JAET

Journal homepage: http://jae-tech.com

ISSN : 2523-6032 ISSN-L : 2523-2924

Journal of Applied Engineering & Technology

Automobile Suspension Prediction Model Based on Neural Network and Grey Neural Network

Shehroze Mughal[1], Muhammad Arsalan Jalees Abro[1], Irfan Ahmed Halepoto [2,*], Mehran Muhammad Memon[2]

[1]Department of Mechatronic Engineering, Mehran UET, Jamshoro, Sindh, Pakistan.
[2]Department of Electronic Engineering, Mehran UET, Jamshoro, Sindh, Pakistan.

*Corresponding Author

DOI: https://doi.org/10.55447/jaet.06.02.90

Abstract: Vehicle Vibration is a major issue in automobile industry which hinders the stability of the vehicle and also adds to the discomfort levels of the passengers. The proposed work models a suspension prediction system using a combination of both Neural Network and Grey Neural Network for more efficient predictions. The research was divided into three stages. First stage is to develop a hardware to acquire the vibrational acceleration data of the test vehicle at different suspension types and road types. The data acquired was then used to train the designed neural model which was the stage two of the project. The final stage consisted of testing the prediction model by acquiring dynamic data with unknown parameters including the road type and the suspension tune settings. The research is effectively efficient to predict suspension tune settings for a vehicle traveling on dynamic road conditions with very little mean absolute percentage error. The training, learning, and the testing of the prediction model was done on a real-time system. The real-time vibration prediction model allows easy suspension tunings and improved drive experience for both the driver and the passenger. The incorporation of machine learning allows the reduction of MAPE thus, producing highly efficient results.

Keywords: Grey Neural Network; Neural Network; Automobile; Suspension Prediction Model; Real-time data

1. Introduction

The transportation industry is one of the most demanding industries in this era. The human beings rely highly on vehicles to move from one place to another and transport the goods as well. The vehicles are made up of mechanical components which are highly susceptible to wear and tear. The wear and tear is caused by multiple factors and one such factor is the vehicular vibration which is produced due to loose components or uneven terrains [1]. This induced vibration has multiple negative effects on the consumers. With increased vibrations, the drive stability is widely affected. The vibration produced due to an uneven or on bumpy road are transmitted to the steering wheel of a vehicle and while applying brakes, there are high chances that vehicle may drift-off from the track

*Corresponding author: irfan.halepota@faculty.muet.edu.pk

and cause an accident. Due to vibrations, vehicle wear and tear increases as a result, vehicle parts can be damaged quickly thus can reduce the age of the vehicle. Passengers comfort level is another concern related to vibrations, which directly effects the overall vehicle reputation and performance in the market. Although vibrations cannot be eliminated completely but can be controlled at acceptable levels by numerous methods. The different opted methods can results in a permanent change in vehicular dynamics. Once installed, the components cannot be altered. So, researchers have focused on the suspension system of the vehicles which allows the flexibility of variation in accordance to the track the vehicle where it is driven upon. There are various suspension types available that focus mostly on the vehicular height and the damping factor adjustments. These tune settings allow the limitation in the frequency of vibrations occurring on different road types. The only drawback is that the tuning is made manually after knowing parameters such as the road type, speed of the vehicle, driving style of the driver, etc. The traditional method is effective but cannot predict the tune settings of a dynamic road type without the hit and trial method to get the optimum suspension setting. This research work propose a machine learning-based vibration prediction model that can optimally suggests the driver for ideal suspension tune settings for any particular road type. Using the combination of both the neural network and the grey neural network, the propose work reduces the MAPE significantly which allows highly accurate suspension tune settings. Tuning suspension in this manner allows the elimination of hit and trial methods traditionally used and produces lower levels of vibration which in return increases the drive experience and the comfort level of the consumers.

The rest of the research paper is classified as: Section 2 briefly discuss the related work, whereas Section 3 includes the hardware implementation details and acquiring of the training data of the experimental setup. The prediction model design and training is explained in Section 4 while section 5 provides the predicted suspension tune settings obtained through the trained model. Finally Section 6 concludes the work and highlights the future research potential.

2. Background and Literature Review

The fatigue life of car-coil springs was predicted with great precision in [2] using a hybrid multi-layer perceptron artificial neural network (HMLP-ANN) model that was based on the vehicle's suspension system's inherent frequencies and on vertical vehicle vibrations. In [3] deep neural networks are used to forecast the shock absorber squeak noise using the original temporal data and frequency spectra (DNNs). The researchers in [4] explore the usefulness of ANN for seated body apparent mass prediction while using two different sitting postures and varying amounts of vibration excitations in 0.5–20 Hz frequency range (with and without back support. A new method to evaluate passenger car vibration comfort based on the specific contents of vibration signals was presented in [5] by utilizing deep learning. Four-passenger automobiles were tested at various speeds and on various types of roads. The prediction loss is decreased by 76.9% when two neural networks, feed-forward neural network, and gated recurrent units, are employed to create two fundamental models. According to the authors of [6], semi-active suspension systems for cars using smart dampers (SmDs) are the desirable way for enhancing ride comfort and sedans. The SmDs' are used to estimate the time-varying control signal precisely. A semi-active low-cost suspension is proposed in [7] to replace the passive ordinary suspension in cars. A hydraulic piston with a proportional throttle valve located outside the piston's cylinder between the two inlet ports makes up the newly proposed mechanism. In comparison to magnetorheological dampers, semi-active systems and conventional systems, the results demonstrated good performance in terms of vibration reduction and response time. The comfort of the vehicle has received more attention from the authors in [8]. Engine, powertrain, and motor-related issues are the major areas under which Noise, Vibration, and Harshness (NVH) related issues fall. Each category or problem type is given a thorough description, and many NVH-suppression techniques for Hybrid Electric Vehicle (HEVs) are explained along with their individual benefits. In [9] authors have presentenced an indirect technique to identify the available adhesion level at the wheel-rail interface which is an important factor to accelerate the vehicles quickly. In study [10] authors have tested the brake system of a genuine automobile. Using a piezoelectric-type accelerometer, the vibration data was collected from the brake system under various fault scenarios. Using feature extraction techniques, useful statistical data was recovered from the raw signals. The influence of the number of features studied was then used in the feature selection procedure with classification accuracy of 85.52%. Based on common vehicle sensors, [11] proposes a novel system that can categorize various road types and their circumstances. The technique utilizes time and frequency based features extended with a physical vehicle sub model. The proposed approach was claimed to be effective for driving assistance systems or to update route maps to reflect current conditions by modifying the car suspension system and driver dynamics. In [12] authors have proposed a prediction model for automotive body vibration acceleration that is efficient, and closely resembles with actual situations. Multiple sensors were used to collect a vast amount of data on railway factors, and various correlation coefficients were chosen to filter out the parameters that were connected with the acceleration of automobile body vibration. In [13], based on vibration signals, an adaptive online terrain classification method is proposed. The original vibration signal's time domain and combined features of frequency, time, and time-frequency domains are initially extracted. To create classification models with various dimensions, these features were used as inputs to the random forest method. Then, an adaptive selection of the classification model with various dimensions is made for online classification. In [14], Fiat Panda III's rear suspension system is discussed where in-wheel electric motor dynamics analysis is presented. The impact of spring stiffness coefficients and shock absorber damping coefficients on the dynamic response of the suspension was then examined through a series of computations. The researchers studied the severe consequences of vibration on a person's health and physique in [15], where they suggested that daily workplace vibration exposure occurs for workers in a variety of occupational fields. Occupational vibration exposure has increased the risk of getting hand, back, shoulder, neck, and hip musculoskeletal pain. A three layers ANN model was created in [16] for a study to accurately predict the real-time travel comfort of bus passengers in a bus guidance systems. This research work focuses on the predictability of an ideal suspension tuning for a dynamic road by combining the features of both the Grey Network and Neural Network. This allows incorporating machine learning to increase both the drive experience and the comfort of the consumers. The literature review summarize that traditionally, grey system theory and neural networks are used individually for predicting the model parameters, but as a standalone techniques, both have certain limitations. Vibrations are only predicted on small cars or test models designed with ideal condition. In this work, grey system theory and neural network algorithms are be combined together as nonlinear extrapolation prediction technique to predict the nonlinear issues like the vibration of cars, internal mapping and relationship between data after learning and training.

3. Research Methodology

This study examine the accelerations of vibrations at all measuring places within a vehicle on various roads and at various speeds. The experimental setup was deployed close to the rest point near the clutch pedal. Figure 1 depicts the vibration acceleration sensor installation diagram in the frame near the transmission which consists of an Arduino UNO, laptop, a test vehicle. The specifications of the test vehicle are given in Table 1. The ADXL 345 Accelerometer was used to acquire the vehicle vibrational-acceleration (VA) data. The hardware mount position is shown in Figure 2. For two reasons, the rest point near the clutch pedal was chosen. First being easy to mount the hardware near clutch pedal and secondly, it is directly above the gearbox and is near the engine too. So, this is one of the points which records the highest vibrations in a vehicle. This vibration is a combination of multiple factors such as the engine’s working, suspension system including shocks and steering box, working of the gearbox, etc. After hardware mounting, test vehicle was driven on three separate road types (i) normal road, (ii) bumpy and (iii) Highway; and then vibrational data was acquired and used for the training and learning of the prediction model. This route selection was made accordingly for three different cases. One with a zero occurrence of bumps, the second one had limited bumps, and the third route was highly bumpy. The selected routes are shown in Figures 3 (a), (b), and (c). After the route selection, for the effective training of the model, three suspension tune settings were chosen: Normal Suspension, Stiff Suspension, and Soft Suspension. After the selection of learning route and suspension type, the test vehicle was driven on these road types with different sets of suspension. The Figures 4 (a), (b) and (c) show the graphical data of the VA. The data is compared to the idle VA which is basically the vibration recorded in the vehicle when the vehicle is stationary and the data is acquired by starting the vehicle and reviving the stationary vehicle to 3.5 revolutions per second.

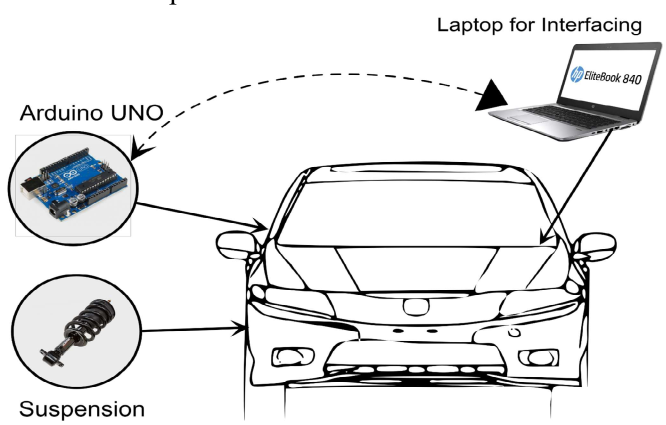


Fig. 1 - Designed experimental setup

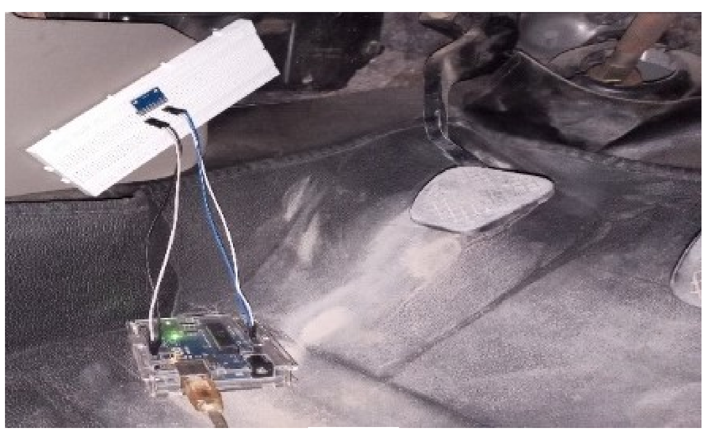


Fig. 2 - Hardware mounting position

Table 1: Test specifications of the test vehicle

Test Specifications	
Vehicle Make	Honda City
Vehicle Make	2016
Vehicle Engine Type	1.3 L L13Z1
Vehicle Transmission Type	5-Speed Manual
Horse Power	98 hp
Test Model Speed Range	20-100 KM/H

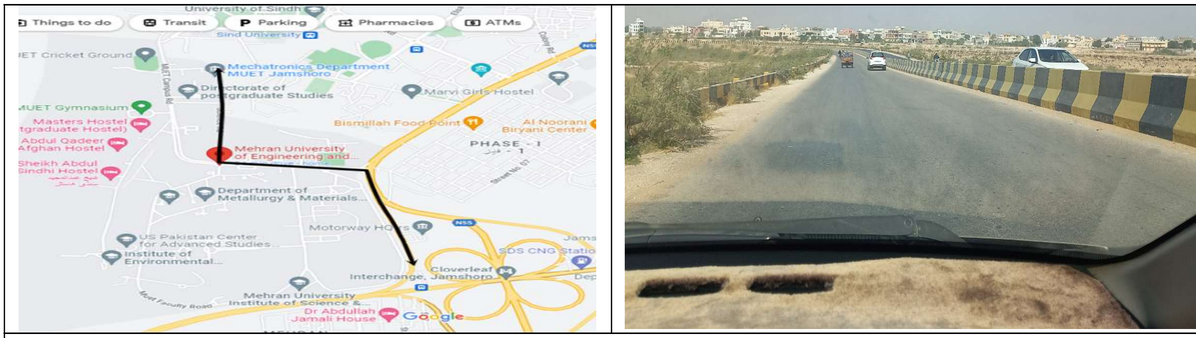


Fig. 3(b) - Map and Route of Normal Road

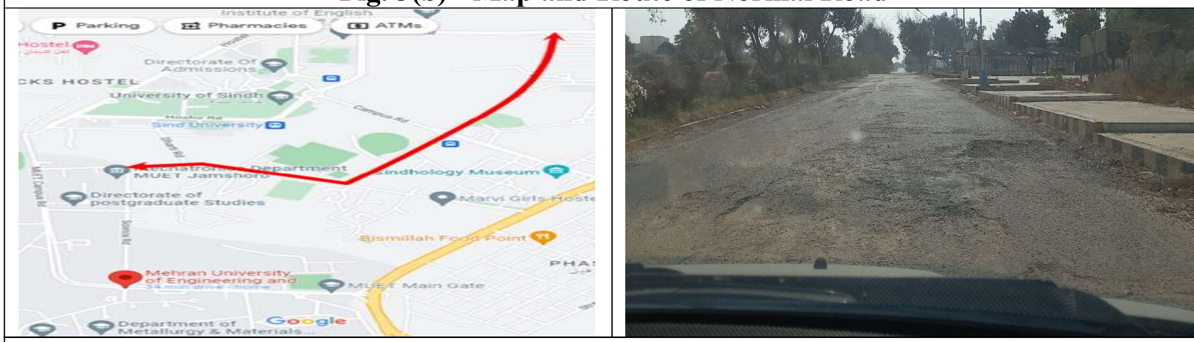


Fig. 3(b) - Map and Route of Bumpy Road

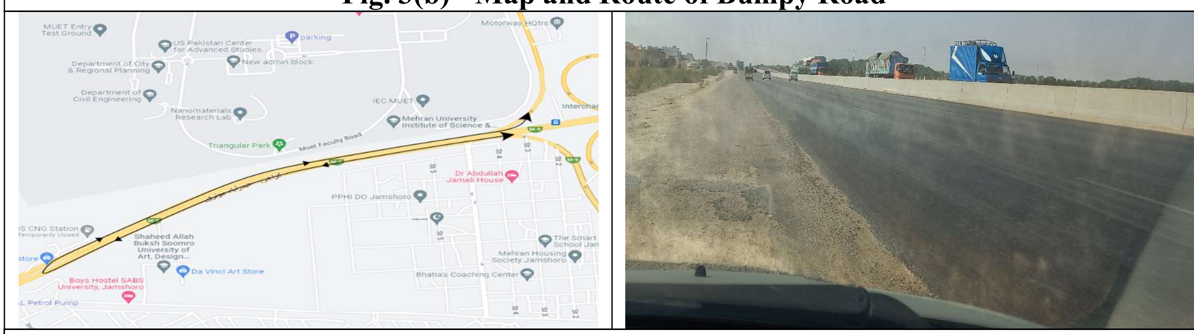
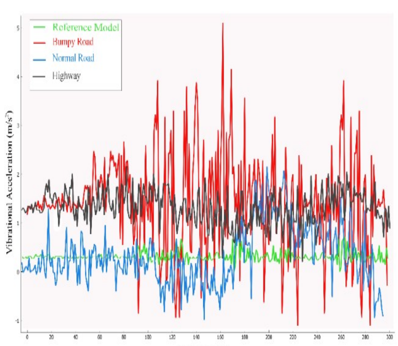
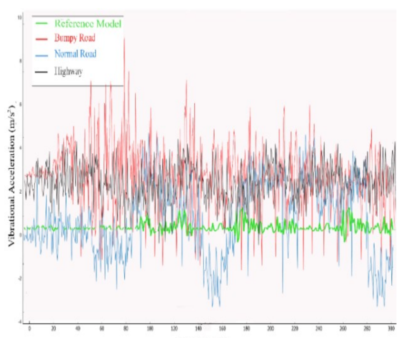


Fig. 3(c) - Map and Route of Highway Road





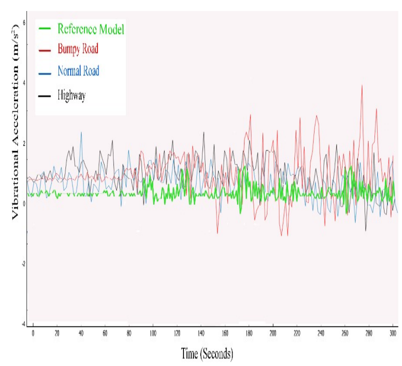


Fig. 4(a) - Suspension Type: Normal

Fig. 4(b) - Suspension Type: Soft

Fig. 4(c) - Suspension Type: Stiff

Table 2 which illustrates the deviation of the acquired VA peaks from the idle conditions. The peaks are recorded in both directions: positive peak deviation denoted by $\triangle P_1$ and negative peak deviation denoted by $\triangle N_1$.

Table 2: Vibrational acceleration learning and training data.

Suspension	Road Type	PPva	$\triangle P_1$	NPva	$\triangle N_1$
N/A	Idle Start	0.86	0	0.35	0
Normal	Bumpy	5.1	4.24	-1.1	0.75
Normal	Normal	2.2	1.34	-1.33	0.98
Normal	Highway	2.35	1.49	0.2	0.15
Soft	Bumpy	9.18	8.95	-2.2	1.85
Soft	Normal	4.18	3.32	-2.52	2.17
Soft	Highway	4.75	3.89	0.55	0.2
Stiff	Bumpy	4.08	3.22	-0.88	0.53
Stiff	Normal	2.07	1.21	-0.55	0.2
Stiff	Highway	2.08	1.22	0.73	0.38

Where, PPva is Positive Peak Vibrational Acceleration (m/s^2) and NPva is Negative Peak Vibrational Acceleration (m/s^2), $\triangle P_1$ = ||PPva| - (Idle Pva)| and $\triangle N_1$ = ||NPva| - (Idle Nva)|.

4. Results and Discussion

4.1 Prediction Model

In this paper, grey system theory and neural network algorithms are be combined together as nonlinear extrapolation prediction technique to predict the nonlinear issues like the vibration of cars, internal mapping and relationship between data after learning and training. The GNN can potentially increase the prediction's accuracy and reliability. The GNN prediction is based on the GM (1, 1) model which is more suited for first-order univariate differential equations with features such as difference, exponential compatibility, differential, and, etc. The combined prediction model of a sliding window grey neural network is created in this work by connecting the grey model (GM), neural network unbiased grey model (PGM), and weighted unbiased grey model (WPGM) with a feed-forward neural network (SGMNN). Three grey model outputs are used as the neural network's inputs, and a 3-layer NN structure with 2 hidden layers is created to produce results for drift rate prediction. This is shown in Figure 5.

Modeling Steps:

Step 1- Sliding Window Grey NN: In order to create the GNN prediction model GMNN, the prediction results of GM (1, 1), PGM (1, 1), and WPGM (1, 1) with sliding windows are input into the feedforward NN (FNN) and are trained. A back propagation (BP) technique modifies the weights and thresholds of neurons in FNN. The loss function is minimized using the gradient descent approach. The parameters of the network are iteratively adjusted to match the specified training step size or error accuracy requirements based on the learning rate. The layout is shown in Figure 6.

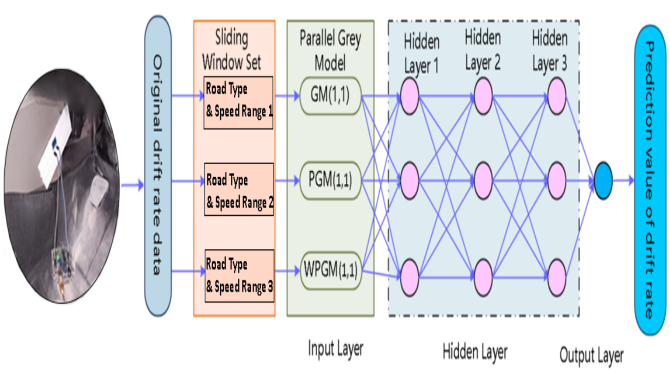


Fig. 6 - Prediction Model Flowchart

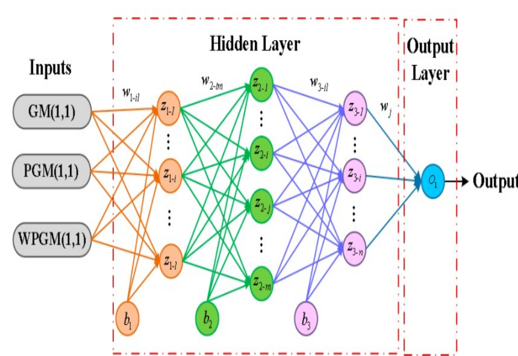


Fig. 6 - Sliding Window GNN layout

Step 2- Suspension Tuning Prediction: The historical test drift rate data is used to train the SWGNN model, which then predicts the system's drift rate value for the given time period. The flowchart of the entire model is shown in Figure 7.

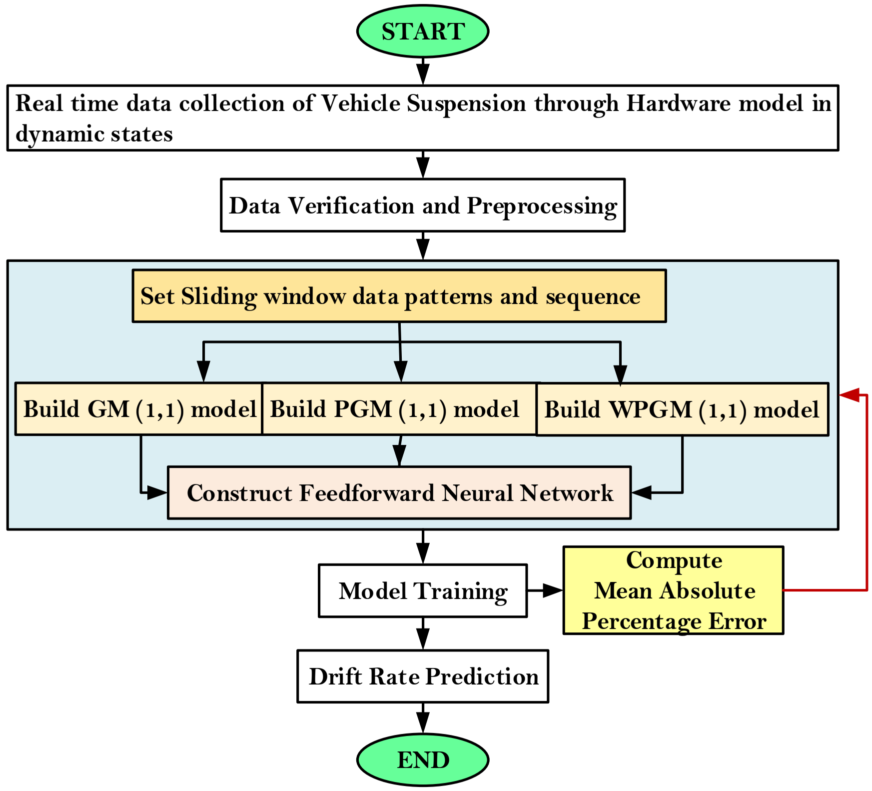


Fig. 7 - The SWGNN algorithm's flowchart

At the beginning, using the GM (1, 1) data prediction network for three measuring points, three data sequences of actual values and predicated values on five vehicle speed ranges in the range of 20-100 km/h separated by 20km apart are taken. The actual values and predicted values are used as the input and output vector of the NN. The network is than initialized and trained with respect to network structure, thresholds, and weights of each associated node. After simulation, corresponding outputs, which represent the final predictions of the vibration acceleration of each measuring point at a speed of 20–100 km/h are obtained. By contrasting the anticipated outcomes of the combined model and the GM (1, 1) prediction model, the mean absolute error for each test was calculated.

Step 3- Adjustment of the Proposed Model: The projected results are compared to the actual numbers to get the MAPE. To get the best prediction model, the model parameters, such as the sliding window length and NN parameters, are updated based on error.

4.2 Testing and Recalibration

To evaluate the prediction model, four dynamic road conditions were chosen at random and marked as: Test 1, Test 2, Test 3, and Test 4 as shown in Fig 8 and d. Based on the series of tests, the prediction model predicted the best possible suspension selection for the vehicle. The suspension selection was based on the PPva and NPva which are denoted by δP1 and δN1 respectively. The test values can be seen in the Table 3 which is extracted from the VA test data graphs in Figure 10.

Table 3: Vibrational acceleration test data

Test #	PPva	δP1	NPva	δN1	Predicted Suspension Type
Test 1	1.299	0.439	0.3	0.05	Stiff + Normal
Test 2	2.057	1.197	0.106	0.244	Normal + Stiff
Test 3	6.036	5.176	-4.441	4.091	Normal + Soft
Test 4	2.72	1.86	0.7386	1.121	Normal + Stiff

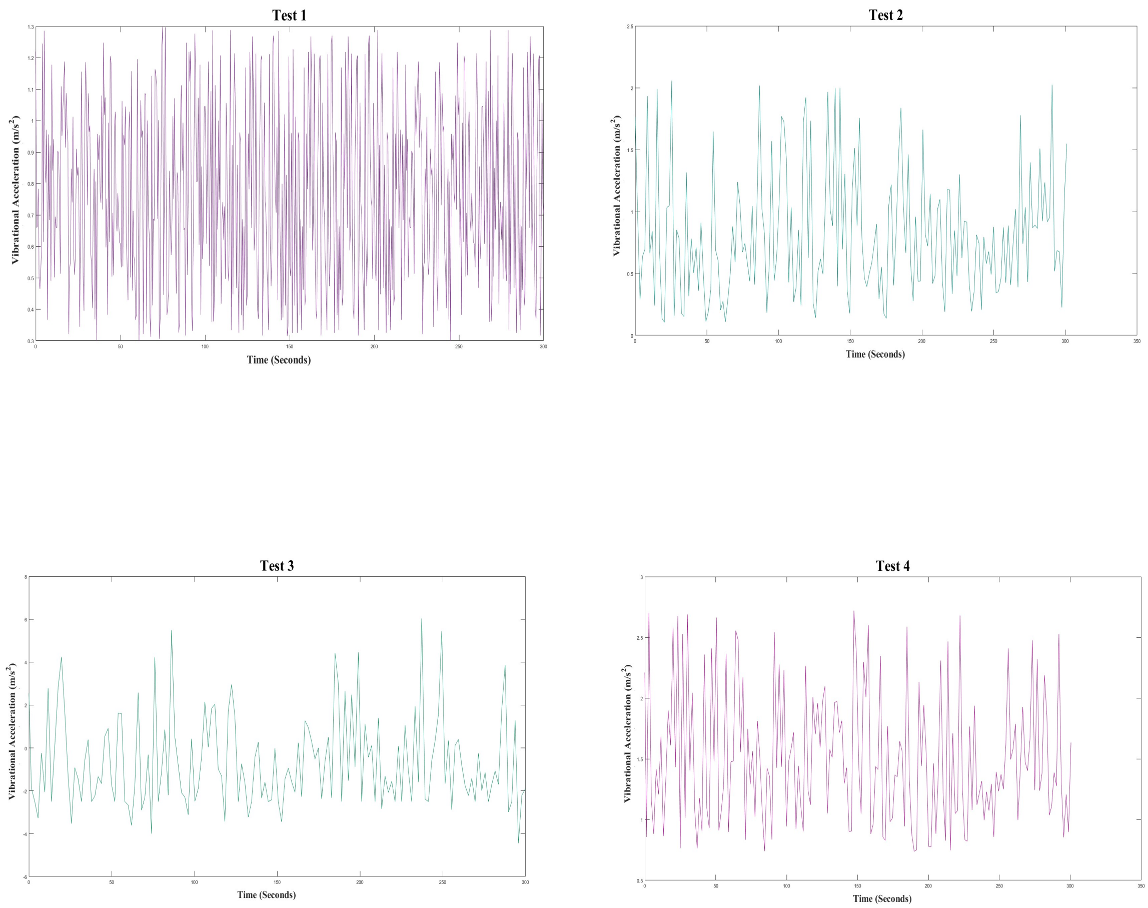


Fig. 8- Vibrational acceleration test data acquired from unknown road and suspension types

The predicted suspension is represented by radar charts due to their flexibility and convergence ability to represent comparative results. In accordance with the VA, prediction model predicts a suspension type as a balance between positive and the negative vibrational acceleration peaks which aim is to reduce the effect of vibration over both the peaks for a smoother drive experience. The combination or the balance of these suspension types will result in an optimum drive on that particular road. Figure 9 is the radar chart representation of all the tests. From the predicted data, to verify the results, MAPE was generated which is shown in Table 4.

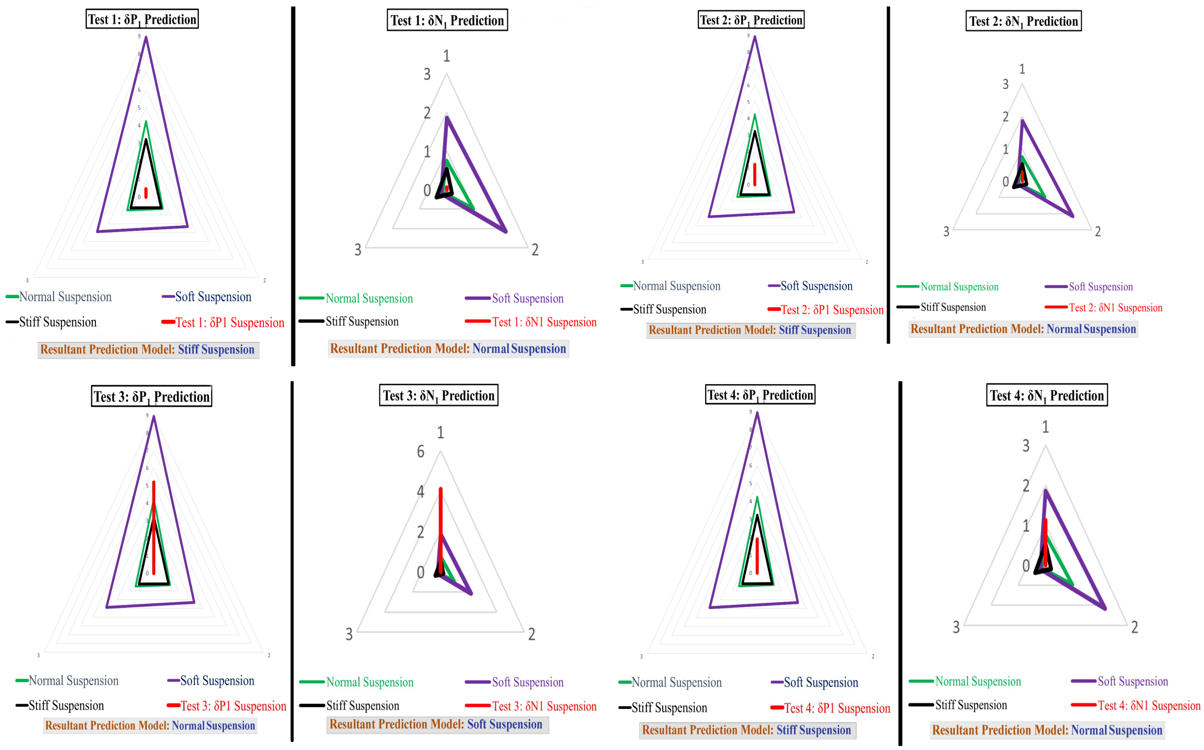


Fig. 9 - Radar chart prediction representation of Test 1, 2, 3, and 4 with δP1 and δN1 values.

Table 4: Predicted suspension tuning MAPE

Vibration Acceleration	Test Values	GM Prediction Model		GNN Prediction Method	
		Predicted Values	MAPE (%)	Predicted Values	MAPE (%)
Test 1	0.639	0.265	37.04%	0.683	4%
Test 2	1.368	0.178	11.9%	0.814	6%
Test 3	3.215	0.300	31%	0.653	4%
Test 4	1.506	0.354	67%	1.503	0.3%
Avg	**1.682**	**0.274**	**36.75%**	**0.913**	**3.52%**

5. Conclusion

This research work proposes a method for forecasting vehicle vibration using a grey and neural network model. The research demonstrates that, in comparison to a single GM (1, 1) model, the grey and neural network method has a greater prediction accuracy. A novel technique for multi-sequence linked data prediction is presented in this research. The research can be made better by including more datasets in the learning model and training model and then carrying out more such tests as mentioned above. In this work, the possibility of achieving a low percentage error in terms of predicting the efficient suspension type for any dynamic road is achieved.

Acknowledgment

Authors highly acknowledge that this work could not have been completed without the resources provided by Mehran University of Engineering and Technology, Jamshoro. We would like to share our gratitude towards the management who aided in the success of this research.

References

[1] Halepoto, I. A., Shoro, G. M., Abro, M. A. J., Nizamani, M. A., & Bhand, M. A. (2021). Design, Development and Control of Gesture Based Unmanned Vehicle. NEW ARCH-INTERNATIONAL JOURNAL OF CONTEMPORARY ARCHITECTURE, 8(2), 542-551.

[2] Kong, Y. S., Abdullah, S., Schramm, D., Omar, M. Z., & Haris, S. M. (2019). Optimization of spring fatigue life prediction model for vehicle ride using hybrid multi-layer perceptron artificial neural networks. Mechanical Systems and Signal Processing, 122, 597-621.

[3] Huang, H. B., Huang, X. R., Wu, J. H., Yang, M. L., & Ding, W. P. (2019). Novel method for identifying and diagnosing electric vehicle shock absorber squeak noise based on a DNN. Mechanical Systems and Signal Processing, 124, 439-458.

[4] Taghavifar, H., & Rakheja, S. (2018). Supervised ANN-assisted modeling of seated body apparent mass under vertical whole body vibration. Measurement, 127, 78-88.

[5] Du, X., Sun, C., Zheng, Y., Feng, X., & Li, N. (2021). Evaluation of vehicle vibration comfort using deep learning. Measurement, 173, 108634.

[6] Nguyen, S. D., Lam, B. D., & Choi, S. B. (2021). Smart dampers-based vibration control–Part 2: Fractional-order sliding control for vehicle suspension system. Mechanical Systems and Signal Processing, 148, 107145.

[7] Ghoniem, M., Awad, T., & Mokhiamar, O. (2020). Control of a new low-cost semi-active vehicle suspension system using artificial neural networks. Alexandria Engineering Journal, 59(5), 4013-4025.

[8] Qin, Y., Tang, X., Jia, T., Duan, Z., Zhang, J., Li, Y., & Zheng, L. (2020). Noise and vibration suppression in hybrid electric vehicles: State of the art and challenges. Renewable and Sustainable Energy Reviews, 124, 109782.

[9] Hussain, I., Halepoto, I. A., Kumar, W., & Kazi, K. (2013). Anti-slip traction control of railway vehicle based on estimated wheel-rail contact condition. Sindh University Research Journal- Science Series, 45(2), pp. 373-378.

[10] Ghoniem, M., Awad, T., & Mokhiamar, O. (2020). Control of a new low-cost semi-active vehicle suspension system using artificial neural networks. Alexandria Engineering Journal, 59(5), 4013-4025.

[11] Beilfuss, T., Kortmann, K. P., Wielitzka, M., Hansen, C., & Ortmaier, T. (2020). Real-Time Classification of Road Type and Condition in Passenger Vehicles. IFAC-Papers Online, 53(2), 14254-14260.

[12] Siłka, J., Wieczorek, M., & Woźniak, M. (2022). Recurrent neural network model for high-speed train vibration prediction from time series. Neural Computing and Applications, 34(16), 13305-13318.

[13] Wang, M., Ye, L., & Sun, X. (2021). Adaptive online terrain classification method for mobile robot based on vibration signals. International Journal of Advanced Robotic Systems, 18(6), 17298814211062035.

[14] Dukaiski, P., Będkowski, B., Parczewski, K., Wnęk, H., Urbas, A., & Augustynek, K. (2019). Dynamics of the vehicle rear suspension system with electric motors mounted in wheels. Eksploatacja i Niezawodność, 21(1), 125-136.

[15] Krajnak, K. (2018). Health effects associated with occupational exposure to hand-arm or whole body vibration. Journal of Toxicology and Environmental Health, Part B, 21(5), 320-334.

[16] Nguyen, T., Nguyen-Phuoc, D. Q., & Wong, Y. D. (2021). Developing artificial neural networks to estimate real-time onboard bus ride comfort. Neural Computing and Applications, 33(10), 5287-5299.