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บทความวิจัย

Reducing Harmful Effects on Human Health of Car Vibrations using a Combination of Unsupervised and Supervised Machine Learning Algorithm

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Abstract: Car vibrations are typically common, but it's crucial to determine the level of shaking that signifies a potential threat to human health. In this research, the machine learning algorithm was employed to predict potential failures in car suspension systems, with the goal of enhancing vehicle reliability and safety. A combination of unsupervised and supervised machine learning algorithms is applied to classify data, isolate outlier, and predict fault diagnosis outcomes in the simulation context with a dataset of a car suspension system. In general, either unsupervised or supervised learning techniques can contribute to a valuable predictive maintenance when dealing with larger datasets in a car suspension system either usual or unusual conditions. Therefore, the results may not cover unknow patterns within unusual conditions, such as high amplitude sinusoidal and step road profile. In this research, a combination of unsupervised and supervised learning techniques is proposed to identify car suspension issues caused by poorly maintained vehicles, potentially impacting human health. The findings from the simulation indicate that a combination of unsupervised and supervised machine learning algorithms can effectively classify fault diagnosis and isolate unknow patterns for future training models. Moreover, the identification of non-groupable elements using a combination of these learning techniques is illustrated through outlier detection on unknown patterns. Therefore, the research results enable engineers to assess devices for maintenance and repair needs, aiming to reduce or eliminate car vibrations, which can pose serious harm to human health.

Keywords: Car Suspension Systems; Machine Learning Algorithm; Predictive Maintenance; Supervised; Unsupervised Learning Techniques

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1. Introduction

Several research studies have explored the effects of whole-body vehicle vibrations on human health over the last few decades. Furthermore, based on a study by the Land Transportation Safety and Health Association in Japan 2022 [1], there has been a rise in occupational accidents involving workers in the road transportation industry falling from heights during loading and unloading activities after driving. The data reveals that in Japan, more than 10,000 work-related accidents occur annually in cargo-handling operations, constituting 10% of all occupational accidents. As, the causes of car vibration can be harmful to human health, leading to issues such as motion sickness, lower back pain, stomach and digestive conditions, and so on. According to the study by Junya Tatsuno and Setsuo Maedo in 2023 [2], which investigated the effects of whole-body vibration exposure in vehicles, car vibrations were found to be linked to health problems, including back pain, sciatica, digestive disorders, genitourinary problems, and hearing damage. As the positive effects of car vibrations have drawn the attention of researchers in the medical field, there have consequently been reported experiments investigating the effects of vibration on car suspension. For example, Sedeh and Keivan's research in 2006 [3] employed a car model with an active suspension system to assist in controlling and achieving a smooth ride, optimizing and amplitude, and minimizing variations in car acceleration. Similarly, Ufuk Kirbas (2022) [4] conducted a study on the effects of car speeds on manholes cover, exploring the impact on vibrations and the potential to cause discomfort and affect human health. The research results found that whole body vibration is not adversely affected by the human body according to the vibration dose value scale defined in the standard. However, it can be influenced at various ride speeds with depths of 7.5 cm and above in 50 passes. Hence, while previous experimental studies have applied various techniques to minimize the potentially dangerous effects of vibrations on a vehicle suspension, machine learning (ML) emerges as another important tool that can be used to assess and predict variations in car suspension that can impact human health. Researchers have shown how machine learning has had a deeply impact for predictive and detection purposes in different contexts. For example, Yorulmus, Bahadir, and Bolat [5] employed machine learning algorithm to predict brake quality defects in the automobile industry during quality inspection operations. The study found that two specific machine learning models, Gradient Boost and CatBoost algorithms, provided the most significant benefits for detecting the correlation between quality control data and customer complaints. Kong G, Lin K, and Hu Y [6] developed machine learning-based tools for

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accuracy prediction about the risk number of patients' death with sepsis in intensive care units (ICUs). The medical information for intensive care consisting of medical records such as heart rate, systolic blood pressure, diastolic blood pressure, and so on from 86 predictor variables was used as a primary data source. The work of these researchers [7] also serves as another example of applying machine learning-based approaches to predict maintenance in health care sector. Various machine learning techniques were employed, including supervised and unsupervised learning, to develop precise predictive models for IoT maintenance in healthcare. These models were trained using historical data to establish the relationship between sensors readings and maintenance events. The models can also differentiate between various stages or severity levels of a diabetic retinopathy as evidenced by the increased classification accuracy. Theissler et al. [8] has conducted a study with the aim of reviewing papers to explore the use of four main types of machine learning. For example, studies of Wang and Yin [9], Yin and Huang [10], Ying Wang et al [11] and Safavi S et al. [12] focus on fault detection and isolation for vehicle suspensions systems using a clustering-based method.

The main contribution of the research work is twofold. Firstly, a car suspension system model was built, incorporating simulation datasets for both the front and rear suspensions. The model was then simulated to generate various virtual measurements corresponding to different types of faults. Second, a combination of unsupervised and supervised machine learning techniques was proposed for detecting anomalies as high amplitude sinusoidal and step road profile in car suspension systems. Simulations have been conducted with propose a combination of these learning techniques to classify data, isolate outlier, and predict fault diagnosis outcomes in a full car suspension model. Moreover, these models are not only applicable for training datasets but also testing with new different types of fault diagnosis.

2. Human Health and Car Vibration

2.1 Effects of Car Vibration on Human Health

Several studies have shown the positive impact of car vibrations on human safety and health. For example, Sitnik, Magdziak-Tokowicz, Wrobel, and Kardasz [13] investigated vehicle vibration's impact on human health and found that both vibrations and noise may lead to harmful effects, including balance disorder or motion sickness, neck, and occiput area pain. Similar to the research conducted by Tatsuno and Maeda [2], the study examined the impact of whole-body vibration exposure during vehicle rides, revealing potential health problems such as back pain, sciatica, digestive, disorders, genitourinary problems, and hearing damage.

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2.2 Automobile Suspension Model

In this study, the utilized non-linear full vehicle model [14],[15] is comprised of seven degrees of freedom shown in Fig. 1

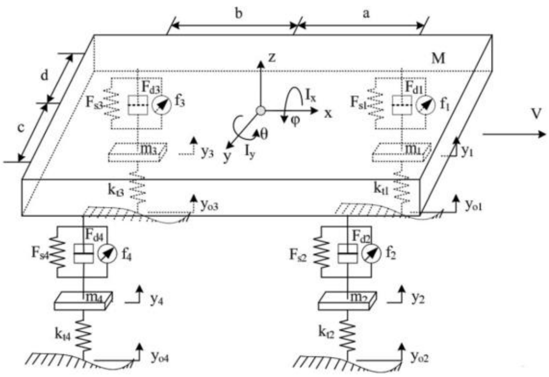

Fig. 1 Car suspension model

F_{si} and F_{di} denote the forces generated by the nonlinear stiffening spring and the piece-wise linear damper, respectively, which can be calculated using Eq. (1) and (2), where i is 1 to 4 [9]. These equations are:

$$F_{si} = k_i\left(\Delta y_i\right) + k_{ni}(\Delta y_i)^3 \quad (1)$$

$$F_{di} = \begin{cases} b_{ei}\Delta\dot{y}_{i,}\Delta\dot{y}_i > 0 \\ b_{ci}\Delta\dot{y}_{i,}, \Delta\dot{y}_{i,} \leq 0 \end{cases} \quad (2)$$

where, k_i is the linear stiffness coefficient and k_{ni} is the nonlinear stiffness coefficient; b_{ei} and b_{ci} are the extension movement and the compression movement damping coefficients, respectively; Δy_i denotes the suspension deflections and $\Delta\dot{y}_{i,}$ denotes the deflection velocity. Through the utilization of Lagrange equations, one can employ the subsequent nonlinear motion equations to depict the complete car suspension model as follow:

$$M\ddot{y} + \sum_{i=1}^{4} F_{di} + \sum_{i=1}^{4} F_{si} = \sum_{i=1}^{4} f_i \quad (3)$$

$$I_y\ddot{\theta} + cos\theta\left[a\sum_{i=1}^{4} F_{di} + b\sum_{i=1}^{4} F_{si}\right] = a(f_1 + f_2) - b(f_3 + f_4) \quad (4)$$

$$I_x\ddot{\varphi} + cos\varphi\left[d\sum_{i=1}^{4} F_{di} - c\sum_{i=1}^{4} F_{si}\right] = d\left(f_2 + f_4\right) - c\left(f_1 + f_3\right) \quad (5)$$

$$m_1\ddot{y}_1 - F_{d1} - F_{s1} + k_{t1}\left(y_1 - y_{01}\right) = -f_1 \quad (6)$$

$$m_2\ddot{y}_2 - F_{d2} - F_{s2} + k_{t2}\left(y_2 - y_{02}\right) = -f_2 \quad (7)$$

$$m_3\ddot{y}_3 - F_{d3} - F_{s3} + k_{t3}\left(y_3 - y_{03}\right) = -f_3 \quad (8)$$

$$m_4\ddot{y}_4 - F_{d4} - F_{s4} + k_{t4}\left(y_4 - y_{04}\right) = -f_4 \quad (9)$$

Here, M represents the mass of the car body, while I_x and I_y denote the rotary inertias for the roll motion and the pitch motion, respectively. Moreover, the variables are defined as: y_i represents the unsprung mass displacement, y_{0i} is the road input, θ and φ represent the pitch and roll motions, respectively. m_i denotes the unsprung mass, k_{ti} is the stiffness of the tire, and f_i corresponds to the force generated by the corresponding actuator. *a*, *b*, *c*, and *d* represent the corresponding distances from the suspension to the mass center of the car body.

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3. Related Algorithm

Machine learning algorithms can be divided into four categories according to the purpose and the main categories. First, the supervised learning relies on labeled training data to learn patterns and make predictions on new or unseen data which commonly used for classification and regression. Secondly, the unsupervised learning involves in finding patterns and structures in data without explicit labelling or targeting outcomes which commonly used for tasks such as clustering, anomaly detection, and dimensionality reduction. Thirdly, the semi-supervised learning is a combination of both labeled and unlabeled data during the training process which commonly used in various real-world applications. Lastly, Reinforcement learning is a form of machine learning that focuses on learning by trial and error.

3.1 PCA algorithm

The Principal Component Analysis (PCA), which is one of the earliest methods based on data, is capable of efficiently transforming measurements into a lower-dimensional space of principal components and capturing the variabilities within the data. Let's assume that $X \epsilon R^{Nxm}$ denotes a dataset obtained through measurements.

$$X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_N^T \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nm} \end{bmatrix} \quad (10)$$

In this context, where $x_i, i = 1,2, \dots N$ represents a single sample, N represents the number of samples, and m represents the number of variables. It is generally necessary to preprocess the measurements X by performing zero mean visualization and unit variance processing. The matrix X^0 has been adjusted to have zero mean and unit variance. The Singular Value Decomposition (SVD) algorithm is employed to process the covariance matrix of X^0. The matrix X^0 can be expressed in the following manner:

$$X^0 = TP^T + \acute{X} \quad (11)$$

Where $\acute{X}$ represents the residual subspace, while $T \epsilon R^{Nx\beta}$ and $P \epsilon R^{Nx\beta}$ represent the score matrix and the loading matrix, respectively.

3.2 K-means algorithm

The K-means algorithm [16], [17] is used for clustering data without expert guidance using an unsupervised approach. The main purpose is to extract information from the data automatically. Data points within the same group, referred to as a cluster, are closer to each other than to points in other clusters, based on a criterion of similarity or dissimilarity. Each data point is assigned to a cluster when it is located close to the cluster's centroid or center of gravity.

Where $(x_1, \dots, x_n)$ are the dataset. Γ is the classification distance criterion, which measures the distance between a specific data point and the

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centers of the established classes. $C = (c_k, \ldots, c_n)$ represent the collection of class centers, and $G = (g_1, \ldots, g_n)$ represent the set of clusters. The criterion Γ is the sum of Euclidean distances between each data point and the center of the nearest class.

$$\Gamma(C, G) = \sum_{k=1}^{K} \sum_{i=1}^{n} g_{ik} \|x_i - c_k\|^2 \tag{12}$$

g_{ik} is a binary variable equal to 1 if the cluster of the indexed data is k and 0 . Otherwise, the Euclidean distance is determined by the following definition.

$$\mathrm{d}(x_i, c_k) = \|x_i - c_k\|^2 = \sqrt{\sum_{j=1}^{d} \left(x_{ij} - c_k\right)^2} \tag{13}$$

3.3 ANN algorithm

Artificial Neural Networks (ANNs) aim to emulate natural brains and demonstrate remarkable capabilities in data processing and learning. The basic building block of a neural network, known as a neuron, functions as a processing unit with multiple inputs and a single output. Fig. 2 illustrates a multilayer neural network consisting of multiple layers of neurons, typically three layers [18] (an input layer that receives signals from a specific source, a hidden layer that processes the data, and an output layer that transmits the processed data externally). Therefore, the network results are calculated with a continuous function $G(x)$ that can be represented as

$$G(x) = W\sigma(Vx + b) + \varepsilon(x) \tag{14}$$

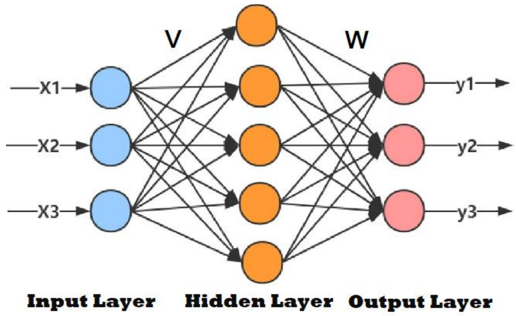

Fig. 2 Neural Network layers

In this context, the input vector is represented as x, while *V* and *W* denote the weight matrices for the hidden layers and output layer, respectively. The hidden layer utilizes an activation function, often a sigmoidal or RELU function denoted as $\sigma(.)$. The threshold is denoted as b. $\varepsilon(x)$ represents the bounded approximation error of the neural network. During the error backpropagation training procedure, the feed-forward phase involves presenting an input pattern x to the network and generating a response *y* in the layers. In training mode, the error of the output layer ($\left\|y_d - y\right\|$, where y_d is the desired output) is propagated back to the input layer of the network. The weights are adjusted using the steepest descent gradient method. The updating rules described in Eq. (15) and Eq. (16) are used to modify the weights of the output and hidden layers in order to discretize the output error.

$$\dot{W} = -\eta_1 \left(\frac{\partial \bar{E}}{\partial W}\right) \tag{15}$$

$$\dot{V} = -\eta_2 \left(\frac{\partial \bar{E}}{\partial W}\right) \tag{16}$$

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The learning rates, η_1 and η_2, are chosen by the designer. The output errors are denoted as $\bar{E} = \left(\frac{1}{2}\right) E^T E$ and $E^T = y_d - y$. The updating rules can be simplified to the following equations:

$$\dot{W} = -\eta_1 \sigma(V^T x)\, E^T \tag{17}$$

$$\dot{V} = -\eta_2\, (\sigma_d W E)^T \tag{18}$$

Where σ_d represents the derivative of the activation function of the hidden layer, denoted as $\sigma(.)$. The introduction and utilization of the Rectified Linear Unit () activation function addresses the issue of "vanishing and exploding gradients" encountered in the sigmoid functions. ReLU as follows.

$$\mathrm{ReLU(x)} = \begin{cases} x \text{ } if \text{ } x > 0 \\ 0 \text{ } if \text{ } x \le 0 \end{cases} \tag{19}$$

The ReLU formula shows that if the input x is less than 0, the output is equal to 0; if the input x is greater than 0, the output is equal to the input.

4. Research Methods

Chamseddine and Noura [19] revealed that the vehicle suspension faults involve the reduction or alteration of suspension component functions, such as changes in the spring or damper coefficients. Table 1 provides a comprehensive summary of all the parameter values pertaining to the full car suspension [10]. The research focuses on simulating spring damage to the vehicle suspension regarding the assumption of an usual road with amplitude of 5 mm. The simulation scenarios including four categories with various coefficient reductions are employed as shown in Table 2 that used in the research paper study.

Table 1 Parameters of the full car suspension model

PARAMETERS	
Vehicle body mass	$M = 1000\ kg$
Front wheels unsprung mass	$m_1 = m_2 = 25\ kg$
Rear wheels unsprung mass	$m_3 = m_4 = 45\ kg$
Pitch motion rotary inertia	$I_x = 550\ kg\ m^2$ $I_y = 1848\ kg\ m^2$
Front and Rear wheels linear stiffness coefficient	$k_1 = k_2 = 15000\ N\ s/m$ $k_3 = k_4 = 17000\ N\ s/m$
Front and Rear wheels nonlinear stiffness coefficient	$k_{n1} = k_{n2} = 15000\ N\ s/m^3$ $k_{n3} = k_{n4} = 17000\ N\ s/m^3$
Positive and Negative damping coefficient	$\mathrm{b_{ei}} = 1500\ N\ s/m$ $\mathrm{b_{ci}} = 1000\ N\ s/m$
Stiffness of tires	$k_{ti}\ (i = 1,2,3,4) = 250000\ N\ s/m$
Distance	$a = 1.2, b = 1.4, c = 0.7, d = 0.8$ (m)
Vehicle velocity	$V = 10\ m/s$

Table2 Simulation scenarios

Categories	Spring Coefficient Reduction (%)
Good	10%-30%
Usual	40%-50%
Fail	60%-80%
Fail high (Severe)	90%-100%

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5. Research Simulation

The acceleration data obtained from the left front wheel suspension is studied and the car parameters are used from Table 1. The event occurs at the 20-second mark, with the spring coefficient reductions starting from 10% up to 100% for every 2% increment, at a sampling frequency of 100 Hz. At every increment value of spring reductions, the simulation generates for 2000 data points with the time consumption of 20 s. The fault scenario in the spring coefficient is ranged from 60% to 100% reduction.

5.1 Fault Detection

Fault detection consists of cluster and classification data. First, data preparation and K-Means Clustering were used to cluster the acceleration data obtained from simulation. Second, data preparation and Artificial Neural Network (ANN) were applied to classify all acceleration data and then the categories were labeled as following: Good, Usual, Fail, Fail high.

5.2 Data Preparation:

The acceleration data from research simulation section were analyzed the standardize using mean and standard deviation; then the standardized data were performed using the Principal Component Analysis (PCA). K-Means clustering was applied to categorize data into clusters.

5.3 K-Means Clustering:

The K-Means algorithm was used to group the data into four clusters by aligning the number of simulation categories (K = 4) and calculate its membership values based on the similarity of the extracted features. The K-Means algorithm is configured with the following parameters. The distance metric utilizes the squared Euclidean distance, one replicate is employed, a singleton action is applied for the empty cluster action, and the maximum number of iterations are set as 100. Each cluster represents a distinct pattern of acceleration measurements associated with a specific level of suspension damage. The algorithm provides the different types and levels of damage as shown in Table 3 and Fig. 3.

Table 3 Spring reduction clusters acceleration data using the K-Means Clustering

Spring Reduction (%)	Cluster	Membership (%)	Centroid points		
			Mean	Stdv.	PCA
0%-40%	3	41.17	2.65×10^{-5}	1.6828207×10^{-2}	-5.2803×10^{-3}
43%-65%	2	29.41	3.62×10^{-5}	1.6775919×10^{-2}	-4.038×10^{-4}
68%-80%	1	17.64	4.69×10^{-5}	1.6750805×10^{-2}	5.65447×10^{-3}
83%-90%	4	11.76	5.66×10^{-5}	1.6773612×10^{-2}	11.00909×10^{-3}

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Each centroid point represents the main suspension characteristic of its cluster. However, the differences between the centroid points reflect the variations in the level of fault in each group. Therefore, the centroid points obtained from the K-Means Clustering process will be useful for understanding the distinct fault diagnosis outcomes in a spring pattern in the suspension system based on the grouped accelerometer data.

5.4 Artificial Neural Network (ANN)

After extract feature process, the acceleration data were labeled into each category as shown in Table 2. The data were used to train the ANN classification model to better classify the datasets which used to predict the new acceleration data. The ANN classification model has the hyperparameter values as follows:

- The network consists of two hidden layers, where the first layer has 20 and the second layer has 10.
- The Rectified Linear Unit (ReLU) was applied as the activation functions to both layers with the iteration limit of 1000.

The cross-validation datasets were chosen to verify the machine learning model from 5% of total dataset; these validation datasets are not part of the training data. Thus, this training model gives an accuracy of results at 97.1%. A confusion matrix was employed to evaluate the model's performance in identifying fault categories of car suspension as shown in Fig. 4. The model can predict and perform well for all suspension outcomes. However, only Fail high datasets are predicted 88.9% in Fail high category and 11.1% in Fail category.

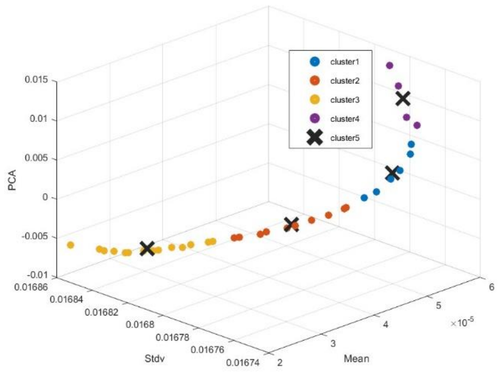

Fig. 3 Four clusters acceleration data using the K-Means Clustering

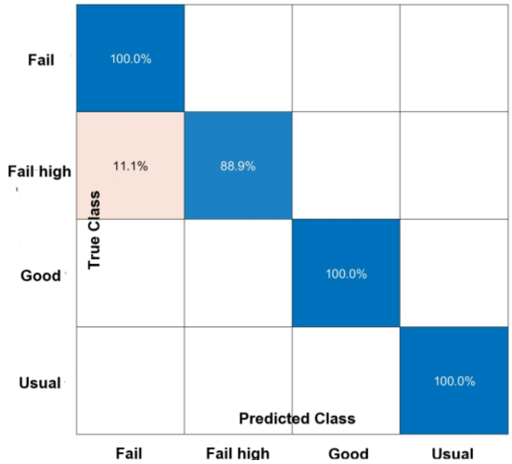

Fig. 4 Confusion matrix trained in ANN model

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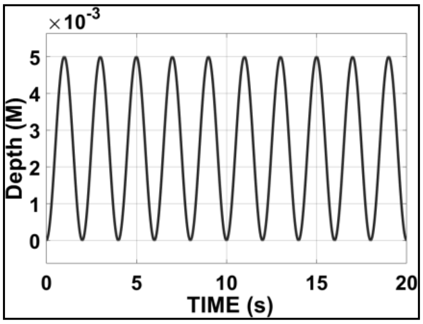
5.5 Road Profiles Simulation

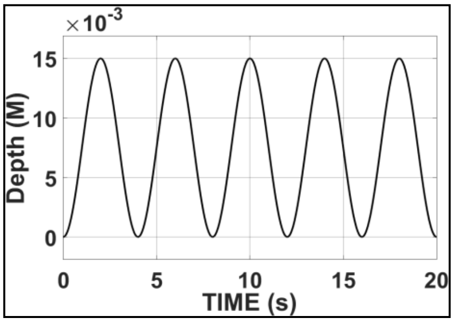
In this section, usual and unusual road profiles are explored. The road profile is assumed to be the sinusoidal form. According to Mohammed H.U. Bhuiyan [20], the drowsiness is most effectively induced by low frequency whole-body vibration, which is less than 10 Hz. Also, Nurkan Yagiz [14] presented the control of a vehicle active suspension for the road profiles with amplitudes from 5 to 30 mm.

The unusual road profiles consist of high amplitude sinusoidal and step road profile as shown in Fig.5. These road profile variations are frequently observed in real-world situations.

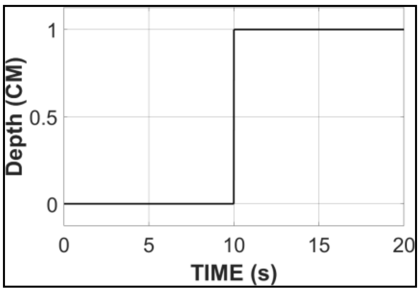
Whereas "a" defines as 5-mm amplitude road profile "b" defines as 15-mm sinusoidal road profile; "c" defines as 1-cm step up road profile; and "d" defines as 1-cm step down road profile. A step-up road typically refers to a road that suddenly transitions from a lower elevation to a higher elevation while a step-down road profile denotes a road that undergoes an abrupt transition from a higher, creating a sudden change in slope.



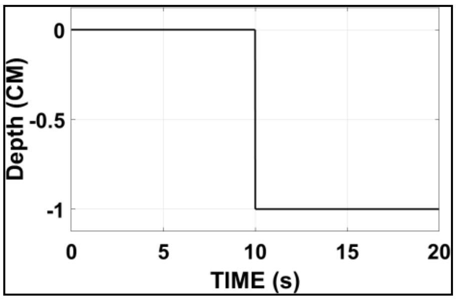
(a) 5 mm amplitude



(b) High amplitude



(c) Step-up



(d) Step-down

Fig. 5 Road profiles

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6. Results

For car suspension purposes, all new datasets for both usual and unusual road profiles were examined. All conditions of road profiles are explored including usual road with amplitude of 5 mm, 15-mm sinusoidal road profile, 1-cm step up road profile, and 1-cm step down road profile with spring reduction of 30% (good) and 100% (Fail high). Table 4 shows the results of car suspension prediction by using ANN model. As seen from Table 4, it can be concluded that the model provides accurate predictions for usual road profiles but struggles to predict correctly under unusual road profile conditions.

In order to predict unusual road profiles, each dataset was plotted alongside the clusters using the K-Means Clustering model. In Figure 6 (B, C, D), it is apparent that the unusual datasets do not align neatly with the clusters, classifying them as outliers.

Then, the distances between the outliers and centroids of all clusters were calculated as shown in Table 5. The boundary for the entire dataset will be calculated and established by utilizing the farthest member dataset. Each dataset from the cluster has its distance value. The simulation demonstrates that if a dataset's distance of each spring reduction (%) for any road profiles falls outside the established boundary, the data will be identified as an outlier and prediction may not be reliable. As shown in Table 5, in the case of 15-mm sinusoidal, 1-cm step-up, and 1-cm step-down road profiles, all distance values exceed the established boundaries, resulting in outlier data. Thus, the fault car suspension cannot be predicted.

Table 4 Fault car suspension prediction for each road profiles

Dataset	Road Profiles	Spring Reduction (%)	Prediction
Set-1	5-mm Sinusoidal	30	Good
Set-2	5-mm Sinusoidal	100	Fail high
Set-3	High amplitude sinusoidal	30	Fail high
Set-4	High amplitude sinusoidal	100	Good
Set-5	1-cm Step-up	30	Fail high
Set-6	1-cm Step-up	100	Fail high
Set-7	1-cm Step-down	30	Good
Set-8	1-cm Step-down	100	Good

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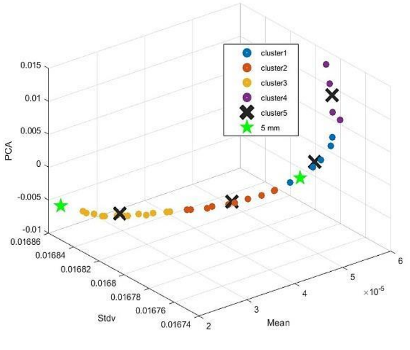
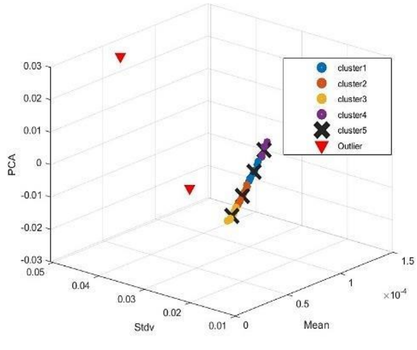
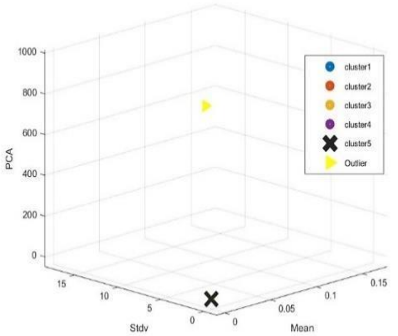


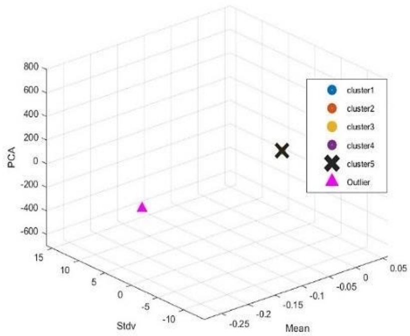
A. 5-mm amplitude



B. 15-mm sinusoidal



C. 1-cm Step-up



D. 1-cm Step-down

Fig. 6 shows the dataset falls inside and outside the cluster

7. Discussion and Conclusions

As the car suspension is a crucial component that significantly impacts both vibration and overall car performance. Excessive car vibrations can have various effects on humans. Although the vibrations are not considered harmful in the short term, prolonged exposure to vibrations can lead to health issues, such as discomfort and fatigue, muscle strain, impact on the spine, and so on. Moreover, numerous human health issues, such as low back pain and musculoskeletal disorders, can be attributed to the whole-body vibrations induced by the car vibrations. When vibrations are transmitted to the driver through a contact surface, they can pose a potential risk, contributing to musculoskeletal diseases and joint pain. Bhuiyan, Fard, and Robinson [21] investigated the interrelationships between the various components of whole-body vibration, physiological and cognitive parameters leading to driver drowsiness, as well as the effects

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Table 5 Distance between the outliers and centroids

Road Profiles	Spring Reduction (%)	Cluster	Boundary	Distance
5-mm Sinusoidal	30	1	0.0025462	0.00160
		2	0.00279005	0.00445
		3	0.00205699	0.00933
		4	0.00204542	0.00695
	100	1	0.0025462	0.01198
		2	0.00279005	0.00592
		3	0.00205699	0.00105
		4	0.00204542	0.01733
1-cm Step-up	30	1	0.0025462	608.985
		2	0.00279005	608.991
		3	0.00205699	608.996
		4	0.00204542	608.979
	100	1	0.0025462	611.396
		2	0.00279005	611.402
		3	0.00205699	611.407
		4	0.00204542	611.390
15-mm Sinusoidal	30	1	0.00254620	0.03874
		2	0.00279005	0.04201
		3	0.00205698	0.04503
		4	0.00204542	0.03641
	100	1	0.00254620	0.0451
		2	0.00279005	0.04127
		3	0.00205698	0.03857
		4	0.00204542	0.04883
1-cm Step-down	30	1	0.00254620	565.651
		2	0.00279005	565.645
		3	0.00205698	565.64
		4	0.00204542	565.656
	100	1	0.00254620	567.481
		2	0.00279005	567.475
		3	0.00205698	567.47
		4	0.00204542	567.487

of vibration parameters, including frequency, amplitude, waveform, and duration of the vibration. The paper found that a data link exists between whole-body vibration and driver drowsiness.

Hence, there is a need for research to identify methods for minimizing or predicting car vibrations before they occur. Therefore, a thorough examination of a comprehensive car suspension model was conducted, and fault diagnosis outcomes related to road profiles and spring reductions were identified to ensure the functional safety and long-term reliability of vehicle throughout their operational lifespan. The results showed that the model is equipped to effectively detect and isolate unfamiliar patterns in car suspension faults through the utilization of both unsupervised and supervised machine learning algorithms. This simulation results in decreased errors and time, while concurrently improving the accuracy of predictive outcomes. As a result, drivers can perform car maintenance to prevent the occurrence of detrimental vibrations. Moreover, all obtained results demonstrate that utilizing a combination of unsupervised and supervised machine learning algorithms is very effective and can be used to improve outcomes in car suspension. Future work will focus on further enhancing these values and elevating the performance of the model by exploring additional health studies related to vibration induced effects in other sports, such as cycling.

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