring meaningful categorization for analysis.

(iii). Simulink Model for MR Fluid Actuator Optimization: Developing a Simulink model that integrates the optimized control strategies for MR fluid actuators, providing a platform for simulations and testing.

Timeline: 3 Months (Tentative)

- **Month 1 (Weeks 1-4): Project Initiation, Data Collection, and Preprocessing:** Established the project roles. Set up the experimental infrastructure for data collection from MR fluid actuators.

  – Week 1-2: Data Collection and Segregation: Gathered raw data from the MR fluid actuators. Segregate and organize the data into relevant categories based on experimental parameters.

  – **Week 3-4: Data Preprocessing and Analysis:** Preprocess the collected data to remove noise and inconsistencies. Analyze the preprocessed data to identify initial patterns and characteristics of MR fluid behavior.

- **Month 2 (Weeks 5-8): Data Analysis and Machine Learning Model Development:**

  – Analyze the preprocessed data to understand MR fluid behavior.

  – Develop and train the machine learning model for predicting unknown values.

- **Month 3 (Weeks 9-12): Simulink Model Development and Validation:**

  – Implement the optimized control strategies in a Simulink model.

  – Validate the models through simulations and refine them based on the results.

Literature and References

Literature Overview:

The primary literature reference for this project is the paper titled "Exact Physical Model of Magnetorheological Damper" by Cezary Graczykowski and Piotr Pawłowski. Published in *Applied Mathematical Modelling* (47, 2017), this paper delves into an exact physical model of magnetorheological dampers. The authors comprehensively explore key aspects such as hysteresis modeling and the behavior of smart fluids, providing valuable insights for our research. Link to the paper: https://www.sciencedirect.com/science/article/pii/S0307904X17301312

Graphical Analysis:

One of the foundational components of our project involved a thorough analysis of hysteresis loops, as depicted in the following graphs:

Comparison of Hysteresis Loops:

- Frequency: 0.5 Hz, Current: 1 A
- Frequency: 1.5 Hz, Current: 0.3 A
- Frequency: 3.5 Hz, Current: 0.6 A

These graphs played a crucial role in our project, forming the basis for data extraction and subsequent analysis to develop the machine learning model.

References:

1. Graczykowski, C., & Pawłowski, P. (2017). Exact physical model of magnetorheological damper. *Applied Mathematical Modelling*, 47(2017), 400-424.

Data Extraction and Methodology

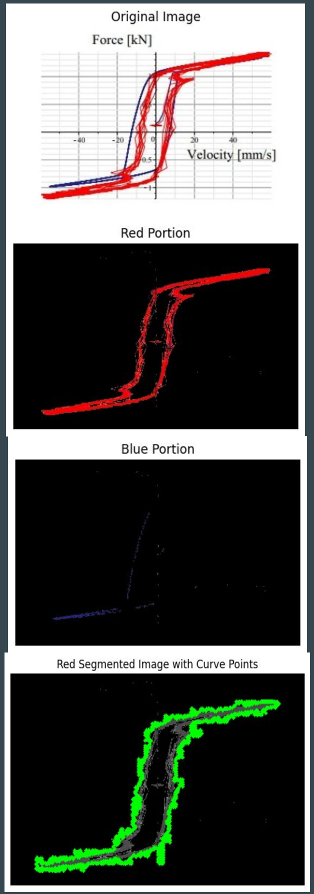
Data Extraction: Data extraction was performed to gather critical information from three different graphs, each corresponding to distinct operating conditions:

- Frequency: 0.5 Hz, Current: 1 A
- Frequency: 1.5 Hz, Current: 0.3 A
- Frequency: 3.5 Hz, Current: 0.6 A

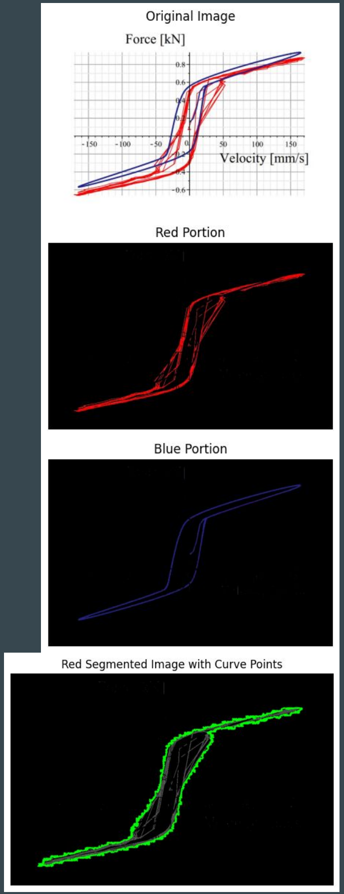
Methodology:

- The red and blue segments of the images were isolated using color thresholds for further analysis.
- Contour detection was employed to locate the primary curve of interest, selecting the largest contour for analysis.
- Interpolation was then used to estimate additional points along the curve, ensuring an adequate number of data points for subsequent analysis.
- Due to sparse data points near the middle of the curve, manual data inclusion was performed using the online software WebPlotDigitizer.
- A transformation was applied to convert image coordinates to the desired real-world coordinate system.

The extracted data points were saved to CSV files for each graph, facilitating subsequent analysis and modeling.



0.5Hz / 1A



1.5Hz / 0.3A

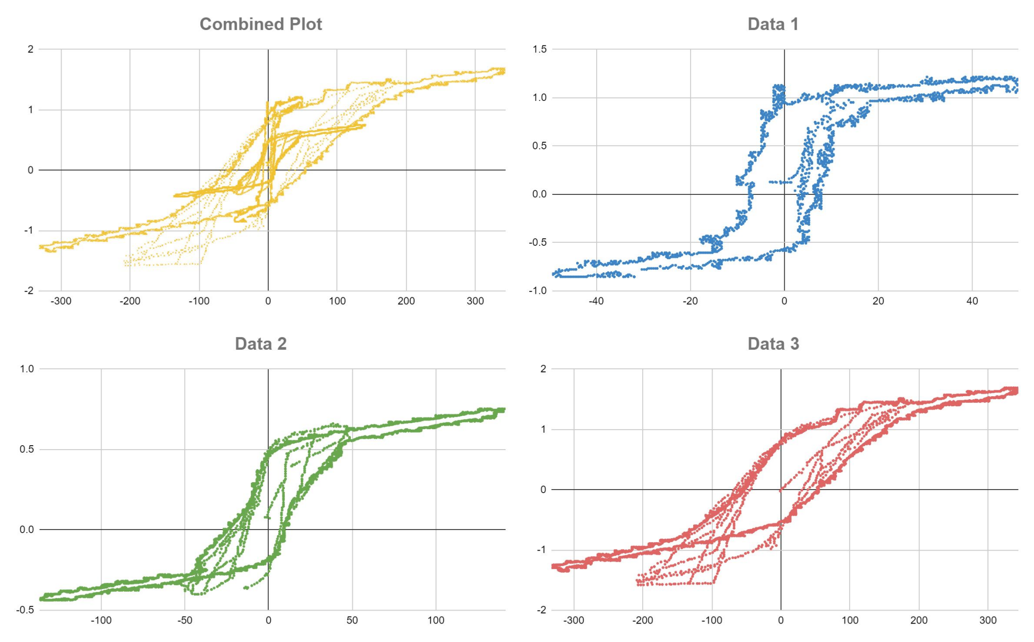
Links to the .csv & codes and results obtained

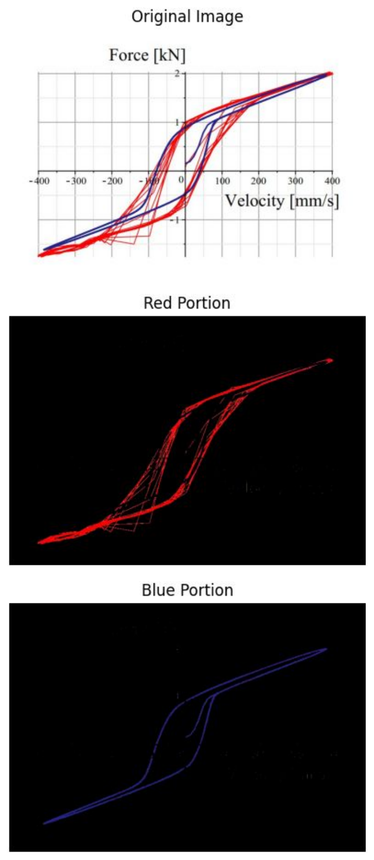
Code and CSV for 1st graph: graph-1.ipynb and data for graph-1.

Code and CSV for 2nd graph: graph-2.ipynb and data for graph-2.

Code and CSV for 3rd graph: graph-3.ipynb and data for graph-3.

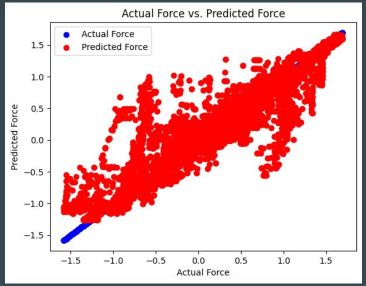
So, the combined data is: Combined graph and data extracted.





3.5 Hz / 0.6 A

Modeling Approach and Results:



Model Selection:

We employed Support Vector Regression (SVR), Random Forest, and Neural Networks as our main models for predicting magnetorheological damper force based on input parameters such as velocity, frequency, and current.

Accuracy Comparison:

- SVR, our main model, closely followed with an R^2 Score of 0.84, showcasing robust predictive capabilities.
- Random Forest exhibited the highest predictive R^2 Score, achieving an impressive 0.87. But, we have used SVR as our main model.
- Neural Networks delivered competitive results with an R^2 Score of 0.82 or 0.83.

Prediction of Force: When it comes to modeling mechanical systems such as dampers and suspensions, the choice between Support Vector Regression (SVR) and Random Forest (RF) may depend on the specific characteristics of the problem and the goals of the analysis. Here are some considerations in the context of dampers and suspensions:

1. Nonlinear Behavior: Dampers and suspensions often exhibit nonlinear behavior due to the complex interactions of various mechanical components. SVR, with its ability to model nonlinear relationships using kernel functions, can be a good choice for capturing these nonlinearities.

2. Physical Interpretability: Understanding the physical behavior of dampers and suspensions is crucial in mechanical engineering. SVR can provide better interpretability by focusing on the support vectors and the hyperplane, which might align better with the underlying physical principles.

3. Computational Efficiency: For larger datasets or when you need to train multiple models with different hyperparameters, RF can be computationally expensive. SVR, in some cases, can be more computationally efficient.

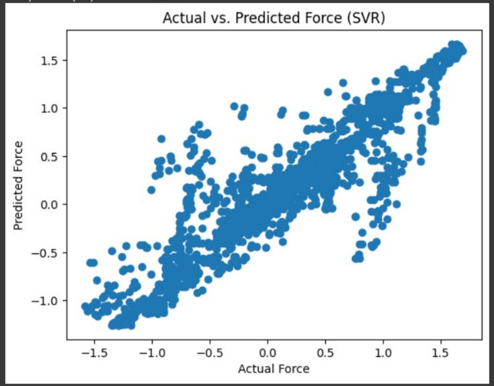
4. Hyperparameter Tuning: Both SVR and RF have hyperparameters that need tuning. SVR allows you to fine-tune parameters like the choice of kernel function and epsilon, which can be beneficial when you have domain-specific knowledge about the behavior of dampers and suspensions.

Best Hyperparameters we got using GridSearch in SVR

RESULTS (SVR)

COLAB LINK: [Link to the model]

```
Best Hyperparameters: {'C': 10, 'epsilon': 0.1, 'gamma': 500, 'kernel': 'rbf'}
Mean Squared Error (MSE): 0.09
R-squared (R2) Score: 0.84
```

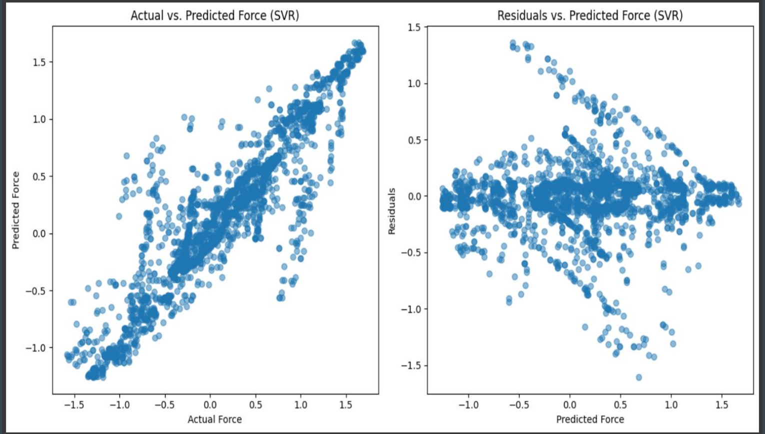



```
print(f"Explained Variance Score: {explained_var:.2f}")
```

```
Best Hyperparameters: {'C': 10, 'epsilon': 0.1, 'gamma': 500, 'kernel': 'rbf'}
Mean Squared Error (MSE): 0.09
Root Mean Squared Error (RMSE): 0.29
Mean Absolute Error (MAE): 0.18
R-squared (R2) Score: 0.84
Explained Variance Score: 0.84
```

Predicted value from our model

Actual Values of data




```
# Define a function to make predictions
def predict_force(frequency, velocity, current):
    # Scale the input features using the same scaler
    input_data = scaler.transform([[velocity, frequency, current]])

    # Predict the force using the trained SVR model
    predicted_force = best_svr.predict(input_data)

    return predicted_force[0]

# Create a user-friendly input box in the terminal
try:
    frequency_input = float(input("Enter Frequency: "))
    velocity_input = float(input("Enter Velocity: "))
    current_input = float(input("Enter Current: "))

    predicted_output = predict_force(frequency_input, velocity_input, current_ir
    print(f"Predicted Force: {predicted_output:.2f}")
except ValueError:
    print("Invalid input. Please enter numeric values for Frequency, Velocity, a
```

```
Enter Frequency: 0.5
Enter Velocity: -32.2826087
Enter Current: 1
Predicted Force: -0.74
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
  warnings.warn(
```

1 to 10 of 12967 entries Filter

velocity	force	frequency	current
-31.95652174	-0.8533333333	0.5	1
-32.2826087	-0.8425	0.5	1
-32.2826087	-0.8316666667	0.5	1
-31.95652174	-0.8208333333	0.5	1
-31.63043478	-0.81	0.5	1
-31.30434783	-0.7991666667	0.5	1
-31.30434783	-0.7991666667	0.5	1
-30.97826087	-0.7991666667	0.5	1
-30.32608696	-0.7775	0.5	1
-30.32608696	-0.7775	0.5	1

Show 10 per page

1 2 10 100 1000 1200 1290 1297

Problems we have faced and Future Work to be done

Challenges Faced:

1. Data Extraction Challenges:

- Extracting accurate data from the graphical image proved to be a significant challenge.
- Multiple approaches were attempted, ultimately leading to the current refined data extraction method mentioned earlier.

2. Modeling Challenges:

- Initially encountered low accuracies with the models, necessitating further optimization.
- Challenges were addressed through extensive data preprocessing and techniques such as grid search for hyperparameter tuning.

Future Work:

1. Model Optimization:

- Further fine-tuning and optimization of the models to enhance predictive accuracies.
- Exploring advanced modeling techniques and algorithms to improve the performance of the predictive models.

2. Simulink Model Preparation:

- Development of a comprehensive Simulink model integrating the optimized control strategies for magnetorheological dampers.
- Rigorous validation and testing of the Simulink model to ensure its accuracy and reliability in vehicle dynamics simulations.

THANK YOU !!