Bitlis Eren Üniversitesi Fen Bilimleri Dergisi
BİTLİS EREN UNIVERSITY JOURNAL OF SCIENCE
ISSN: 2147-3129/e-ISSN: 2147-3188
VOLUME: 11 NO: 2 PAGE: 421-428 YEAR: 2022
DOI: 10.17798/bitlisfen.1014488

Development of a Machine Learning Based Control System for Vehicle Active Suspension Systems

Ali Rıza KALELİ[1], Halil İbrahim AKOLAŞ[2*]

[1]*Department of Electrical-Electronics Engineering, Faculty of Engineering, Samsun University, Samsun 55080, Turkey*
[2]*Vocational School of Balıkesir, University of Balıkesir, Balıkesir Turkey*
(ORCID: 0000-0002-3234-5922) (ORCID 0000-0002-3153-8044)

Keywords: Vehicle Active Suspension system, Machine Learning Methods, Linear Quadratic Optimal Control, Random Road Profile.

Abstract
In this paper, the Gaussian process (GP) algorithm, which is one of the machine learning methods, is designed to control the vehicle active suspension system (VASS). Experimental data were used to create the supervised learning method (regression method). The data was obtained from an optimal linear quadratic controller tuned based on a full state feedback optimal control approach. The results demonstrated that the proposed machine learning based (GPR) ML controller outperforms the optimal controller under uncertainties in terms of reducing the oscillation in spring mass position, vehicle body acceleration, and suspension deflection with 39.08%, 52.18%, 58.10%, and 17.81%, 15.63%, and 21.64% improvement for bump and sine sweep road conditions, respectively.

1. Introduction

The road irregularities that affect passenger comfort are one of the main sources of vibration in vehicles. Vehicle vibrations and undesirable noise have negative effects on human health, especially on the spinal cord and nervous systems [1]. Therefore, the improvement in road comfort is very important, and it is possible by designing active vehicle suspension systems (AVSS).

In the active suspension system, there are nonlinear components such as springs and dampers to generate force for adaptation to unknown road profiles. Owing to uncertain nonlinear dynamics and unknown road disturbances, it is difficult to design active suspension systems. Therefore, it is necessary to focus on advanced control techniques for these systems. Until today, the design of controller problems in AVSS has been widely discussed in the literature. For the sake of simplicity, researchers attempted to overcome these uncertainties by designing PID [2] and linear–quadratic (LQ) controllers [3]. However, these approaches are not satisfactory because the parameters of both controllers are determined based on linearized models. Due to the nonlinear nature of the system, adaptive backstepping control considering the model uncertainties and actuator delays was discussed in [4]. In another study, five different continuous sliding-mode controllers were used to avoid the chattering effect, and the effectiveness of the proposed controllers was compared to the linear control approach [5]. Adaptive backstepping control for AVSS with hard constraints was proposed to ensure the stabilizing attitude of the vehicle under road disturbance driving conditions in [6]. Robust control structure studies [7] using adaptiveness contain a lot of complex mathematical expressions, and the designing processes of the controller are therefore difficult to formalize. To improve performance against disturbance effects or uncertainties, robust controllers such as H_∞ control [8], gain scheduling, linear parameter varying control [9] were designed for active suspension systems to improve performance against disturbance effects or uncertainties. Also, a robust H infinity controller was investigated for an active suspension under

*Corresponding author: *halil.akolas@balikesir.edu.tr*
Received: 25.10.2021, Accepted: 06.06.2022

non-stationary operating conditions [10]. On the other hand, model-free approaches were applied to compensate for vehicle vibrations, unlike model-based approaches. For this purpose, data-driven approaches such as fuzzy logic and neural-networks were applied to deal with the nonlinear and time-varying characteristics of AVSS for improving the controller performance. In the experimental investigation of a multiple-input single-output fuzzy logic controller on an AVSS was compared with passive and classical fuzzy logic controllers [11]. An adaptive network based fuzzy inference (ANFIS) controller was designed by using the training data obtained from the system [12]. The performance of the designed controller was tested using an experimental setup and it was observed to have satisfactory closed loop performance. In [13], the neural network adjusts its weight parameters and learns from sliding mode control to prevent vibrations from vehicles due to ride irregularities. Besides, data-based methods are used to tune the parameters of different control structures. A back propagation neural network (BPN) was applied to determine the gain parameters of a PID controller for AVSS [14]. Data driven modeling methods are based on a machine learning approach. These techniques are applied in many different fields, like engineering, finance, and optimization problems, and they provide the ability to predict the complex dynamic behavior of systems [15].

As can be seen from the literature reviews above, data-driven methods can estimate the unknown system dynamics and external disturbances and improve control performance. Therefore, the main purpose of this research paper is to investigate the Gaussian process (GP) machine learning controller design for AVSS considering road disturbance conditions and system uncertainties. Besides, bump and sine sweep of the road profile are used to define road deterioration and irregularities as input to AVSS. Then, the performance of the designed controller is compared with conventional control methods in terms of wheel deflection, suspension deflection, and vehicle displacement. Finally, validation results of the proposed learning-based control scheme are given to show the effectiveness of the designed controller.

2. Material and Method

We start in this section with an explanation of the physical background of active suspension systems and the test set-up, which enable us to understand the vehicle suspension properties and the designing of the controller problems.

2.1. AVSS System

The configuration of the VASS is sketched in Figure 1. As seen this Figure 1, m_s and m_{us} are the vehicle body (spring mass) and wheel (unsprung mass) masses. k_s and b_s are stiffness and damper elements that support the vehicle body over the wheel. The k_{us} spring and b_{us} damper represent stiffness and the damping of the tire in contact with the road. The force F stands for the active damper.

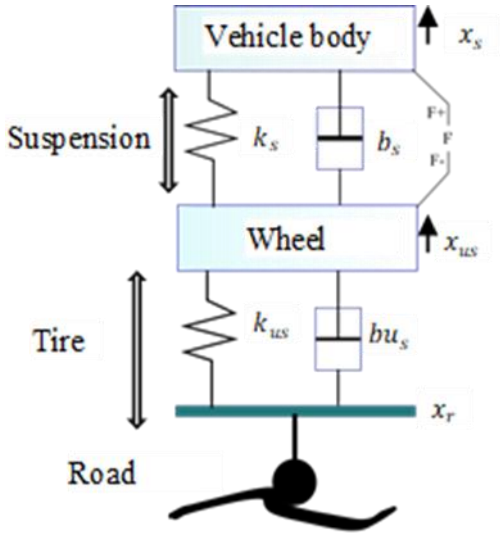

Figure 1. The active suspension system

The state space definition of VAAS is given as follows [16]

$$\dot{x} = Ax + B_1u + B_2f$$
$$y = Cx + Du + Ef$$

$$x = \begin{bmatrix} x_s - x_{us} \\ \dot{x}_s \\ x_{us} - x_r \\ \dot{x}_{us} \end{bmatrix}, u = F, f = \dot{x}_r, \quad (1)$$

$$y = \begin{bmatrix} x_s - x_{us} \\ \ddot{x}_s \end{bmatrix}$$

where, x is the state variables vector, u is the control inputs and f denotes the vector of external inputs and disturbances and y is the output vectors. $x_s - x_{us}$ state stands for suspension travel, while $x_{us} - x_r$ defines the tire travel and the fourth state is wheel velocity.

$$A = \begin{bmatrix} 0 & 1 & 0 & -1 \\ -\frac{k_s}{m_s} & -\frac{b_s}{m_s} & 0 & \frac{b_s}{m_s} \\ 0 & 0 & 0 & 1 \\ \frac{k_s}{m_{us}} & \frac{b_s}{m_{us}} & -\frac{k_{us}}{m_{us}} & -\frac{b_s + b_{us}}{m_{us}} \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 0 \\ \frac{1}{m_s} \\ 0 \\ -\frac{1}{m_s} \end{bmatrix}, \quad B_2 = \begin{bmatrix} 0 \\ 0 \\ -1 \\ \frac{b_{us}}{m_s} \end{bmatrix}, \qquad (2)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\frac{k_s}{m_s} & -\frac{b_s}{m_s} & 0 & \frac{b_s}{m_s} \end{bmatrix}$$

$$D = \begin{bmatrix} 0 \\ \frac{1}{m_s} \end{bmatrix}, E = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

2.2. GP machine Learning Approach

The Gaussian process (GP) is a nonparametric kernel-based probabilistic modeling approach [17]. The GP approach is widely used in engineering applications such as modeling, prediction, and optimization [18]. The GP is one of the machine learning methods, and the main goal of this technique is to define a mathematical relationship between input and output variables depending on the experimentally obtained data.

In recent years, the GP technique has been used as a modeling tool in the machine learning area. The most important feature of the GP approach compared to other machine learning methods is the determination of the covariance matrix defined by the independent variables. Other methods use algebraic relationships between these variables. Therefore, much less input-output system data are required while creating the GP model [19].

A GP can be a collection of random variables that is determined with average $\mu(x)$ and covariance matrix $\kappa(x,\hat{x})$ as follows.

$$\mu(x) = \mathbb{E}[y(x)] \qquad (3)$$

$$\kappa(x,\hat{x}) = \mathbb{E}[(y(x) - \mu(x))(y(\hat{x}) - \mu(\hat{x}))]$$

$$f(x) \sim GP(\mu(x), \kappa(x,\hat{x}))$$

where, $\mu(x)$ and β stand for the mean of the input data and estimated coefficient, $\kappa(x,\hat{x})$ kernel function. The function is parameterized according to the generation of a set of hyperparameters. In the machine learning literature, there are several types of kernel functions with different features that are used to fit actual data and model output. Squared exponential, rational quadratic, and exponential are the best known kernel functions. The appropriate kernel function is determined according to the characteristics of the experimental data.

The output estimation with GP is derived by Equations (4) by using Eq. (3):

$$\bar{y}^* = \mu(x^*) + \kappa(x^*, x)\kappa_y^{-1}(y - \mu(x)) \qquad (4)$$

where, $\kappa_y = \kappa + \sigma_n^2 I$ and the $g(x)^T \beta + f(x)$ model is considered. $g(x)^T$ is a basic function and the covariance matrix is obtained by a set of hypermeters. In the GPR modeling process, the vehicle body velocity of the vehicle was applied as input data to the GPR while the actuator force signal was applied as target data.

3. Results and Discussion

The controller algorithm applying GP by using the unsprung mass velocity as the feedback signal of the ML-based control scheme is conducted. The proposed control scheme is shown in Figure 2.

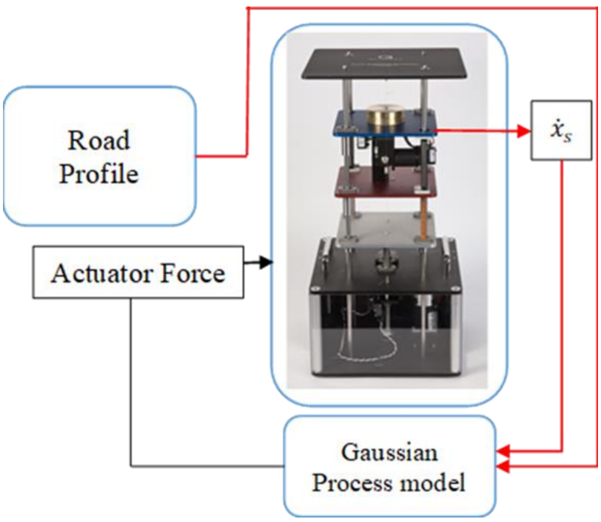

Figure 2. The active suspension system

To construct the GP model, training data was generated from the scaled Quanser VASS test setup shown in Figure 3. A fast response DC electric motor is used as an active suspension element, and an accelerometer exists in the test rig. The position and velocity of the sprung mass, the tire, and the wheel travel are measured using three quadrature encoder sensors. The VASS test set up for mechanical components and sensor properties is given in Table 1.

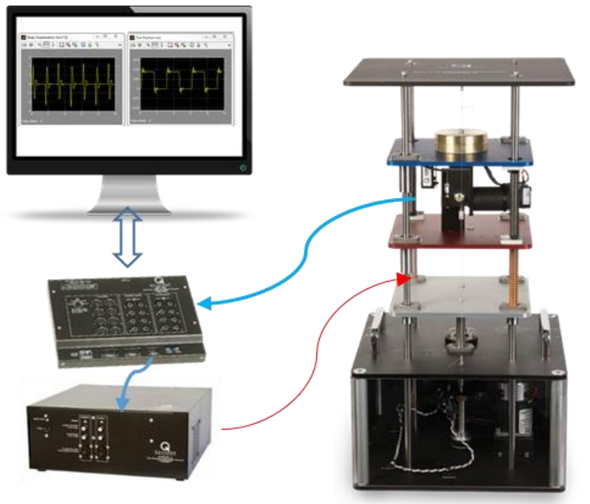

Figure 1. The experimental test rig

Table 1. VASS parameters

Symbol	Description	Value
	Structure Total Height	0.53 m
M_s	Sprung mass	2.45 kg
M_{us}	Unsprung mass	1 kg
k_s	Suspension Passive	900 N/m
k_{us}	Tire Linear Stiffness	2500 N/m
b_s	Inherent Suspension	7.5 N-
b_{us}	Inherent Tire Damping	5 N-s2/m
	Suspension Motor	0.115 N-
	Suspension Motor Shaft	0.006 m
	Suspension Encoder	942 ×

The data from the ASS system was obtained by using LQR full state feedback control. In this study, two road disturbance profiles were applied to investigate the suspension control system: bump-type road disturbance and random road disturbance. The bump road disturbance was simulated to represent bad road quality with discontinuities in the asphalt for a short time. This disturbance input has the most peak of 12 cm as shown in Figure 4.

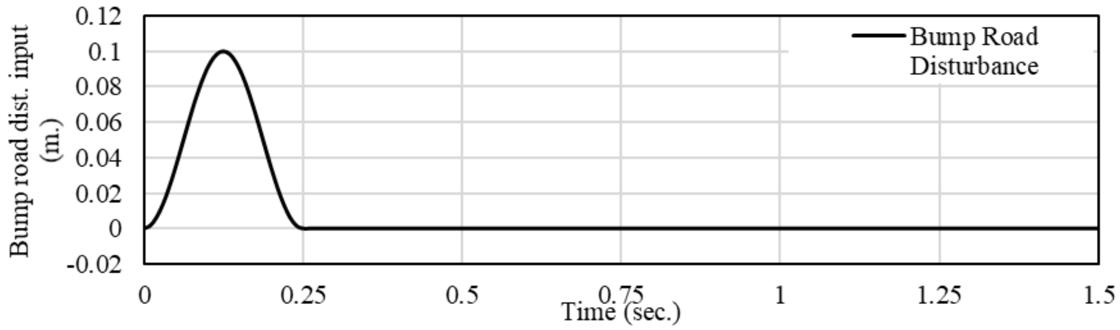

Figure 2. The applied bump disturbance input

The results for the 10 cm bump road disturbance input are shown in Figure 5. ML and LQR controllers are implemented for suspension travel (deflection), vehicle body acceleration, and vehicle body travel states as shown in the Figure 5, 6, and 7, respectively.

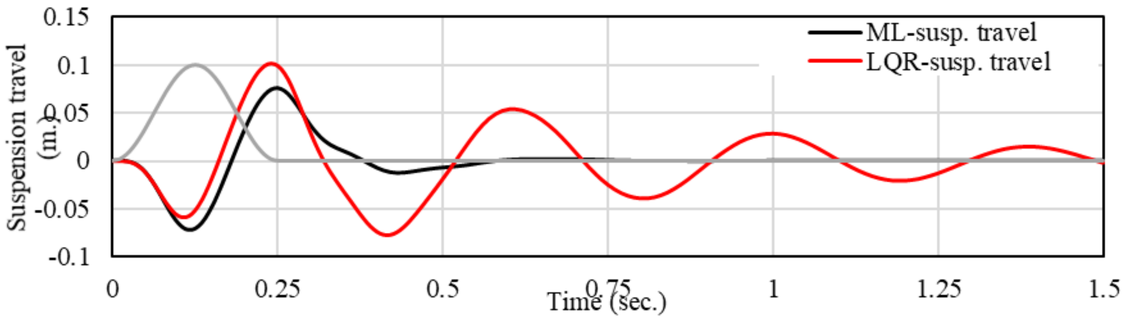

Figure 3. Comparison of suspension travel for LQR and ML based GPR controller (Bump dist.)

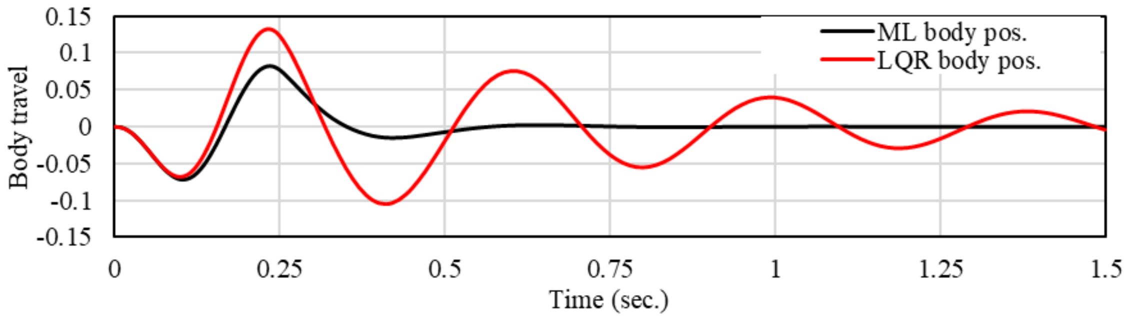

Figure 4. Comparison of vehicle body travel for bump disturbance input

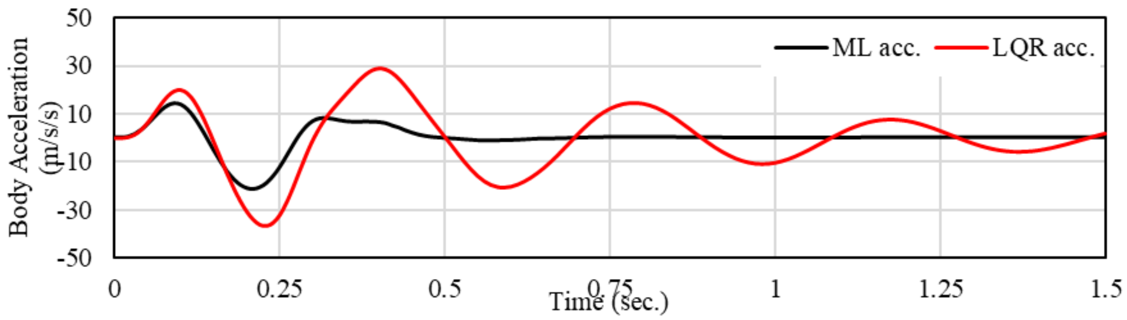

Figure 5. Comparison of vehicle body acceleration for bump road disturbance

As can be seen from Figure 5-7, an ML-based GPR controller is better to suppress the fluctuations around the reference signal than a classical LQR control structure. Figure 8 compares the results obtained from the applied actuator force. When the data in Figure 8 is analyzed, it is clear that the amplitude of the force is larger under the proposed controller. The result is significant because of effectively reduces the oscillations. The actuator force must be applied opposite direction against the road vibrations. Therefore, the actuator gives an instantaneous response.

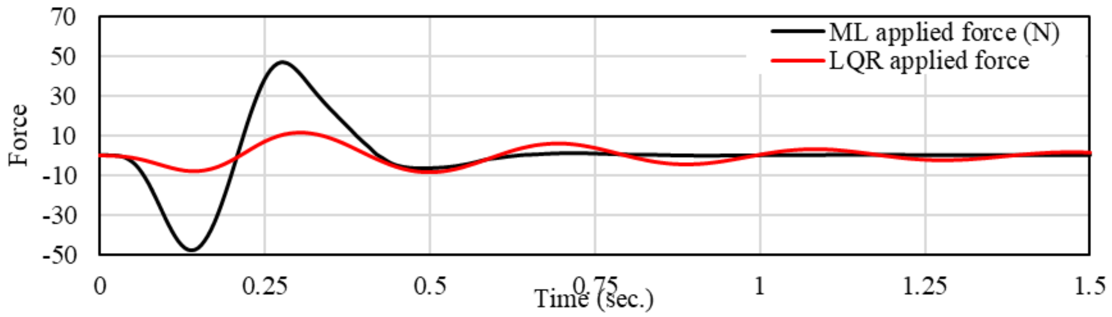

Figure 6. Comparison actuator forces of LQR and ML based controller under bump road disturbance

When the Figure 5-7 were examined, the spring mass position was significantly influenced by the road profile. Therefore, the sine sweep irregularity road profile is used to evaluate the performance of the designed controller as shown in Figure 9 in the second test. The sine sweep disturbance signal is applied to test vehicle suspension systems in all automotive industries.

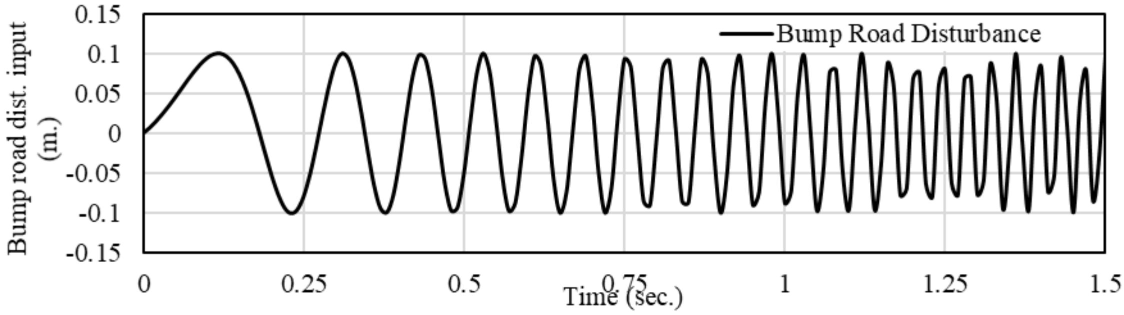

Figure 7. The generated sine sweep road disturbance profile

The tracking performances of developed ML and LQR controllers are demonstrated according to sprung mass positions, suspension travel, and body acceleration in Figure 10-12. It can be clearly seen from the figures that the proposed approach is effective in tracking both spring and non-spring mass position errors. From the graph, the amplitude of sprung mass position oscillation was also reduced in comparison to the classical systems. In this way, passenger comfort can be improved by reducing the impact of road vibrations.

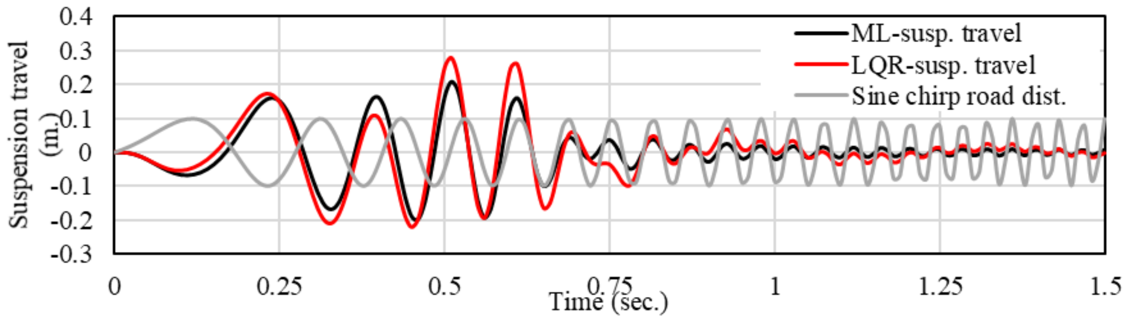

Figure 8. Comparison of suspension travel for LQR and ML based GPR controller (sine sweep road dist.)

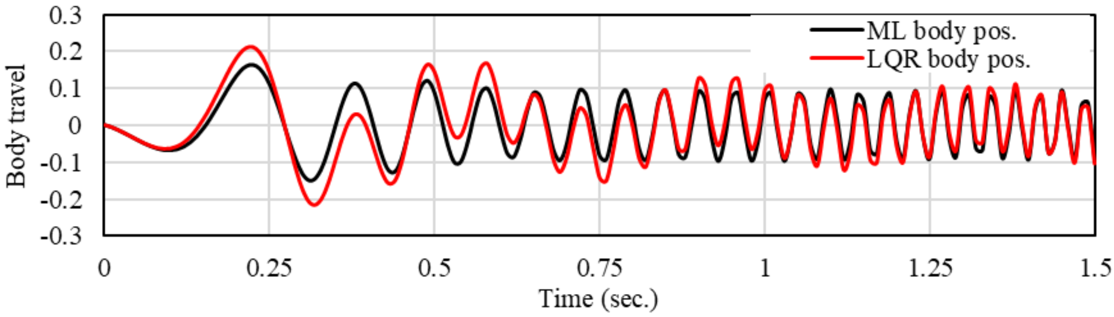

Figure 9. Comparison of vehicle body travel for sine sweep disturbance input

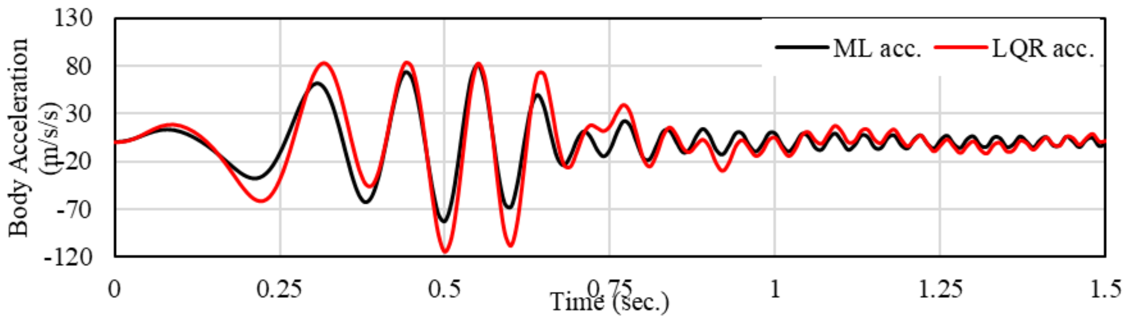

Figure 10. Comparison of vehicle body acceleration for sine sweep disturbance

As can be seen in Figure 13, the applied actuator force changes rapidly to reduce the variable frequency vibrations in the PSD road profile conditions. From this data in Figure 13, there is an amplitude difference between LQR and ML-based GPR controllers in applied force. Interestingly, the amplitude of force for the proposed method is greater than the classical LQR control to suppress the vibration.

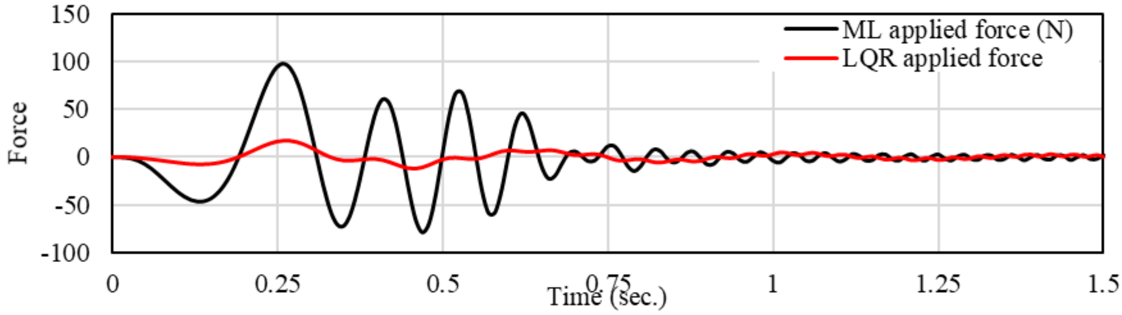

Figure 11. Comparison actuator forces of LQR and ML based controller under sine sweep road profile

The numerical values of VASS output for controlling vehicle body travel, suspension deflection, and body acceleration for two road disturbances are depicted in Table 2. It can be seen from the data in Table 2 that the ML controller shows the best performance according to RMS improvement percentage values in the bump and sine sweep road disturbances.

Table 2. RMS values for LQR and ML controllers and improvement percentage

	Bump road disturbance			Sine sweep road disturbance		
	LQR	ML	Improvement percentage	LQR	ML	Improvement percentage
Vehicle Body travel	0.0371	0.0226	39.08%	0.0887	0.0729	17.81%
Suspension deflection	0.0504	0.0241	52.18%	0.0902	0.0761	15.63%
Vehicle body acceleration	13.5918	5.695	58.10%	35.2248	27.1138	23.03%

4. Conclusion

This study set out to determine the ML-based GPR control method for VASS. The optimal structure of the GPR model was determined by using the trial and error method. Real experimental data was used in the training process of the ML model. Then, the performance of the proposed controller was compared with the classical LQR control according to applied actuator force. In this study, it was designed to investigate the effect of vibrations caused by unevenness on the road surface on passenger comfort. One of the striking findings of the study is the direct control of a mechanical system with ML-based control approaches. The performance of the used proposed and classical control methods is compared in terms of the oscillations in the sprung part of the VASS. Therefore, it has been shown that the proposed ML-based control method outperforms the LQR controller with 39.08%, 52.18%, 58.10%, and 17.81%, 15.63%, 23.03% reductions in both bump and sine sweep profile conditions.

Contributions of the authors

All authors contributed equally to the study.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

References

[1] L. Sitnik, M. Magdziak-Tokłowicz, R. Wróbel, and P. Kardasz, "Vehicle Vibration in Human Health," *J. KONES. Powertrain Transp.*, vol. 20, no. 4, pp. 411–418, 2015, doi: 10.5604/12314005.1137854.

[2] Y. Shahid and M. Wei, "Comparative analysis of different model-based controllers using active vehicle suspension system," *Algorithms*, vol. 13, no. 1, Jan. 2020, doi: 10.3390/a13010010.

[3] J. Watton, K. M. Holford, and P. Surawattanawan, "The application of a programmable servo controller to state control of an electrohydraulic active suspension," *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, vol. 218, no. 12, pp. 1367–1377, Dec. 2004, doi: 10.1243/0954407042707650.

[4] H. Pang, X. Zhang, J. Yang, and Y. Shang, "Adaptive backstepping-based control design for uncertain nonlinear active suspension system with input delay," *Int. J. Robust Nonlinear Control*, vol. 29, no. 16, pp. 5781–5800, Nov. 2019, doi: 10.1002/rnc.4695.

[5] L. Ovalle, H. Ríos, and H. Ahmed, "Robust Control for an Active Suspension System via Continuous Sliding-Mode Controllers," *Eng. Sci. Technol. an Int. J.*, 2021, doi: 10.1016/j.jestch.2021.06.006.

[6] W. Sun, H. Gao, and O. Kaynak, "Adaptive backstepping control for active suspension systems with hard constraints," *IEEE/ASME Trans. Mechatronics*, vol. 18, no. 3, pp. 1072–1079, 2013, doi: 10.1109/TMECH.2012.2204765.

[7] N. Yagiz and Y. Hacioglu, "Backstepping control of a vehicle with active suspensions," *Control Eng. Pract.*, vol. 16, no. 12, pp. 1457–1467, Dec. 2008, doi: 10.1016/j.conengprac.2008.04.003.

[8] S. Kilicaslan, "Control of active suspension system considering nonlinear actuator dynamics," *Nonlinear Dyn.*, vol. 91, no. 2, pp. 1383–1394, Jan. 2018, doi: 10.1007/S11071-017-3951-X.

[9] I. Fialho and G. J. Balas, "Road adaptive active suspension design using linear parameter-varying gain-scheduling," *IEEE Trans. Control Syst. Technol.*, vol. 10, no. 1, pp. 43–54, Jan. 2002, doi: 10.1109/87.974337.

[10] L.-X. Guo, L.-P. Zhang, L.-X. Guo, and L.-P. Zhang, "Robust H∞ control of active vehicle suspension under non-stationary running," *JSV*, vol. 331, no. 26, pp. 5824–5837, Dec. 2012, doi: 10.1016/J.JSV.2012.07.042.

[11] Y. Taskin, Y. Hacioglu, and N. Yagiz, "Experimental evaluation of a fuzzy logic controller on a quarter car test rig," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 39, no. 7, pp. 2433–2445, Jul. 2017, doi: 10.1007/s40430-016-0637-0.

[12] U. Rashid, M. Jamil, S. O. Gilani, and I. K. Niazi, "LQR based training of adaptive neuro-fuzzy controller," in *Smart Innovation, Systems and Technologies*, 2016, vol. 54, pp. 311–322, doi: 10.1007/978-3-319-33747-0_31.

[13] S. J. Huang and W. C. Lin, "A neural network based sliding mode controller for active vehicle suspension," *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.*, vol. 221, no. 11, pp. 1381–1397, Nov. 2007, doi: 10.1243/09544070JAUTO242.

[14] M. Heidari and H. Homaei, "Design a PID controller for suspension system by back propagation neural network," *J. Eng. (United Kingdom)*, vol. 2013, 2013, doi: 10.1155/2013/421543.

[15] S. L. Brunton and J. N. Kutz, "Data Driven Science & Engineering - Machine Learning, Dynamical Systems, and Control," p. 572, 2017, Accessed: Sep. 06, 2021. [Online]. Available: databook.uw.edu.

[16] "Active Suspension - Quanser." https://www.quanser.com/products/active-suspension/ (accessed Sep. 08, 2021).

[17] G. Kopsiaftis, E. Protopapadakis, A. Voulodimos, N. Doulamis, and A. Mantoglou, "Gaussian process regression tuned by Bayesian optimization for seawater intrusion prediction," *Comput. Intell. Neurosci.*, vol. 2019, 2019, doi: 10.1155/2019/2859429.

[18] J. Zhang, W. Li, L. Zeng, and L. Wu, "An adaptive Gaussian process-based method for efficient Bayesian experimental design in groundwater contaminant source identification problems," *Water Resour. Res.*, vol. 52, no. 8, pp. 5971–5984, Aug. 2016, doi: 10.1002/2016WR018598.

[19] X. Chen, Y. Tian, T. Zhang, and J. Gao, "Differential Evolution Based Manifold Gaussian Process Machine Learning for Microwave Filter's Parameter Extraction," *IEEE Access*, vol. 8, pp. 146450–146462, 2020, doi: 10.1109/ACCESS.2020.3015043.