

Prediction of Automotive Ride Performance Using Adaptive Neuro-Fuzzy Inference System and Fuzzy Clustering

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ABSTRACT

Artificial intelligence systems are highly accepted as a technology to offer an alternative way to tackle complex and non-linear problems. They can learn from data, and they are able to handle noisy and incomplete data. Once trained, they can perform prediction and generalization at high speed. The aim of the present study is to propose a novel approach utilizing the adaptive neuro-fuzzy inference system (ANFIS) and the fuzzy clustering method for automotive ride performance estimation. This study investigated the relationship between the automotive ride performance and relative parameters including speed, spring stiffness, damper coefficients, ratios of sprung and unsprung mass. A Takagi-Sugeno fuzzy inference system associated with artificial neuro network was employed. The C-mean fuzzy clustering method was used for grouping the data and identifying membership functions. The prediction results were compared with simulation testing data and experimental data of a typical A-Class automobile.

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INTRODUCTION

In automobile engineering, the ride comfort performance is important. Numerous studies have been conducted on the description and improvement of ride comfort [1, 2, 3]. The automobile suspension system is most related to ride comfort performance. Studies aiming at improving automotive ride comfort usually end up to optimal suspension system parameters such as spring stiffness or damper coefficient. Investigations in optimal ride comfort performance consider the automobile as vibration systems. The whole automobile structure is complex. However, considering it as a vibration system and select only the most influencing parameters to a vibration system can lead to a simplified mathematic model which is most fit for calculation and further optimizations. To evaluate the ride comfort performance of automobiles, national standards [4,5] have been formulated. Indices and their levels of acceptance evaluating ride comfort are described in these standards.

Aiming at enhancing automobile ride comfort performance, Uys, et al. [1] investigated an off-road vehicle ride comfort performance at different road profiles and different speeds. Their study found that optimizations of suspension settings using one pavement and speed could enhance ride comfort at different speeds on the same pavement. Siefert, et al. [2] investigated the ride comfort of automobile considering static and dynamic effects on seating comfort. A finite element model of seat is built in their vibration system. A human body model was applied in their full vehicle model with driving posture. The calculation results was correlated with experimental data. Grujicic, et al. [3] developed a detailed finite element seat model with a seated human. The model was used in research of seat/human interaction ride comfort. The computational results were

compared with those open-literature obtained in experimental studies. Kuznetsov, et al. [6] considered biomechanical effects of passengers to build a Human-Vehicle-Road model. Mehta and Tewari [7] studied the damping characteristics of seat cushion materials to improve ride comfort performance of a tractor. Tong and Guo [8] created a global-coupling torsion-elimination suspension to eliminate the vertical loads of each wheel. Hence the vehicle ride comfort was improved. Typically, the indices of ride comfort are obtained by experiments. However, Kolich, et al. [9] built an artificial neural network (ANN) to predict the seat comfort. Their results showed the effectiveness of seat comfort prediction using artificial intelligence. In this paper, a prediction model for automotive ride comfort is presented. As the relationships of automotive ride indices and input variables are nonlinear and complex, a fuzzy inference system (FIS) is induced to do the prediction.

Like other soft computing methods such as neural network, simulated annealing, genetic algorithm, the fuzzy inference system is also widely used in different areas including automotive industry. Carman [10] measured soil compaction under tire at different tire loads and inflation pressure, and investigated the relationship between tire working parameters and soil compaction characteristics using fuzzy expert system. His work showed that fuzzy expert system might pay an important role in prediction of soil. Monjezi, et al. [11] predicted the rock fragmentation caused by bench blasting at Gol-E-Gohar iron mine using both regression analysis and fuzzy expert system. The models were validated and compared. It is observed that the fuzzy predictor performs better than the regression analysis method. Fisne and Kuzu [12] presented a prediction of ground vibration induced by quarry blasting using fuzzy expert system. They used the distance

from blast face to vibration monitor point and charge weight per delay as input parameters in fuzzy expert system and peak particle velocity as output. The correlation coefficient between the measured and predicted results obtained by fuzzy system is 0.96. Raja and Arasu [13] predicted the cold start hydrocarbon emissions of air cooled two wheeler spark ignition engines by fuzzy expert system. Based on the experimental data, the fuzzy logic rules are set. The prediction model showed significant accuracy on hydrocarbon emission of the particular engine. Hossain, et al. [14] predicted the lift coefficient and drag coefficient of an aircraft model using fuzzy expert system. They used angle of attack and free stream velocity as input parameters. The prediction results are well fitted with the experimental data. Fleming, et al. [15] studied the cholera disease in South Africa and built a fuzzy logic system implemented in a Geographic Information System. The expert system in their fuzzy logic was based on a simulation model that was used to simulate the knowledge gained from the cholera experts. Lin and Cobourn [16] combined a Takagi-Sugeno fuzzy system and a nonlinear regression model for ozone predictions in six metropolitan areas of Kentucky. They trained the fuzzy model using experimental data of 1999-2003 and predicted the ozone data of 2004. The result was statistically better than the nonlinear regression model. Moller and Reuter [17] discussed the uncertain structural responses with the aid of fuzzy time series. Firat, et al. [18] used a Mamdani fuzzy inference system (MFIS) and an adaptive neuro-fuzzy inference system (ANFIS) for predicting municipal water consumption time series. The result shows that the ANFIS is superior in this problem. Tajdari, et al. [19] predicted the shear strength of Ni-Ti alloys using a fuzzy inference system, and the predicted results were compared with the test data. The fuzzy system showed better performance. Ozger [20] investigated the relationship between ocean wave energy and meteorological variables with the aid of fuzzy logic. The result showed that fuzzy inference system could be used in prediction of spectral wave measurements. Martino, et al. [21] used fuzzy logic on a set of input-output pairs to determine a mapping from the input space to output space. The results are well comparable with those using Wang-Mendel method. Pan, et al. [22] applied fuzzy regression to the prediction of pavement condition. In their study, pavement conditions were exemplified by five membership functions and estimated by fuzzy regression. Adnan, et al. [23] pointed that in prediction of machining performance, triangular and centroid membership functions are mostly used, which are also effective. Rahman, et al. [24] investigated relationship between vehicle's input parameters of power supply, moisture content and output parameter of traction force. The mean relative error of predicted and measured data is 7%. Cismodi, et al. [25] applied a fuzzy multi-criteria function for performance evaluation of medical classification and prediction. Liu, et al. [26] applied fuzzy neural network and fuzzy cluster in prediction of accident frequency rate of an enterprise. Qin, et al. [27] developed a traffic crash prediction model based on fuzzy logic to estimate roadway section safety. The predicted data was in agreement with the measured data from a roadway section. Abdolreza, et al. [28] pointed out that road header performance in tunneling was nonlinear and complex. Thus, they applied a Takagi-Sugeno fuzzy system to this problem. The prediction data matches with measured data. Sowon, et al. [29] integrated fuzzy C-means and the Apriori approach

for road traffic performance prediction. The results are better than a traditional fuzzy inference system. Stembrek, et al. [30] presented a fuzzy logic based approach to estimate the stiffness reduction of concrete in the compressed zone of the cross section which took into account of cyclic loading. Adoko, et al. [31] predicted the rockburst intensity based on fuzzy inference system and adaptive neuro-fuzzy inference system. Results suggest that the developed models can be used for rockburst prediction. Singh, et al. [32] applied the fuzzy time series to the prediction in mobile ad hoc network delay. Guven and Buczak [33] applied an openCL framework for fuzzy associative classification. The application to disease prediction showed advantages of this approach. Darain, et al. [34] presented a fuzzy logic based prediction model for predicting the serviceability of reinforced concrete beams strengthened with near surface mounted reinforcement. The goodness of fit of the predicted and measured values was close to 1.0. Khairul, et al. [35] presented a fuzzy inference system for heat transfer performance prediction in helically coiled heat exchanger with spirally corrugated wall operated with water and CuO/water nanofluids. Moon, et al. [36] pointed out that empirical and theoretical formulas could vary significantly for the prediction of confinement effect and confined compressive strength of a circular concrete-filled steel tube. Thus, they developed a fuzzy-based prediction model to do the work with a satisfactory result. Alimohammadlou, et al. [37] combined the adaptive neural network and fuzzy clustering theory to estimate the rain-fall induced landslide in Saen Slope. Isaza, et al. [38] presented a fuzzy clustering approach for predicting situations in complex process industries. Experimental results indicate that this approach is effective in industrial process decision making. Gonzalez-Gonzalez, et al. [39] presented a fuzzy logic based regression for estimating reliability in a degradation process. An, et al. [40] presented a regression algorithm based on fuzzy rough sets and approached it on a wind speed prediction. Numerical experiments data and wind speed prediction showed the effectiveness of their algorithm.

With various advantages, the control methods based on fuzzy logic is also widely used. Gering and Adamy [41] presented two step procedure fuzzy controller to a single optimization problem. The computational efficiency is impressive. Sui, et al. [42] proposed an adaptive fuzzy backstepping output feedback tracking control system. This system is applied on a stochastic multi-input and multi-output nonlinear system in pure-feedback form. In Wu and Karkoub' study [43], a fuzzy-adaptive tracking control system was developed. The Takagi-Sugeno fuzzy model is used to approximate the nonlinear system, and a fuzzy adaptive controller is developed to overcome the nonlinearities of the model.

VEHICLE RIDE COMFORT PERFORMANCE

Evaluation Indices and Calculation

The ride comfort performance of automotive indicates whether the vehicle is comfortable or not for passengers when it is running. It is an important index for evaluating the full automobile performance. In design phase, vehicle designers would pay much attention to improving ride performance of vehicles.

The most commonly used index to evaluate automotive ride performance is the Weighted Root Mean Square of Acceleration (WRMS) $\bar{a}_w$. This index is calculated based on the sensitivity of human body to each vibration frequency. The value of WRMS can be obtained by the following calculation process.

(1). Obtaining the WRMS for a single axis $\bar{a}_w$

First, obtain the auto-power spectral density (auto-PSD) function $G_a(f)$ by Equivalent Bandwidth Frequency Analysis. Then, the 1/3 octave root mean square (RMS) of acceleration is obtained as follow.

$$\bar{a}_j = \left[\int_{f_{lj}}^{f_{uj}} G_a(f) df \right]^{\frac{1}{2}} \quad (1)$$

where $\bar{a}_j$ is RMS of acceleration of the j th 1/3 octave band with the central frequency of f_j . f_{lj} and f_{uj} are the upper limit frequency and lower limit frequency respectively. $G_a(f)$ is the auto-power spectral density function of acceleration. The central frequency, upper and lower limit frequency of 1/3 octave bands are shown in Table 1.

Finally, the WRMS for a single axis $\bar{a}_w$ is obtained as follow:

$$\bar{a}_w = \left[\sum_{j=1}^{23} (w_j \times \bar{a}_j)^2 \right]^{\frac{1}{2}} \quad (2)$$

where $\bar{a}_w$ is the WRMS for a single axis, w_j is the weight of j th 1/3 octave band. The values are shown in Table 1.

(2). Obtaining the Weighted Root Mean Square of acceleration $\bar{a}_v$.

When the WRMS of each single axis is obtained, the Weighted Root Mean Square of Acceleration can be written as follow:

$$\bar{a}_v = \left(k_x^2 \bar{a}_{wx}^2 + k_y^2 \bar{a}_{wy}^2 + k_z^2 \bar{a}_{wz}^2 \right)^{\frac{1}{2}} \quad (3)$$

where $\bar{a}_{vj}$ is the WRMS of j th testing point. $\bar{a}_{wx}$, $\bar{a}_{wy}$, $\bar{a}_{wz}$ are the WRMS of longitudinal, lateral and vertical axis of automotive, respectively. k_x , k_y , k_z are the weighted coefficients of each axis. When the testing point is on the floor of driver's feet area, the weighted values are 0.25, 0.25, and 0.4, respectively.

Generally, an automobile with lower WRMS has better ride comfort performance. With higher speed and worth pavement, this value tends to be larger. The relationship between WRMS and human objective sensation is shown in Table 2.

Table 1. 1/3 octave band and weighted coefficients

Band number	Central frequency	Upper limit	Lower limit	Weighted coefficient
1	0.50	0.45	0.57	0.418
2	0.63	0.57	0.71	0.459
3	0.80	0.71	0.9	0.477
4	1.0	0.9	1.12	0.482
5	1.25	1.12	1.4	0.484
6	1.6	1.4	1.8	0.494
7	2.0	1.8	2.24	0.531
8	2.5	2.24	2.8	0.631
9	3.15	2.8	3.55	0.804
10	4.0	3.55	4.5	0.967
11	5.0	4.5	5.6	1.039
12	6.3	5.6	7.1	1.054
13	8.0	7.1	9.0	1.036
14	10.0	9.0	11.2	0.988
15	12.5	11.2	14.0	0.902
16	16.0	14.0	18.0	0.768
17	20.0	18.0	22.4	0.636
18	25.0	22.4	28.0	0.513
19	31.5	28.0	35.5	0.405
20	40.0	35.5	45.0	0.314
21	50.0	45.0	56.0	0.246
22	63.0	56.0	71.0	0.186
23	80.0	71.0	90.0	0.132

Table 2. WRMS and human objective sensation

WRMS	Objective sensation
<0.315	Comfortable
0.315-0.63	A bit uncomfortable
0.5-1.0	More uncomfortable
0.8-1.6	Uncomfortable
1.25-2.5	Very uncomfortable

Test of Ride Performance

The automotive ride performance test should be done on flat and straight pavement. Testing distance is about 200 meters. Among which, a distance of 30-50 m is set as buffer section at both side of road. Longitudinal slope of the road should be less than 1%. The road should be clear and dry.

The test automobile should be fully equipped including basic hand tools and spare tire. Tire inflation pressure must be agreed with vehicle technique conditions, the error should be less than 3%. Ride performance test of full loaded automobile is needed. Tests of other load conditions can be processed if needed. The load spare should be tightened and even-distributed.

According to the pavement quality, test speed should be 40 km/h - highest vehicle design speed (should not be more than limit speed of pavement) per 10 km/h or 20 km/h. Test speed on a general pavement for a passenger car can be 40 km/h, 50 km/h, 60 km/h, 70 km/h. The speed should be held steady during data acquisition.

The three-direction accelerometers are needed during data acquisition. They should be fixed on the floor of driver feet area. There could be more positions for the arrangement of three-direction accelerometers, such as on the driver's seat or on the backrest of seat. The suggested parameters in data acquisition and analysis process are shown in Table 3.

Table 3. Suggested parameters

Parameters	Suggestion
Cut-off frequency	$f_c \geq 90 \text{ Hz}$
Frequency resolution	$\Delta f \leq 0.2 \text{ Hz}$
Power spectral density calculation	Using Hanning window function
Number of independent samples	$q \geq 25$

Parameters Influencing the Ride Performance

The automobile running on a random pavement surface can be considered as a vibration system. Figure 1 shows a simplified quarter vehicle system. In this model, the suspension stiffness and damper coefficient are assumed as constants, the tire damper is neglected. In Figure 1, m_1 and m_2 are unsprung and sprung mass respectively, Z_1 and Z_2 are vertical displacements of unsprung and sprung mass respectively, K is suspension stiffness, K_t is tire stiffness, C is the damper coefficient of suspension system, q is the function of pavement surface irregularity.

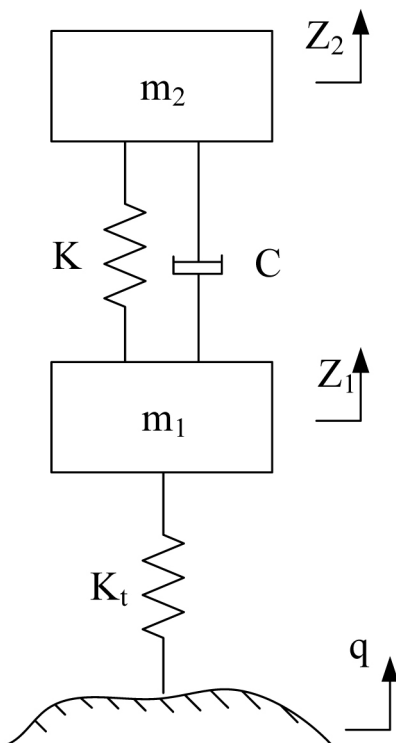


Figure 1. Quarter vehicle vibration model.

The dynamic equation of quarter vehicle system is given as follows:

$$\begin{cases} m_2 \ddot{z}_2 + C(\dot{z}_2 - \dot{z}_1) + K(z_2 - z_1) = 0 \\ m_1 \ddot{z}_1 + C(\dot{z}_1 - \dot{z}_2) + K(z_1 - z_2) + K_t(z_1 - q) = 0 \end{cases} \quad (4)$$

Solve Eq. (4) and get the transfer function of sprung and unsprung mass displacement in response of pavement irregularity $H(j\omega)_{z_1-q}$, $H(j\omega)_{z_2-q}$ as follow:

$$\begin{cases} H(j\omega)_{z_1-q} = \frac{K_t(-\omega^2 m_2 + j\omega C + K)}{A} \\ H(j\omega)_{z_2-q} = \frac{K_t(j\omega C + K)}{A} \\ A = (-\omega^2 m_2 + j\omega C + K)(-\omega^2 m_1 + j\omega C + K + K_t) - (j\omega C + K)^2 \end{cases} \quad (5)$$

The amplitude-frequency characteristics $|H(j\omega)|_{\ddot{z}_2-\dot{q}}$ of sprung mass acceleration $\ddot{z}_2$ in response of derivative of pavement irregularity $\dot{q}$ is given as follow:

$$\begin{cases} |H(j\omega)|_{\ddot{z}_2-\dot{q}} = 2\pi f \gamma \left[\frac{1 + 4\xi^2 (f/f_0)^2}{B} \right]^{\frac{1}{2}} \\ B = \left[1 - (f/f_0)^2 \left(1 + \gamma - \frac{1}{\mu} (f/f_0)^2 \right) - 1 \right]^2 \\ \quad + 4\xi^2 (f/f_0)^2 \left[\gamma - \left(\frac{1}{\mu} + 1 \right) (f/f_0)^2 \right]^2 \end{cases} \quad (6)$$

where $f_0 = \sqrt{k/m_2}/2\pi$ is the natural frequency of vehicle body. $\mu = m_2/m_1$ is the mass ratio of sprung and unsprung mass.

$\gamma = K_t/K$ is the stiffness ratio of tire and spring.

$\xi = C/2\sqrt{K \times m_2}$ is the damping ratio.

With Eq. (5) given, the vehicle body acceleration root mean square can be obtained by:

$$\sigma_{\ddot{z}_2} = \sqrt{4\pi^2 G_q(n_0) n_0^2 v \int_0^\infty |H(j\omega)|_{\ddot{z}_2-\dot{q}}^2 df} \quad (7)$$