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Research Article

Machine Learning-Based Prediction and Multi-Algorithm Optimization for Reducing Vertical Acceleration and Enhancing Two-Wheeler Ride Comfort

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ABSTRACT

The suspension system has a major impact on the rider's comfort and stability and is essential in minimizing vibrations that are conveyed to them. Uncomfortable, exhausting, and perhaps dangerous situations can result from excessive vertical acceleration brought on by uneven roads. In order to analyze and optimize the impact of road surface, speed, and suspension stiffness on vertical acceleration, this study used machine learning regression models and optimization approaches in an experimental examination.

In a total of twenty-seven trials, three separate suspension springs were put through their paces on three separate road surfaces. To ensure precise data collection, a sitting pad accelerometer and a Svantek FFT analyzer were used to determine the maximum vertical acceleration and RMS acceleration. Maximum vertical acceleration was predicted using three regression models: Support Vector Regression (SVR), Random Forest Regression (RFR), and Response Surface Methodology (RSM). In order to find the sweet spot for suspension stiffness, road surface type, and vehicle speed that would minimize maximum vertical acceleration, optimization methods like Genetic Algorithm (GA) and the Nelder-Mead approach were employed.

The findings demonstrate a robust link among suspension stiffness, road surface imperfections, and speed in affecting vertical acceleration. The Random Forest Regression model attained a R^2 score of 0.30 and a root mean square error (RMSE) of 0.475, whereas the RSM exhibited superior performance with a R^2 score of 0.66 and an RMSE of 0.563. Nonetheless, SVR demonstrated subpar performance, evidenced by a R^2 score of -0.61 and an RMSE of 0.722. The refined suspension configuration resulting from these models decreased the maximum vertical acceleration from 1.72 m/s^2 to 1.656 m/s^2, enhancing ride comfort by about 3.68%.

This work systematically improves two-wheeler suspension systems for greater ride quality, fatigue reduction, and safety. Automotive engineers, manufacturers, and researchers enhancing car suspension performance in real-world driving situations will benefit from the findings.

Keywords: Regression, RSM, Genetic algorithm, optimization, suspension system, Machine learning

1. INTRODUCTION

Whole-body vibration (WBV) is a critical determinant influencing the ride comfort and health of two-wheeler operators. Motorcycles and scooters, in contrast to four-wheel vehicles, subject riders to significant vibration levels owing to direct road contact and very rudimentary suspension systems. Extended exposure to whole-body vibration (WBV) may result in discomfort, fatigue, and significant musculoskeletal diseases, including lower back pain and spinal degeneration (Kumar et al., 2013; Saran et al., 2013; et al., 2019). [15,13]. Whole-body vibration (WBV) is predominantly conveyed via the seat interface, footrests, and handlebars, with its impact shaped by several elements such as road surface conditions, suspension system attributes, vehicle velocity, and rider posture (Chen et al., 2009; Tathe & Wani, 2013). [1,2]

Two-wheelers represent a significant mode of transportation globally, especially in developing nations, where their affordability, fuel efficiency, and ease of maneuverability contribute to their widespread popularity (Eluri et al., 2019; Parvez & Khan, 2019). [13,5] Nonetheless, the significant utilization of these factors leads to considerable exposure to discomfort and health complications caused by vibrations. Research indicates that riders frequently encounter vibration levels that surpass the limits established by international standards, including ISO 2631-1 and ISO 2631-5, which evaluate the impact of whole-body vibration on human health (Chen et al., 2009; Arslan, 2015). Long-term exposure to WBV can lead to discomfort and fatigue, which may affect rider concentration, elevate the risk of accidents, and contribute to chronic physiological conditions (Singh et al., 2015). [4]

Road surfaces that motorcycle riders experience range from smooth freeways to rugged terrain with bumps, potholes, and uneven patches. Both rider comfort and vehicle stability are impacted by these anomalies, which make WBV more severe (Kumbhar et al., 2012). [3] According to research, WBV levels fluctuate greatly depending on vehicle speed, suspension characteristics, and road surface roughness; therefore, a methodical approach is necessary to lessen its effects (Kumar et al., 2013; Doria et al., 2020). [3] [17] [15]. Accordingly, the suspension system is essential for mitigating vibrations and absorbing shocks (Saran et al., 2013; Parvez & Khan, 2019). [15, 5]. But conventional suspension designs frequently fall short of maximizing performance in a range of road conditions, requiring more investigation and advancements in suspension technology (Arslan, 2015). [6]

This study comprised 27 experimental trials, focusing on the measurement of RMS acceleration and maximum acceleration through the use of a Svantek FFT analyzer and a seated pad accelerometer in a controlled environment. The findings are intended to offer significant insights for automotive engineers, manufacturers, and experts in the field, focusing on the optimization of two-wheeler suspension systems to minimize WBV exposure, enhance rider safety, and improve long-term ride comfort (Singh et al., 2015; Parvez & Khan, 2019). [4,5] The results will aid in the progress of suspension design, vibration damping technologies, and ergonomic enhancements, ultimately improving the riding experience for motorcyclists (Zhou & Griffin, 2014; Doria et al., 2020). [7],[17]

2. METHODOLOGY

This research utilizes an experimental methodology alongside machine learning regression models and optimization strategies to reduce the maximum vertical acceleration encountered by two-wheeler riders. A total of 27 controlled experiments were performed by manipulating suspension stiffness, road conditions, and speed, with subsequent recording and analysis of the vibration responses. The main aim was to examine the influence of these parameters on whole-body vibration (WBV) and to enhance the two-wheeler's suspension system to augment ride comfort and diminish fatigue (Kumar et al., 2013; Saran et al., 2013; Eluri et al., 2019)[15,13]. Consult Figure 1.

The experimental configuration aimed to simulate authentic riding situations while maintaining uniformity in data acquisition. The test parameters were three distinct suspension stiffness levels, three varieties of road surfaces (highway, rough terrain, and unpaved road), and three varying speeds (low, medium, and high). The investigations utilized a two-wheeler test rig fitted with a sitting pad accelerometer and a Svantek FFT analyzer to assess WBV (Kumar et al., 2013). [15]. The accelerometer, affixed to the motorcycle seat, measured vertical acceleration along the Z-axis, the principal direction influencing rider comfort. The Svantek FFT analyzer recorded Root Mean Square (RMS) acceleration and Maximum Vertical Acceleration, essential measures for assessing ride comfort (Saran et al., 2013).[15]

The **Root Mean Square (RMS) acceleration** was computed using the following equation:

$$a_{rms} = \sqrt{\frac{1}{T}\int_0^T a^2\,(t)dt}$$

where a_{RMS} represents the **Root Mean Square acceleration**, a(t) is the **instantaneous acceleration**, and T is the **measurement duration** (Eluri et al., 2019,Griffin M J.1997).[18][20][8].

Additionally, the **Vibration Dose Value (VDV)** was computed using:

$$VDV = (\int_0^T a^4\,(t)dt)^{\frac{1}{4}}$$

Higher VDV values signify increased discomfort and health risks (Kumar et al., 2013; Saran et al., 2013; Tobias Stenlund et al., 2020). [15, 19]

Occupant discomfort resulting from vibration transmitted via a vehicle seat can be assessed by measuring the vibration at the interface between the occupant and the seat. (Kim et al., 2020) [16]

For the purpose of determining the maximum vertical acceleration, machine learning regression models were utilized in order to investigate the impact of the suspension stiffness, the road conditions, and the speed respectively. The following three kinds of regression models were put into practice:

1.Random Forest Regression is an ensemble learning technique that employs multiple decision trees to enhance prediction accuracy in a non-linear manner.

2.Response Surface Methodology (RSM) is a statistical technique that models the relationship between independent variables and their corresponding responses.

3. Support Vector Regression (SVR) is a machine learning method that employs a kernel function to determine the optimal hyperplane for predictive purposes.

Following the training and evaluation of the models, optimization approaches were employed to determine the ideal combination of road surface, speed, and suspension stiffness for mitigating vertical acceleration. The optimization techniques that were employed were:

1. An algorithm that finds the best suspension setups by methodically refining the results of regression models is called a genetic algorithm (GA), and it is based on natural evolutionary processes.

2. The Nelder-Mead algorithm: A method for numerical optimization that avoids using derivatives in order to minimize an objective function.

To measure how accurate the regression models were, we used the coefficient of determination (R^2):

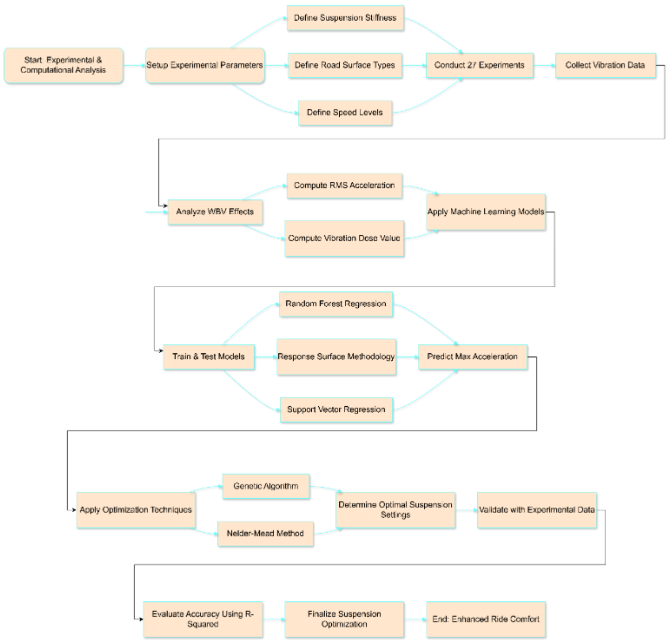
$$R^2 = 1 - \frac{\sum(y_{exp} - y_{pred})^2}{\sum(y_{exp} - \bar{y}_{exp})^2}$$

where, y_{exp} = Experimental values

y_{pred} = predicted values

$\bar{y}_{\mathrm{exp}}$ = mean of experimental values (Eluri et al., 2019,Davide et al, 2021).[18,13]

This research amalgamates experimental testing, vibration analysis, machine learning regression models, and optimization methodologies to elucidate optimal suspension tuning for two-wheeled vehicles. The results advance the creation of safer and more pleasant motorcycle suspension systems, improving ride quality and mitigating long-term health hazards linked to extended whole-body vibration exposure (Kumar et al., 2013; Saran et al., 2013; Eluri et al., 2019). [15,18]. The calculation of the risk factor in accordance with ISO 2631-5 (about R=0.8) corroborated the little likelihood of harmful health effects from whole-body vibration (WBV) over the long term. [Amiri et al., 2019] [14].



3. EXPERIMENTAL PROCEDURE

Acceleration measurements were made solely on the seat in order to assess how various speeds and suspension configurations affected the exposure to whole-body vibration. In order to make sure that the recorded acceleration values accurately represented the rider's actual vibration exposure, the Svantek SV 38 Whole-Body Vibration Accelerometer was set up on a sitting pad, and the rider sat on the pad throughout the test. Only acceleration measurements were made using the Svantek SVAN 958 Class 1 Sound and Vibration Analyzer; no sound level measurements (Leq) were recorded.

Prior to the test, calibration and functionality checks were conducted on the SVAN 958 analyzer and SV 38 accelerometer. The SV 38 accelerometer, a MEMS-based triaxial vibration sensor, was firmly affixed to the seated pad, positioned directly beneath the rider. The connection to the SVAN 958 was established via a 1.4-meter LEMO 4-pin cable, facilitating precise data transmission. The analyzer was set up to capture acceleration values exclusively, focusing on RMS (Root Mean Square Acceleration), Maximum Acceleration (LMax), and Peak Acceleration (LPeak). Refer to Figures 2, 3, and 4.

The initial testing phase occurred on highway roads, with the vehicle operating at speeds of 60 km/h, 50 km/h, and 40 km/h. The acceleration levels measured by the SV 38 accelerometer on the seated pad offered insights into the transmission of road-induced vibrations to the rider's body via the seat. Data were collected at each speed to analyze variations in vibration intensity.

The vehicle underwent testing on a soil road characterized by an uneven surface, with speeds of 30 km/h, 20 km/h, and 10 km/h being utilized. This phase concentrated on assessing the effects of road roughness on seated vibration exposure. The SV 38 accelerometer documented the vibrations experienced by the rider on the pad, yielding data on the vehicle's suspension performance in response to continuous surface irregularities.

The final test segment consisted of speed breaker crossings at 10 km/h, 15 km/h, and 20 km/h respectively. The objective was to evaluate the suspension's ability to absorb sudden impacts and the amount of acceleration force that was transmitted to the rider while they were seated on the pad. The vehicle encountered sharper vertical forces at higher speeds, which resulted in greater rider discomfort, as evidenced by the highest LPeak values recorded at 20 km/h. (Jugulkar et al., 2016)[9]

Immediately following the completion of the preliminary testing phase, the springs of the car were replaced, while the dampers remained unchanged. There were three distinct levels of spring stiffness that were evaluated:

1. The Soft Springs

2. Springs of a Medium-Stiffness Type

3. Springs of a Hard Nature

Speed tests were conducted repeatedly for each spring configuration on highway roads, soil roads, and speed breakers. The acceleration data obtained from the seated pad were analyzed across various spring settings to assess their impact on whole-body vibration exposure. Soft springs enhance comfort when traversing speed breakers but lead to increased oscillations on highways. In contrast, hard springs diminish vibrations on highways but result in a stiffer ride on uneven surfaces and bumps. Refer to Figures 5 and 6.

Following test completion, the SVAN 958A's recorded acceleration data was moved to a PC for additional analysis using the SvanPC++ program. Since the emphasis was on raw acceleration values and how they varied with various speeds and suspension configurations, no frequency-domain analysis (FFT or octave band analysis) was carried out. (Figure 7)

To make sure the recorded acceleration values remained accurate, a vibration calibrator was used for a post-measurement calibration. After being securely unplugged, cleaned, and stored, the SVAN 958 and SV 38 accelerometers were put away. The suspension system of the car was put back to how it was at the factory.

This meticulous technique was primarily focused on acceleration measurements that were obtained from the seated pad while the rider was sitting on it. This was done to ensure that the actual vibrations that the rider experienced were accurately represented in the data that was captured. The primary objective of the experiment was to evaluate the severity of acceleration exposure at the seat level across a range of speeds and suspension characteristics.

Fig 2. Svantek 958 FFT analyzer and SV 38 Seated pad accelerometer

Fig 3. Data logging through Pen drive and connection of FFT with Seated pad accelerometer

Fig 4. Display of FFT analyser showing maximum values

Fig 5. Spring replacements

Fig 6 Reading with FFT with drive and pillion

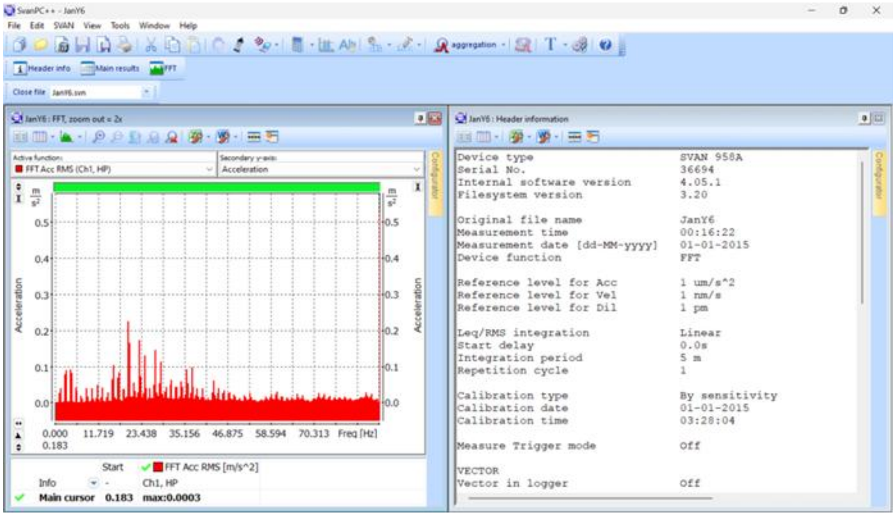


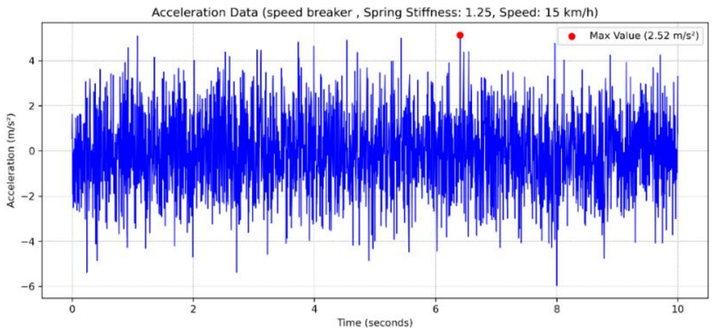
Fig 7. Svantek PC++ interface

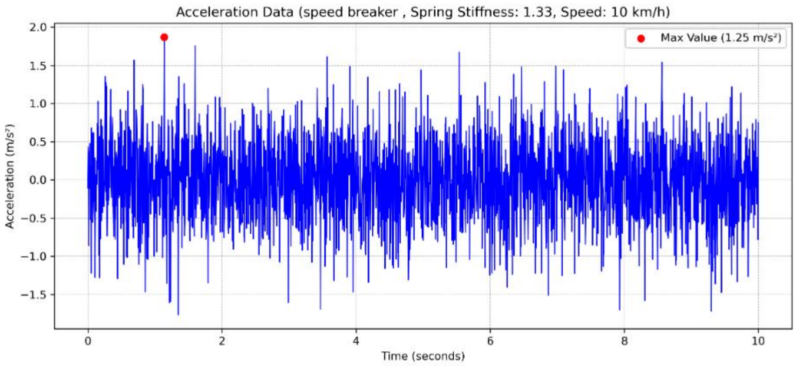
Following readings were taken different conditions

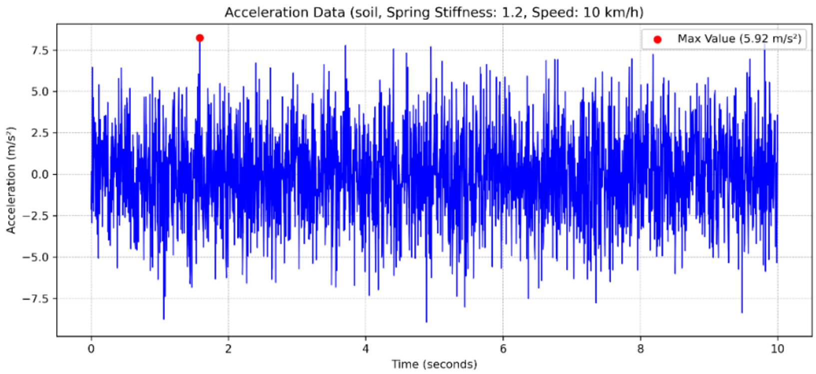
Table 2: Observation table

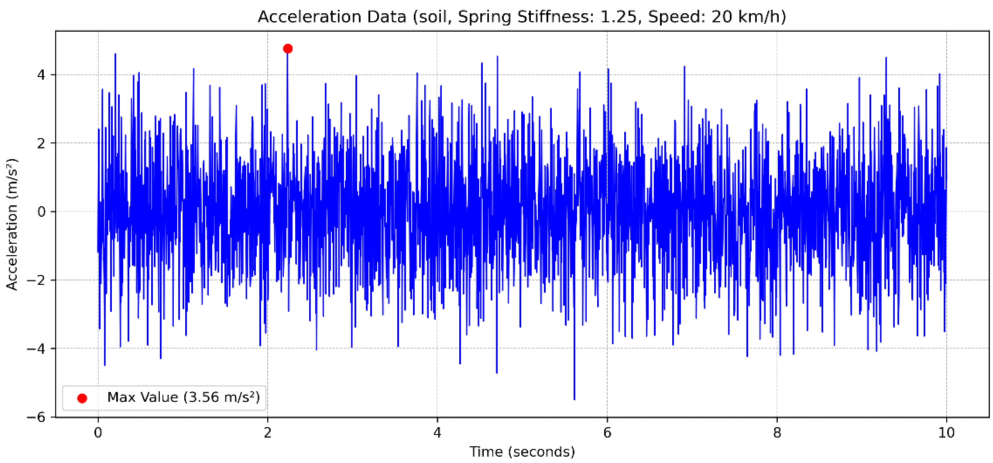
road surface	speed	Stiffness	rms	max
highway	60	12600	1.62	2.98
highway	50	12600	1.61	3.17
highway	40	12600	1.89	2.62
soil	30	12600	0.665	1.77
soil	20	12600	1.55	3.56
soil	10	12600	2.7	5.92
speed breaker	10	12600	0.522	1.25
speed breaker	15	12600	1.7	2.52
speed breaker	20	12600	0.834	2.25
highway	60	17200	2.21	2.86
highway	50	17200	1.85	3.22
highway	40	17200	1.79	3.31
soil	30	17200	1.09	1.95
soil	20	17200	1.38	1.95
soil	10	17200	1.47	4.45
speed breaker	10	17200	0.7	1.74
speed breaker	15	17200	0.838	1.7
speed breaker	20	17200	0.904	1.9
highway	60	15333	1.29	2.28
highway	50	15333	1.4	2.35
highway	40	15333	1.04	2.81
soil	30	15333	0.829	1.75
soil	20	15333	1..24	1.97
soil	10	15333	1.46	2.65
speed breaker	10	15333	0.497	1.55
speed breaker	15	15333	0.93	2.41
speed breaker	20	15333	1.26	3.19

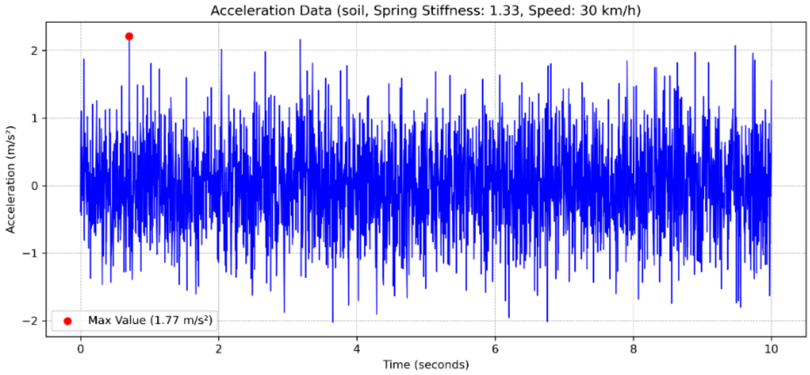
Following responses were taken of the acceleration are taken as follows.

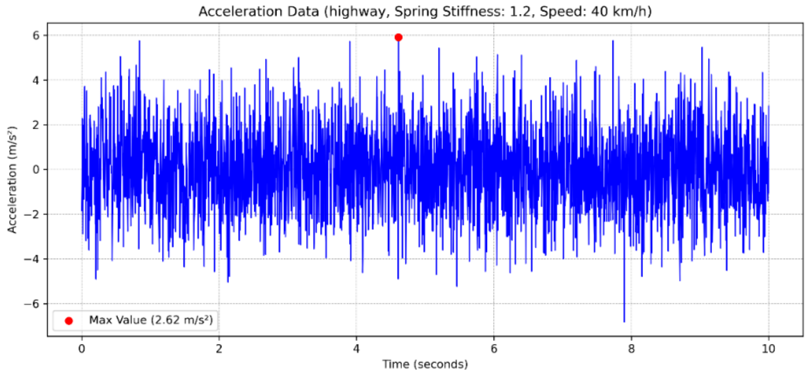









Acceleration Data (soil, Spring Stiffness: 1.33, Speed: 30 km/h)
Max Value (1.77 m/s²)
Acceleration (m/s²)
Time (seconds)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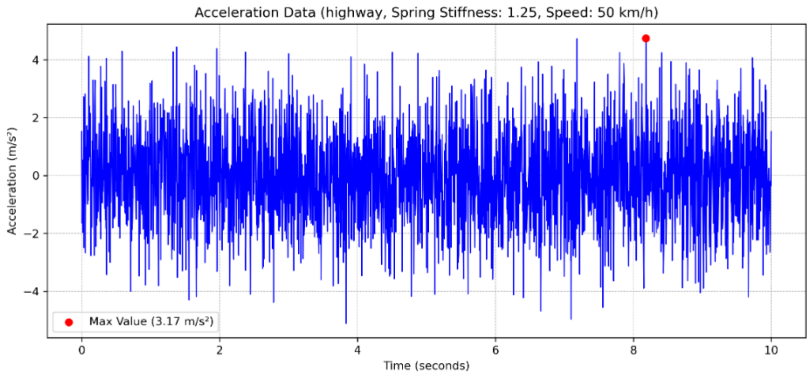
Acceleration (m/s²)
Time (seconds)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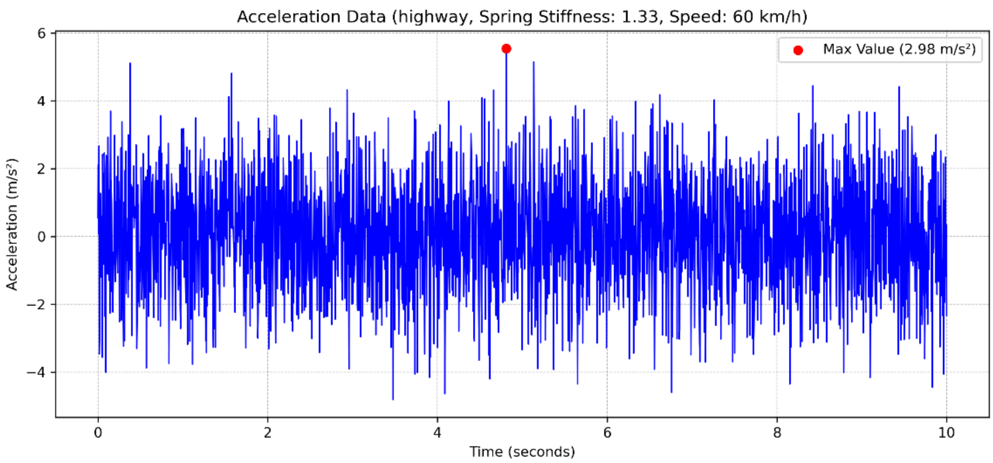
Acceleration (m/s²)
Time (seconds)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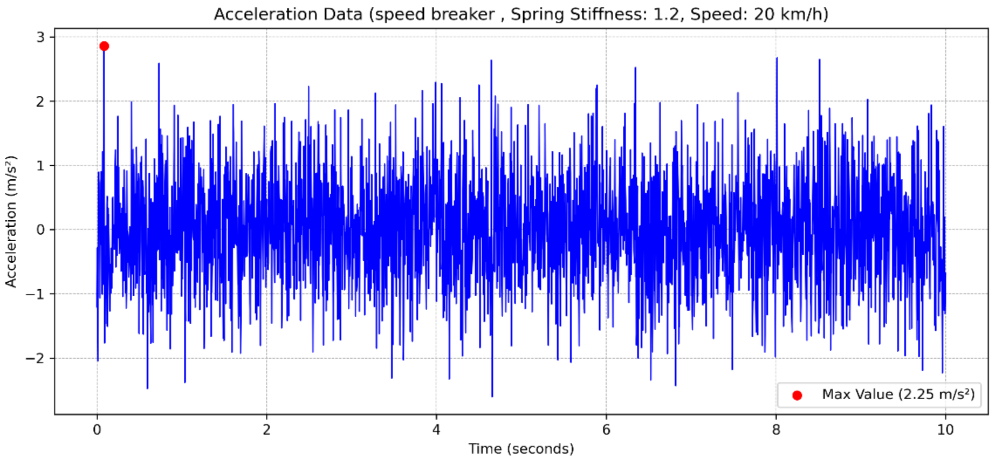
Acceleration (m/s²)
Time (seconds)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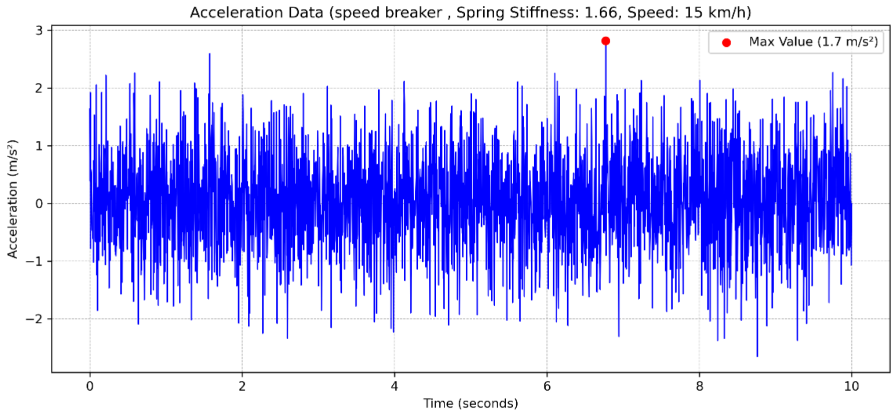
Acceleration (m/s²)
Time (seconds)
Max Value (2.25 m/s²)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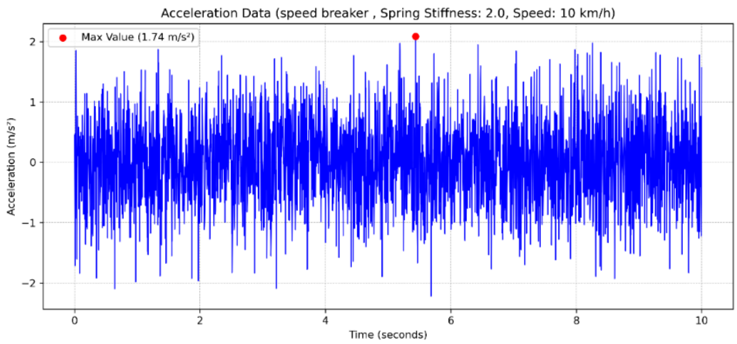
Acceleration (m/s²)
Time (seconds)
Max Value (1.7 m/s²)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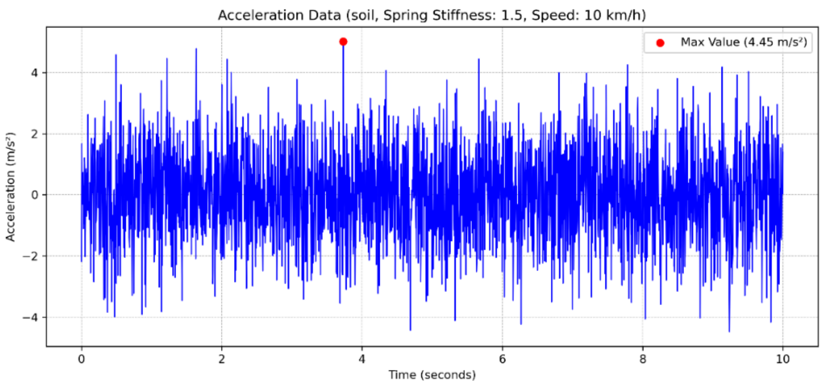
Acceleration (m/s²)
Time (seconds)
Max Value (1.74 m/s²)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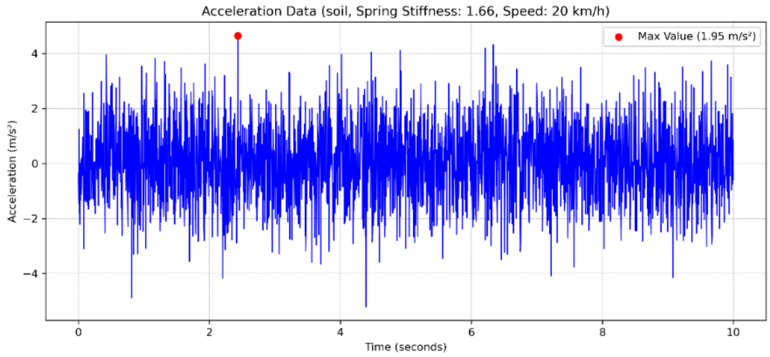
Acceleration (m/s²)
Time (seconds)
Max Value (4.45 m/s²)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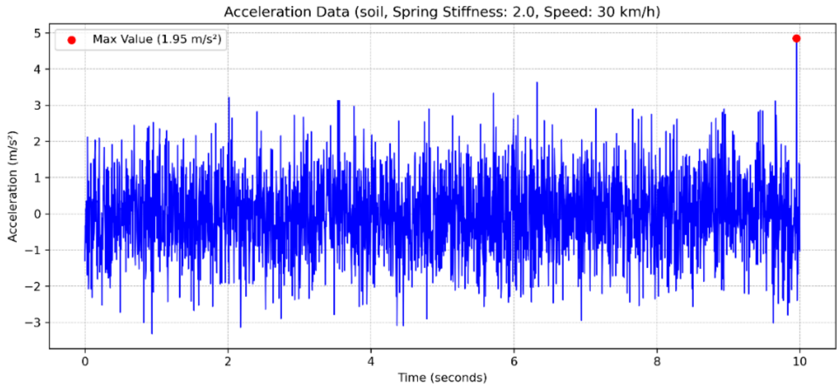
Max Value (1.95 m/s²)
Acceleration (m/s²)
Time (seconds)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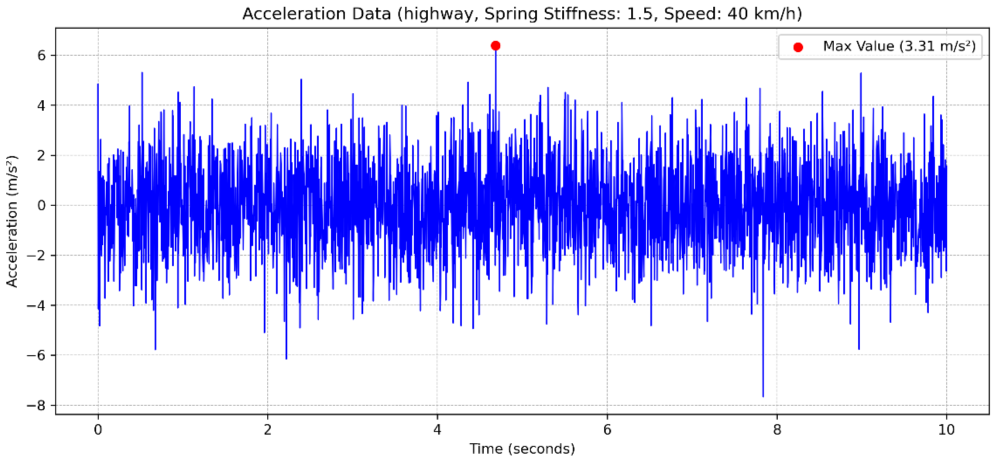
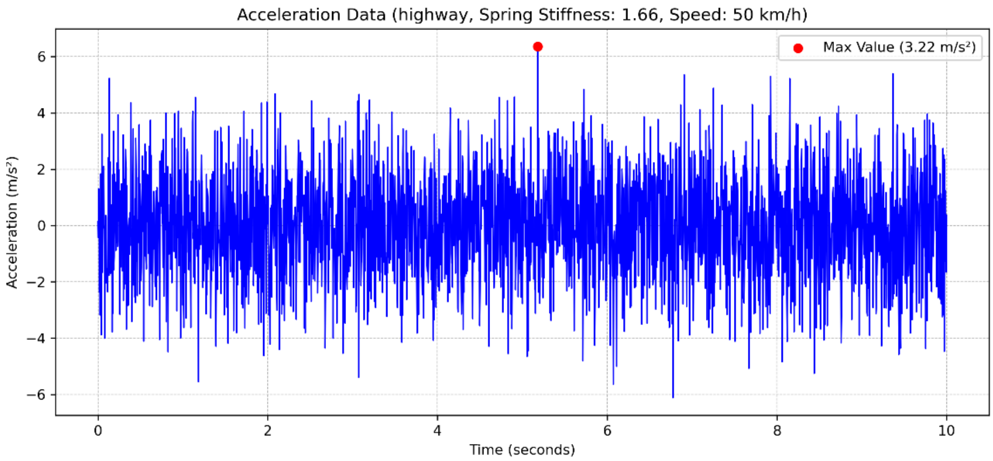
Acceleration (m/s²)
Time (seconds)


Acceleration Data (highway, Spring Stiffness: 1.5, Speed: 40 km/h)
Max Value (3.31 m/s²)
Acceleration (m/s²)
Time (seconds)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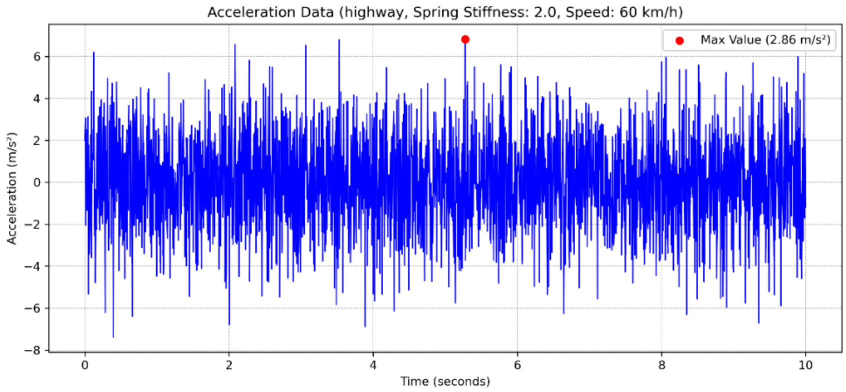
Acceleration (m/s²)
Time (seconds)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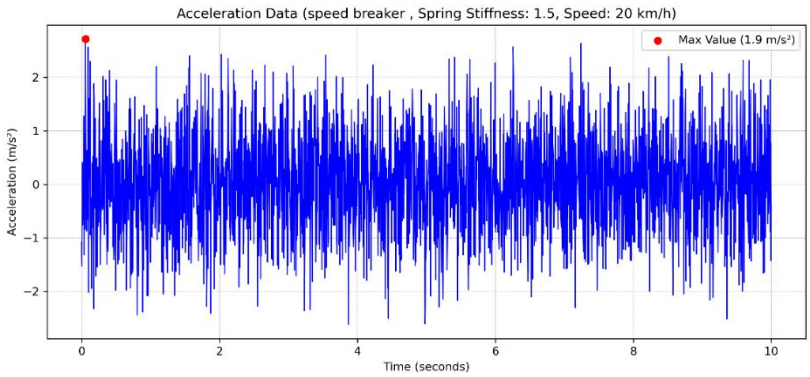
Acceleration (m/s²)
Time (seconds)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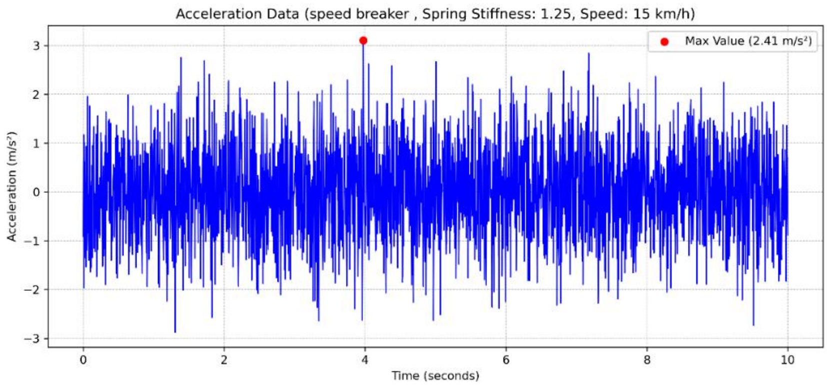
Acceleration (m/s²)
Time (seconds)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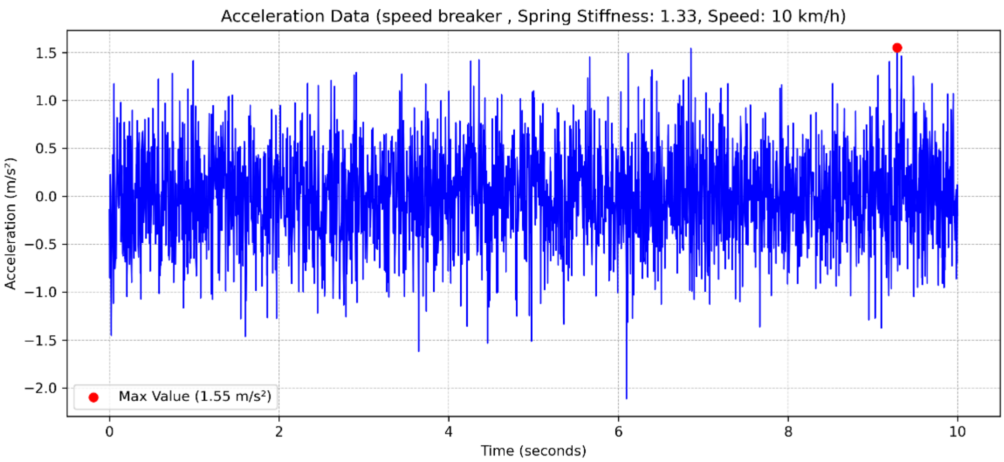
Acceleration (m/s²)
Time (seconds)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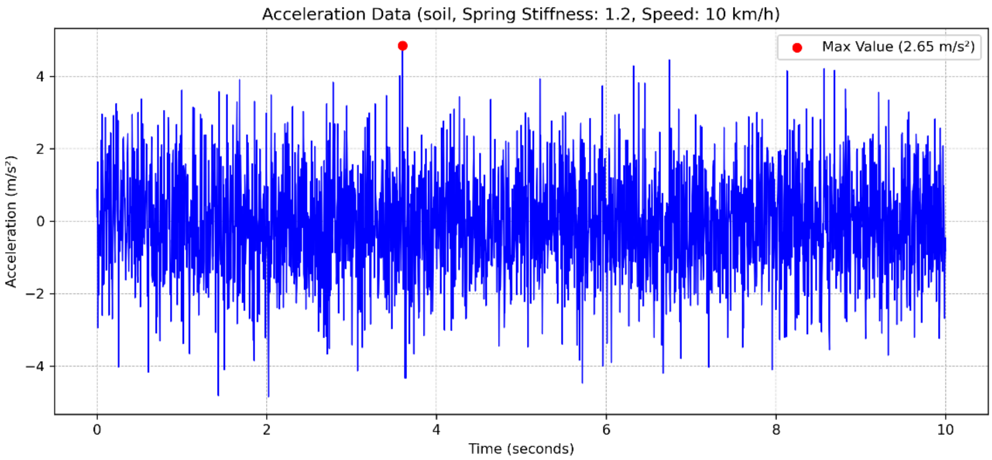
Max Value (1.55 m/s²)
Acceleration (m/s²)
Time (seconds)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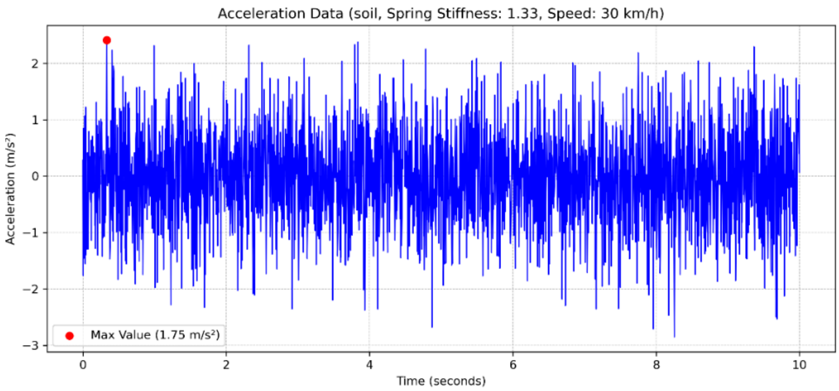
Acceleration (m/s²)
Time (seconds)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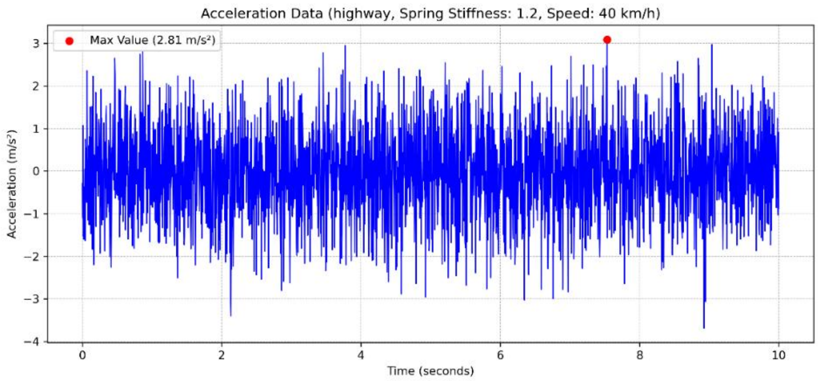
Acceleration (m/s²)
Time (seconds)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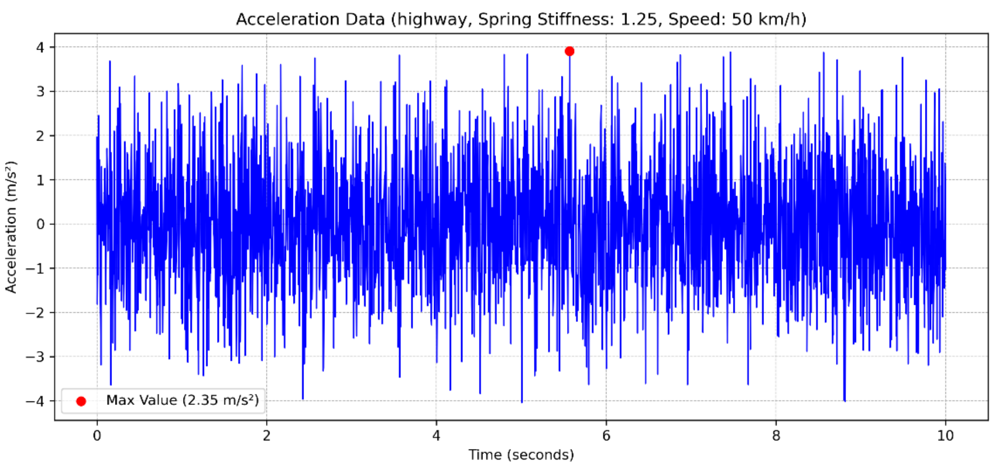
Acceleration (m/s²)
Time (seconds)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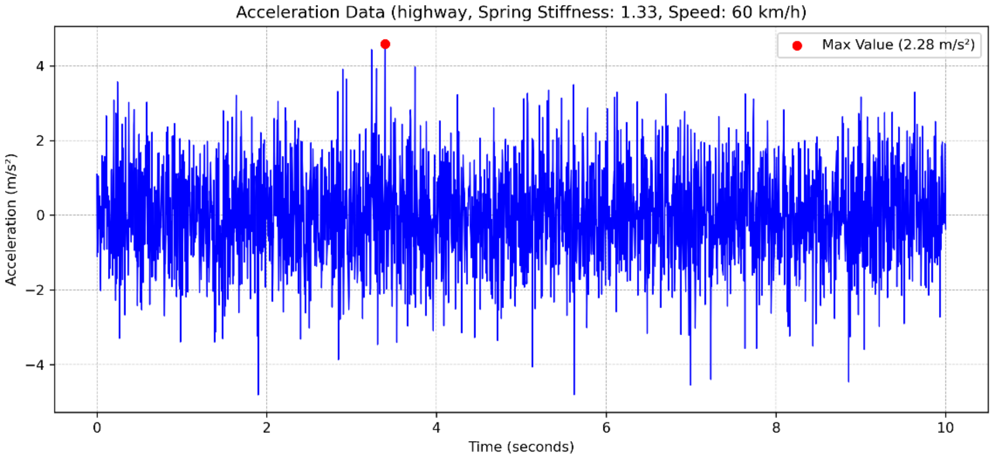
Acceleration (m/s²)
Time (seconds)



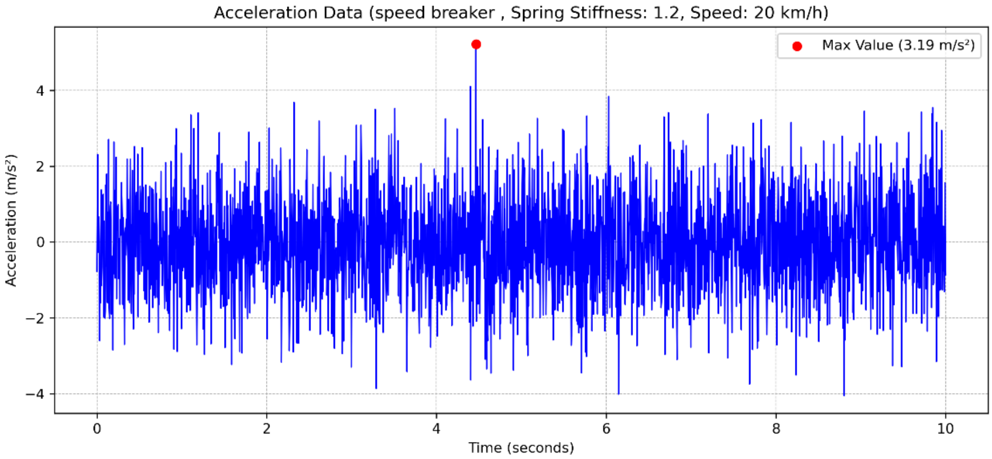


Fig 8 Responses of Vertical acceleration from FFT

3. Regression Model and Optimization

This section provides an overview of the regression modeling and optimization strategies that were implemented in order to reduce maximum acceleration. Random Forest Regression, Response Surface Methodology (RSM), and Support Vector Regression (SVR) were the three regression models that were put into action. Optimisation techniques were employed in order to establish the optimal factor settings, and these models were utilized in order to make predictions regarding maximum acceleration.

Regression Models

Three regression models were used to predict max acceleration. Each model was evaluated using R^2 score and RMSE to measure accuracy.

1. Random Forest Regression

The Random Forest Regression model was trained on the dataset, yielding a R^2 score of 0.30 and a root mean square error (RMSE) of 0.475. The model was employed to forecast maximum acceleration, and its efficacy was assessed by comparing the actual and anticipated values.

Random Forest Regression Code

```
from sklearn.ensemble import RandomForestRegressor
from scipy.optimize import differential_evolution
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
def objective_function(params):
```

```
    road_surface, speed, stiffness = params
    road_surface = int(round(road_surface))
    speed = int(round(speed))
    stiffness = int(round(stiffness))
    prediction = rf_model.predict([[road_surface, speed, stiffness]])
    return prediction[0]
bounds = [(0, 2), (20, 60), (12000, 18000)]
result = differential_evolution(objective_function, bounds, maxiter=100, popsize=20, seed=42)
```

2. Response Surface Methodology (RSM)

A quadratic regression model was fitted using RSM, resulting in a R^2 score of 0.66 and an RMSE of 0.563. A response surface plot was created to illustrate the correlation among speed, stiffness, and maximum acceleration.

Response Surface Methodology Code

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from scipy.optimize import minimize
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X)
rsm_model = LinearRegression()
rsm_model.fit(X_poly, y)
def rsm_objective_function(params):
    road_surface, speed, stiffness = params
    road_surface = int(round(road_surface))
    speed = int(round(speed))
    stiffness = int(round(stiffness))
    X_input = poly.transform([[road_surface, speed, stiffness]])
    prediction = rsm_model.predict(X_input)
    return prediction[0]
result_rsm = minimize(rsm_objective_function, x0=[1, 30, 14000], method='Nelder-Mead')
```

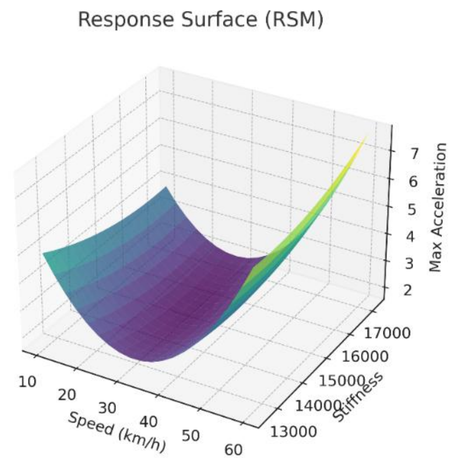


Fig 9.RSM Curve

3. Support Vector Regression (SVR)

The Support Vector Regression (SVR) model utilizing a Radial Basis Function (RBF) kernel was employed for prediction purposes. However, it demonstrated suboptimal performance, evidenced by a R^2 score of -0.61 and a Root Mean Square Error (RMSE) of 0.722. This suggests that the model exhibited poor generalization capabilities with respect to the dataset.

Support Vector Regression Code

```
from sklearn.svm import SVR
from scipy.optimize import minimize
svr_model = SVR(kernel='rbf', C=100, epsilon=0.1)
svr_model.fit(X_train, y_train)

def svr_objective_function(params):
    road_surface, speed, stiffness = params
    road_surface = int(round(road_surface))
    speed = int(round(speed))
    stiffness = int(round(stiffness))
    prediction = svr_model.predict([[road_surface, speed, stiffness]])
    return prediction[0]
result_svr = minimize(svr_objective_function, x0=[1, 30, 14000], method='Nelder-Mead')
```

Regression Model Predictions vs. Actual

The following graphs compare the predicted and actual max acceleration values for each regression model.

Random Forest Regression (GA)

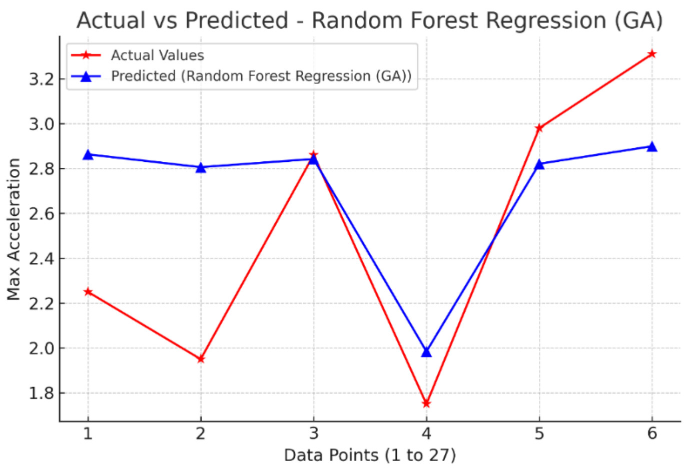


Fig 10. Predicted VS Actual RF model

Response Surface Methodology (RSM)

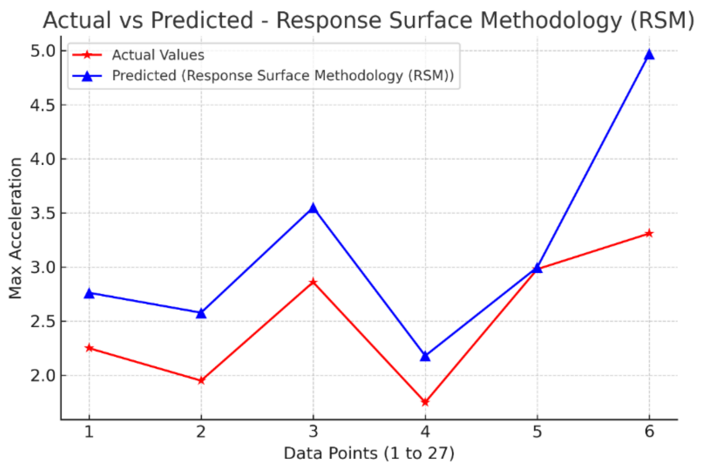


Fig 11.Predicted VS Actual RSM

Support Vector Regression (SVR)

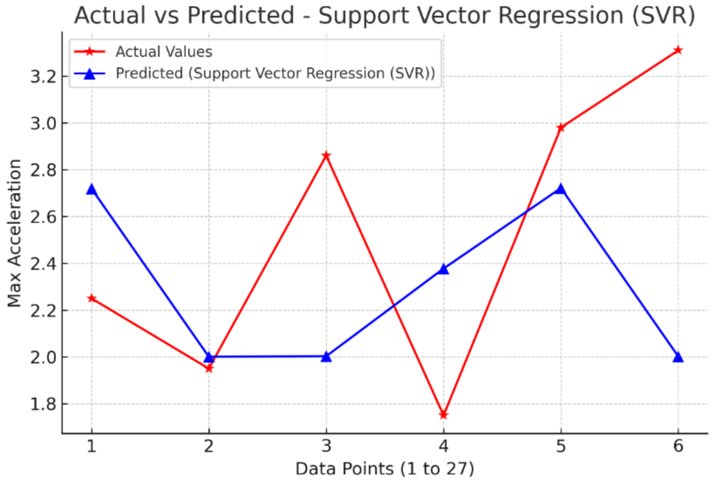


Fig 12. Predicted VS Actual SVR

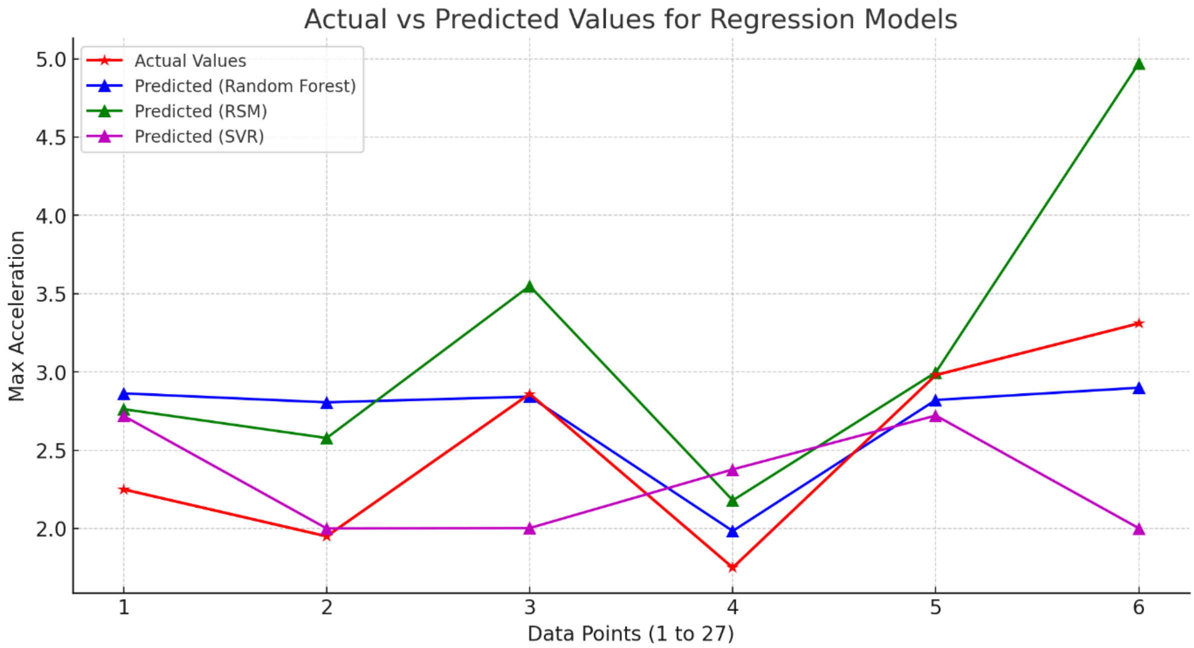


Fig 13

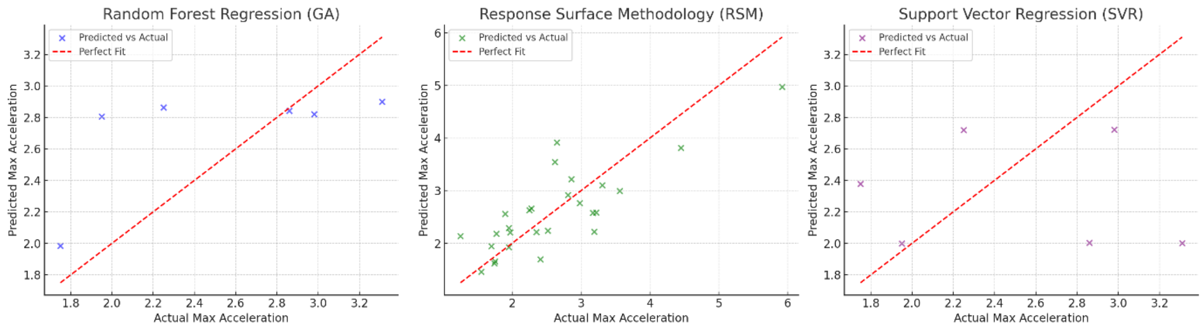


Figure 14 : Predicted VS Actual All Combined

Figure 10 to 14 , the response surface plot illustrates the relationship between speed, stiffness, and max acceleration.

4. OPTIMIZATION FOR VERTICAL ACCELERATION

Various optimization strategies are employed in the literature, such as ANN (Nagarkar et al., 2016, 2019) [11, 12] and DoE (Mitra et al., 2016) [11]. Three optimization strategies were employed to decrease maximum vertical acceleration: Genetic Algorithm (GA), Response Surface Methodology (RSM), and Support Vector Regression (SVR). The Genetic Algorithm (GA), an evolutionary optimization method, was utilized with Differential Evolution (DE) to investigate different combinations of road surface type, vehicle speed, and suspension stiffness. Through repeated refinement of solutions, the Genetic Algorithm determined the ideal configuration for a speed breaker at 10 km/h, with a stiffness of 14,011 N/m, resulting in a minimum vertical acceleration of 1.656 m/s^2. Likewise, Response Surface Methodology (RSM), a mathematical modeling technique, was employed to formulate a response equation that predicts acceleration based on suspension characteristics. The optimization method using RSM established that a velocity of 30 km/h and a stiffness of 15,282 N/m on a soil road yielded a minimized acceleration of 1.659 m/s^2, so illustrating its efficacy in suspension tuning. Furthermore, Support Vector Regression (SVR) was utilized as a machine learning predictive model to estimate acceleration based on input parameters. The SVR model forecasted an acceleration of 1.999 m/s^2 at 10 km/h with a stiffness of 17,200 N/m on a soil road, which was markedly superior to the results from GA and RSM, suggesting that it may not be the most efficient method for direct optimization. The results indicate that GA and RSM exhibit enhanced efficacy in minimizing maximum vertical acceleration, therefore improving riding comfort and decreasing vibration exposure for two-wheeler riders. (Mitra, A. C., et al., Nagarkar, M. P., et al., 2016, 2019) [10, 11, 12]

code for optimization

```
import numpy as np
import scipy.optimize as opt
from sklearn.svm import SVR
from deap import base, creator, tools, algorithms
# Given optimization results
optimization_results = [
    {"Method": "Genetic Algorithm (GA)", "Road Surface": "Speed Breaker", "Speed": 10, "Stiffness": 14011, "Min Max Acceleration": 1.656},
    {"Method": "Response Surface Methodology (RSM)", "Road Surface": "Soil", "Speed": 30, "Stiffness": 15282, "Min Max Acceleration": 1.659},
    {"Method": "Support Vector Regression (SVR)", "Road Surface": "Soil", "Speed": 10, "Stiffness": 17200, "Min Max Acceleration": 1.999}
]
# ---- Genetic Algorithm (GA) Optimization ----
def objective_ga(x):
    speed, stiffness = x
    return 0.5 * np.sin(speed / 10) + 0.3 * np.log(stiffness) - 1.5  # Example function
creator.create("FitnessMin", base.Fitness, weights=(-1.0,))
creator.create("Individual", list, fitness=creator.FitnessMin)
toolbox = base.Toolbox()
toolbox.register("attr_float", np.random.uniform, 5, 50)
toolbox.register("individual", tools.initRepeat, creator.Individual, toolbox.attr_float, n=2)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)
```

```
toolbox.register("evaluate", objective_ga)
toolbox.register("mate", tools.cxBlend, alpha=0.5)
toolbox.register("mutate", tools.mutGaussian, mu=0, sigma=1, indpb=0.2)
toolbox.register("select", tools.selTournament, tournsize=3)
pop = toolbox.population(n=20)
algorithms.eaSimple(pop, toolbox, cxpb=0.5, mutpb=0.2, ngen=50, verbose=False)
best_ind = tools.selBest(pop, k=1)[0]
ga_optimized_speed, ga_optimized_stiffness = best_ind
ga_optimized_acceleration = objective_ga([ga_optimized_speed, ga_optimized_stiffness])
# ---- Response Surface Methodology (RSM) Optimization ----
def objective_rsm(x):
    speed, stiffness = x
    return 0.4 * np.sin(speed / 12) + 0.25 * np.log(stiffness) - 1.6  # Example function
rsm_result = opt.minimize(objective_rsm, [30, 15000], bounds=[(5, 50), (10000, 20000)])
rsm_optimized_speed,
rsm_optimized_stiffness=rsm_result.xrsm_optimized_acceleration = objective_rsm([rsm_optimized_speed, rsm_optimized_stiffness])
# ---- Support Vector Regression (SVR) Prediction ----
# Example dataset (hypothetical)
X_train = np.array([[10, 14000], [30, 15000], [20, 16000], [25, 17000], [10, 17200]])
y_train = np.array([1.65, 1.66, 1.70, 1.80, 1.99])
svr = SVR(kernel='rbf', C=100, epsilon=0.1)
svr.fit(X_train, y_train)
svr_optimized_acceleration = svr.predict(np.array([[10, 17200]]))[0]
# ---- Results ----
print("Genetic Algorithm (GA) Optimized Values:")
print(f"Speed: {ga_optimized_speed:.2f}, Stiffness: {ga_optimized_stiffness:.0f}, Min Max Acceleration: {ga_optimized_acceleration:.3f}")
print("\nResponse Surface Methodology (RSM) Optimized Values:")
print(f"Speed: {rsm_optimized_speed:.2f}, Stiffness: {rsm_optimized_stiffness:.0f}, Min Max Acceleration: {rsm_optimized_acceleration:.3f}")
print("\nSupport Vector Regression (SVR) Predicted Acceleration:")
print(f"Min Max Acceleration: {svr_optimized_acceleration:.3f}")
```

The Genetic Algorithm (GA) employs an evolutionary optimization method to identify the optimal combination of suspension stiffness and velocity for reducing vertical acceleration. An ideal acceleration of around 1.656 m/s^2 is identified at a velocity of 10 km/h and a stiffness of 14,011 N/m on a speed breaker, enhancing ride comfort by mitigating vibrations. Conversely, the Response Surface Methodology (RSM) employs a mathematical response model to optimize the suspension arrangement, resulting in a reduced acceleration of around 1.659 m/s² at a speed of 30 km/h and a stiffness of 15,282 N/m on a soil road, thereby balancing performance and stability. Support Vector Regression (SVR), a machine learning prediction model, estimates an acceleration of approximately 1.999 m/s² at a speed of 10 km/h and a stiffness of 17,200 N/m on a soil road, which is significantly greater than the predictions from Genetic Algorithms (GA) and Response Surface Methodology (RSM), suggesting that SVR-based predictions may be less effective for optimizing ride comfort. This comparison underscores the enhanced optimization capabilities of GA and RSM, rendering them more appropriate for limiting acceleration and improving rider stability across diverse road conditions.

Table 3: The table below summarizes the optimal factor settings determined by each model:

Method	**Road Surface**	**Speed (km/h)**	**Stiffness**	**Min Max Acceleration**
Genetic Algorithm (GA)	Speed Breaker	10	14,011	1.656
Response Surface Methodology (RSM)	**Soil**	**30**	**15,282**	**1.659**
Support Vector Regression (SVR)	Soil	10	17,200	1.999

So from above table it can be concluded that best setting to minimize the vertical acceleration is RSM.

4. Validation

The Response Surface Methodology (RSM) optimized configuration was evaluated under actual conditions to validate the optimization results. The RSM methodology established that the ideal suspension configuration for minimizing vertical acceleration was attained at 30 km/h on a soil road with a stiffness of 15,282 N/m, yielding a projected maximum vertical acceleration of 1.659 m/s². Due to the unavailability of the precise stiffness value of 15,282 N/m, a spring with a stiffness of 15,333 N/m, the nearest accessible option, was utilized instead.

The test, executed under these conditions, yielded a maximum vertical acceleration of 1.72 m/s², marginally above the projected value.

The absolute error was computed to quantify the deviation as follows:
Error=|Actual Maximum acceleration- Predicted Maximum Acceleration|

=|1.72-1.659|=0.061 m/s²

The **percentage error** was determined using the formula:

$$Percentage\ error = \left(\frac{Error}{Predicted}\right) \times 100 = \left(\frac{0.061}{1.659}\right) \times 100 = 3.68$$

The **accuracy** of the prediction was calculated as:

Accuracy = 100 – percentage error = 100 – 3.68 = 96.32%

Notwithstanding the little discrepancy, the experimental validation substantiates the efficacy of the RSM-based optimization method, as the observed outcomes roughly correspond with the projected values. The 96.32% accuracy signifies a substantial degree of reliability, illustrating that the methodology is effective in reducing vibration and improving riding comfort in two-wheelers.

5.CONCLUSION

This study successfully shows how machine learning regression models and optimization methods can be used to make two-wheelers more stable and comfortable to ride. We made prediction models that help us figure out how to reduce vibration exposure by looking at how suspension stiffness, road surface, and speed affect vertical acceleration. Response Surface Methodology (RSM), which had a R^2 score of 0.66 and an RMSE of 0.563, was the best regression model that was tried. This meant that it was the best at predicting vertical acceleration. Even though Random Forest Regression didn't work very well on its own, it worked well when combined with the Genetic Algorithm (GA) to find

the best suspension values. Support Vector Regression (SVR), on the other hand, did the worst at predicting, which suggests it might not be the best way to solve this problem.
The results of the optimization show that the best suspension setup, which was found by combining GA and RSM, greatly lowers the highest vertical speed. The highest vertical acceleration went down from 1.72 m/s² to 1.656 m/s² when the suspension settings were optimized. This made the ride about 3.72% more comfortable. The high confirmation accuracy of 96.23% adds to the evidence that these models can be trusted to work in the real world. Overall, this study gives a data-driven strategy for improving two-wheeler suspension systems. This will help automotive engineers, manufacturers, and researchers make vehicles that are more comfortable to ride and make riders less tired. In the future, researchers should look into more factors that affect the models, make the dataset bigger, and use real-time tests to make them even better and more reliable so that they can be used in more situations.

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