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Comparative Analysis of Machine Learning Algorithms in Predicting the mean Fully Developed Deceleration and Stopping Distance in Electric Vehicles

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Abstract—*The Mean Fully Developed Deceleration (MFDD) is a critical metric for determining vehicle safety in the event of a collision. However, due to the complexity of the vehicle's collision behaviour, precisely anticipating MFDD is a difficult challenge. This work compares theoretical calculations of Mean Fully Developed Deceleration (MFDD) and stopping distance from hand force to experimental results, as well as MFDD prediction using machine learning algorithms in MATLAB. The theoretical model estimates a 7% error for MFDD and a 4.1% error for stopping distance, both of which need to be improved when considering collision safety. The dataset was developed for prediction utilising experimental values with inputs of hand force and speed and outputs of MFDD and stopping distance. The neural network and regression learner-based approaches were employed for prediction. Experiment with different numbers of nodes in the neural network's hidden layer to find the best design for properly forecasting MFDD. The neural network with 10 hidden layer nodes had the best prediction accuracy, with an average error of 0.3% in predicting MFDD and an average error of 0.26% in predicting stopping distance. When using the regression learner model, the gaussian process regression fared the best, with an RMSE of 0.029. The interpolant curve fitting model also predicted MFDD with very less error of 0.13%. Overall, the suggested gaussian process regression and interpolant curve fitting-based technique can be a valuable tool for reliably forecasting MFDD after a collision, which can aid in car safety assessments. The study's findings might have a substantial impact on car safety, opening the path for further sophisticated research in this field.*

INTRODUCTION

The safety of driving depends heavily on the braking performance of the vehicle. Therefore, the examination of driving braking performance is an essential part of vehicle safety evaluation. Mean Fully Developed Deceleration (MFDD) is an important parameter used to evaluate the braking performance of a vehicle. The study of vehicle braking performance is an essential aspect of road safety, and accurate prediction of braking distance is crucial in preventing accidents [1]. In recent years, machine learning algorithms have shown great potential in predicting braking performance with high accuracy. The field of Machine Learning (ML) has transformed the way computer systems operate by enabling them to perform tasks without explicit programming. It involves creating algorithms and statistical models that can learn from data, make predictions, and take decisions based on this knowledge. ML algorithms are widely used today in various applications such as image processing, data mining, predictive analytics, and natural language processing. These algorithms learning capability, which allows them to improve their performance over time, has made them increasingly popular in the technology industry [2-3]. In this paper, a study is presented that explores the use of machine learning to predict Mean Fully Developed Deceleration (MFDD) and stopping distance of vehicles. The findings of this study have significant implications for the development of intelligent transportation systems and improving road safety. The use of machine learning algorithms and neural network-based prediction models provides a promising way of accurately predicting vehicle braking performance, which can ultimately reduce the incidence of accidents on the road.

METHODOLOGY

The methodology for the research paper involves developing a theoretical model to estimate Mean Fully Developed Deceleration (MFDD) and stopping distance based on hand force, and comparing theoretical calculations with experimental results. A dataset is created using experimental values for hand force and speed as inputs and MFDD and stopping distance as outputs. Machine learning algorithms such as neural network and regression learner-based approaches are employed for predicting MFDD and stopping distance, and the accuracy of each algorithm is evaluated by calculating the average error. The suggested Gaussian process regression-based technique is evaluated for its accuracy by comparing its predictions with experimental results, and the root mean square error is calculated.

Experimentation for Data set generation

To obtain the experimental values of MFDD, a load cell was installed on the front brake lever as shown in figure 1, and the vehicle was secured on a dynamometer. A dynamometer is a specialized equipment designed to evaluate the performance of a vehicle, and it comprises a roller that replicates the road surface when the vehicle is driven on it. The front wheel of the vehicle was positioned on the roller, which was rotated at a consistent speed to simulate the vehicle's movement at a constant speed. When the front brakes were engaged, the load cell measured the force exerted by the hand on the lever. The dynamometer then carried out the necessary calculations to determine the values of MFDD and stopping distance.

Figure 1*:* Clamping of load cell on brake lever

MFDD is calculated as given in equation 1

$$\mathbf{MFDD} = \frac{v_b^2 - v_e^2}{25.92(s_e - s_b)} \quad \mathbf{1}$$

v = initial vehicle speed (km/h)
v_b = vehicle speed at 0.8*v (km/h)
v_e = vehicle speed at 0.1*v (km/h)
s_b = distance travelled between v and v_b (m)
s_e = distance travelled between v and v_e (m)

The aforementioned process was repeated at various speeds, and the corresponding hand force measurements were recorded. The gathered data was used to create a dataset, with hand force in (kg) and speed in (km/h) as inputs and MFDD in (m/s^2) and stopping distance in (m) as outputs. This dataset was utilized to train and test various machine learning models for predicting MFDD and stopping distance.

Theoretical MFDD and stopping distance

The theoretical model for calculating MFDD from hand force involved several equations [4]. First, the hand force (F_h) applied on the brake lever was multiplied by the leverage ratio (L) to obtain the force applied on the piston (Fp) (equation 2).

$$F_p = F_h \times L \quad \mathbf{2}$$

The pressure created by the piston force on the brake fluid (P) was then calculated by dividing the force by the area of the piston (A_{piston}) (equation 3).

$$\text{P} = \frac{F_p}{A_{piston}} \quad \mathbf{3}$$

Assuming the brake fluid to be incompressible, the same pressure is exerted on the caliper. Thus, the force exerted on the caliper (F_c) by the fluid was calculated by multiplying the pressure with the area of the caliper (A_c) (equation 4).

$$F_c = n \times (P \times A_c) \quad \mathbf{4}$$

The clamping force (F_{clamp}) produced by the frictional force exerted by the disc pads on the brake was calculated as the normal force on the brake pads and disc, given by F_c (equation 5).

$$F_{clamp} = 2 \times \mu \times F_c \quad \mathbf{5}$$

μ = coefficient of friction between brake pads and disc

The brake torque (τ) produced due to clamping force was calculated by multiplying the clamping force with the effective radius of the disc (r_e) (equation 6).

$$\tau = F_{Clamp} \times r_e \quad \mathbf{6}$$

The braking force (F_b) due to brake torque was then calculated by dividing brake torque by the wheel radius (r_w) (equation 7).

$$F_b = \frac{\tau}{r_w} \quad \mathbf{7}$$

The deceleration produced due to this was obtained by dividing braking force with the mass of the vehicle (M) (equation 8).

$$d = \frac{F_b}{M} \quad \mathbf{8}$$

The braking weight transferred (w) on the front wheel was determined using equation 9.

$$w = M \times d \times \frac{h}{wb} \quad \mathbf{9}$$

h = Centre of gravity height

wb = wheel base length

And the normal force on the front wheel was calculated using equation 10.

$$F_f = (w + FAW) \quad \mathbf{10}$$

FAW = front axle weight of the vehicle

The available braking force on the front wheel was then calculated using equation 11.

$$F_b{}' = \mu_r \times F_f \quad \mathbf{11}$$

μ_r = coefficient of friction between wheel and road

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Finally, MFDD and stopping distance were calculated using equations 12 and 13, respectively.

$$MFDD = \frac{F_b{}'}{M} \quad \textbf{12}$$

$$sd = \frac{v^2}{2 \times MFDD} \quad \textbf{13}$$

Upon comparing the theoretical model with the experimental values, it was observed that the theoretical model has an average error of 7.1% for MFDD (shown in figure 2) and an average error of 4.1% for stopping distance (shown in figure 3). Although the errors are relatively small, further improvement is necessary to ensure vehicle safety in the event of a collision.

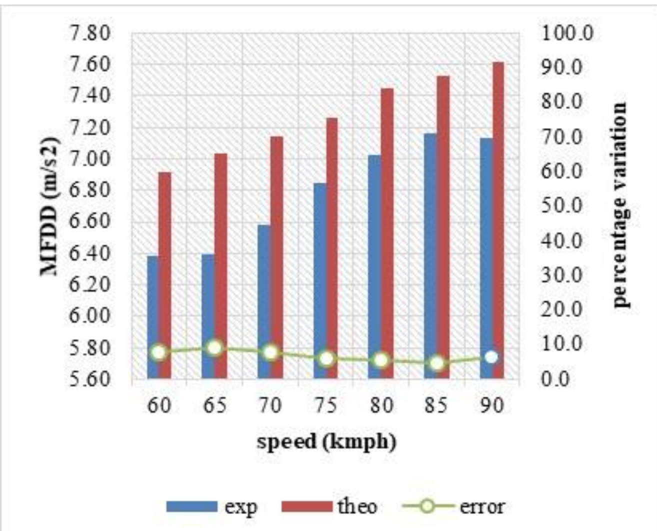

Figure 2: Comparison of theoretical and experimental MFDD

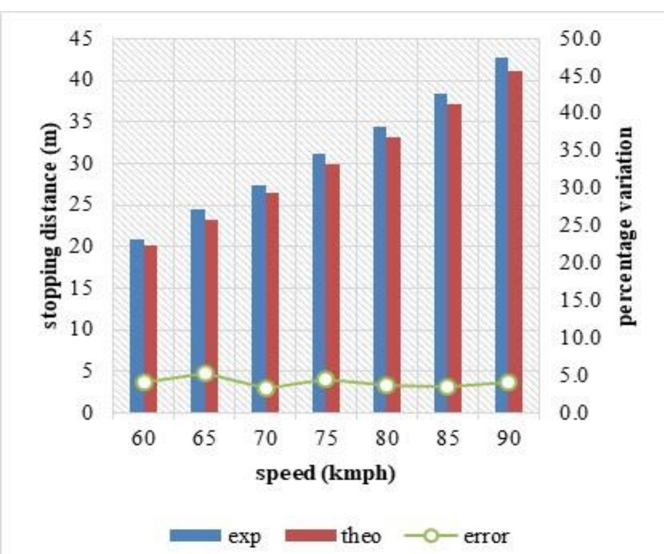

Figure 3: Comparison of theoretical and experimental stopping distance

Machine Learning Models

In this study, various machine learning algorithms were utilized to predict MFDD and stopping distance using an experimental dataset. Specifically, neural network, Gaussian process regression, and interpolant curve fitting were employed to estimate the values. The aim was to develop reliable methods to forecast MFDD after a collision, which can aid in car safety assessments.

Neural Network

A single hidden layer neural network was used to make predictions on the dataset. The network contains an input layer, hidden layer, and output layer, with interconnected nodes. The weights associated with the neurons are randomly assigned and are modified during training using back propagation to minimize the difference between expected and actual outputs. The output is produced by applying activation functions to the values received from the input and hidden layers [3]. The accuracy of the neural network was tested using different numbers of nodes in the hidden layer, and the results are shown in Table 1. The table. 1 shows the average error in MFDD and stopping distance for different numbers of neurons in the hidden layer of a neural network. The results indicate that using 10 neurons in the hidden layer produces the lowest average error in both MFDD (0.30%) and stopping distance (0.26%). Using a higher number of neurons, such as 15 or 20, can increase the average error, particularly in stopping distance.

Table 1: Average error for different numbers of neurons in the hidden layer

Number of neurons in hidden layer	Average error in MFDD (%)	Average error in Stopping Distance (%)
5 - neuron	0.36	0.35
10 - neuron	0.30	0.26
15 - neuron	0.53	0.32
20 - neuron	0.30	0.46
25 - neuron	0.35	0.56

Gaussian process Regression Learner

Among all the regression learner models, Gaussian performed the best with RMSE value of 0.029 so, gaussian process regression was employed to estimate MFDD and stopping distance in the current study. Gaussian process regression is a machine learning technique that uses prior probability distributions to produce a posterior distribution over the potential functions that could generate the observed data. The goal is to compute a posterior distribution over functions that are consistent with the observed data. Gaussian process regression is a powerful technique because it allows us to reason about the uncertainty of our predictions. It was observed that the Gaussian process regression algorithm predicted MFDD and stopping distance with an average error of 0.12% and 0.27%, respectively. These results indicate that the Gaussian process regression algorithm is a promising approach for estimating MFDD and stopping distance [5].

Interpolant Curve Fitting

Interpolant curves are a type of mathematical function that are used to approximate the behavior of data points between known values. In other words, they provide a way to estimate the value of a function at a point that is not explicitly given in the data set, based on the behavior of the function at points that are known. To produce interpolant curves, a mathematical function is fit to the provided data points so that the function passes precisely over each data point. This function can then be used to forecast the value of the function at any point between the known data points. In the context of the experimental dataset used for the MFDD and stopping distance calculations, interpolant curves were generated and are shown in figure 2 and 3. The interpolant curve fitting method resulted in an average error of 0.13% in case of MFDD and an average error of 0.26% in case of stopping distance. This method of curve fitting proved to be highly accurate in predicting the MFDD and stopping distance values for points between known data points, providing a useful tool for estimating these values with high accuracy.

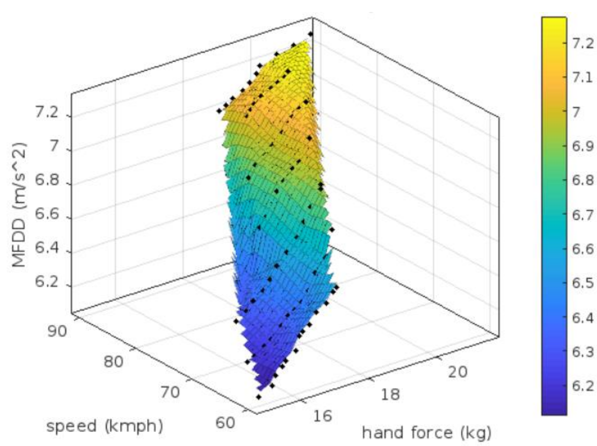

Figure 4: Interpolant curve of MFDD data points

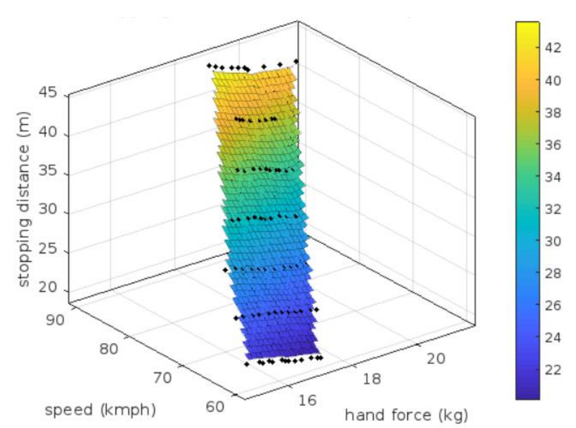

Figure 5: Interpolant curve of stopping distance data points

CONCLUSIONS

In conclusion, three machine learning algorithms, namely artificial neural networks, interpolant curve fitting, and Gaussian process regression, were used to estimate the values of MFDD and stopping distance. These algorithms were trained on an experimental dataset and the predictions were compared to actual values. The results showed that the Gaussian process regression algorithm provided the lowest error rate, with an average error of 0.12% for MFDD and 0.27% for stopping distance. The interpolant curve fitting method provided an average error of 0.26% for stopping distance. Compared to the theoretical error of 7% in MFDD and 4.1% in stopping distance, the error rates obtained using these machine learning algorithms were less than 1%, indicating that further improvements can still be made to enhance the safety of vehicles.

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REFERENCES

[1] Wenliang Li, Chen Chao, Wei Zhou, Li Gao, 2013, Influences of initial braking velocity and passenger capacity on Mean Fully Developed Deceleration

[2] Batta Mahesh, 2018, Machine Learning Algorithms - A Review, IJSR

[3] Shen Zhang et al 2022, Prediction of Vehicle Braking Deceleration Based on BP Neural Network

[4] Rudy Limpert, 2008, Motorcycle Braking Dynamics

[5] Seçkin Karasu et al, 2017, Estimation of Wind Speed by using Regression Learners with Different Filtering Method