ODD-Based Health Monitoring and Predictive Maintenance of Degrading Vehicle Functionality

Yannick Kees[1], Gerald Sauter[1], Ryan Mut[1], Benedikt Franke[1], Frank Köster[1] and Sven Hallerbach[1]

[1]German Aerospace Center (DLR) Institute for AI-Safety and Security

Abstract

The shock absorber of a vehicle is not only needed for a comfortable driving experience, but it is also essential for vehicle safety. Especially in autonomous driving, vehicles must monitor themselves and schedule maintenance before a component fails. In this work, we develop a methodology to predict the degradation of a shock absorber using machine learning methods and perform predictive maintenance recommendations. In the first step, we learn the damping coefficient from acceleration data using a neural network. Afterward, we extrapolate this value to predict future behavior. For this, we use the concept of operational design domains to formalize the point up until vehicle functionality is unrestricted and there is no risk to vehicle safety.

Keywords

Predictive Maintenance, Health Monitoring, Operational Design Domain (ODD), Degradation, Shock Absorber, Machine Learning

1. Introduction

The goal of predictive maintenance [1] is to detect a failure before it happens or spreads to the extent that it endangers vehicle safety. The range in which the vehicle or a specific component can perform all its driving functions as planned can be formulated by operational design domain (ODD) language. The Society of Automotive Engineers (SAE) defines ODD as the "Operating conditions under which a given driving automation system, or feature thereof, is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics" [2]. Right now, formalizing and standardizing the ODD notation receives lots of attention. The British Institute for Standardisation has formulated the ODD in a table format [3]. The Association for Standardization of Automation and Measuring Systems (ASAM) is working on the formalization of an ODD in the form of a new language called OpenODD [4]. This language consists of logical expressions and query semantics that describe the ODD. Similar to the ODD of a vehicle, we define the ODD of a vehicle component for predictive maintenance as the operating conditions under which the component is functional. For this, the ODD specifies conditions and boundaries under which the vehicle component is guaranteed to

OVERLAY 2023: 5th Workshop on Artificial Intelligence and Formal Verification, Logic, Automata, and Synthesis, November 7, 2023, Rome, Italy

yannick.kees@dlr.de (Y. Kees); gerald.sauter@dlr.de (G. Sauter); ryan.mut@dlr.de (R. Mut); benedikt.franke@dlr.de (B. Franke); Frank.Koester@dlr.de (F. Köster); Sven.Hallerbach@dlr.de (S. Hallerbach)

work appropriately. Our research addresses the suspension systems and especially the shock absorbers of a car. The health monitoring task provides the current state within the ODD of the shock absorber, while the predictive maintenance task estimates degradation by predicting violations of the ODD specification. This leads to a timely call for maintenance.

Various shock absorber models have been studied in the past. In [5], the quarter-car model we will also use is verified. In [6], multiple types of sensors that can be installed in a shock absorber are being characterized and tested. All these sensors are useful to obtain information on the health of a shock absorber during vehicle operation. [7] examines the detection and isolation of sensor faults in shock absorbers. For detecting the faults, a support vector machine is employed. Since degradation also means energy loss, it is also possible to monitor the health of shock absorbers using temperature data [8]. In [9], the authors conclude that degradation is a function of the complete energy dispersed over a lifetime and the intensities of the individual shocks. In [10], the monitoring of shock absorbers is modeled as an unsupervised learning problem by monitoring all four shock absorbers of the car through accelerometers. The obtained data is then clustered through a principal component analysis, where the clusters correspond to different types of faults. In [11], a neural network is trained to correctly classify the state of a shock absorber from sensor data. For this, the network obtains preprocessed sensor data as input and outputs a four-dimensional vector, where each dimension represents the state of the shock absorber. Similar approaches can be found in [12], where machine learning classifiers are estimating the leaking of oil from a shock absorber. In [13], the durability of shock absorbers for different types of roads is analyzed, leaving out predictive maintenance recommendations.

In [14], the authors model the degradation process as a stochastic process influenced by random impact events. To monitor the health status of the shock absorber we model it as a regression problem, which we solve by using neural networks. For this, we use domain knowledge and real-life data to extrapolate the health status to make future predictions.

2. Health Monitoring and Predictive Maintenance for Shock Absorbers

Most predictive maintenance methods work according to the same scheme [15]. In the first step, sensor data from the vehicle is acquired and pre-processed. Then, the health indicator (HI) of the vehicle is determined. The HI represents the current condition of the shock absorber. Based on this, we make a rest of useful life (RUL) prediction. If the HI describes the temporal position of the shock absorber within the ODD, the RUL is a metric d between the current HI and the boundary ∂ of the ODD, i.e., $\mathrm{RUL}(n) := d(\mathrm{HI}(n), \partial\mathrm{ODD})$. We then utilize the estimated RUL to make a predictive maintenance recommendation. In our simulation, we use the quarter car model [16]. The basic assumption is that the weight of the car is distributed equally among the four wheels. We can then describe the vertical dynamics by a system of partial differential equations. For the street model, we use road data captured by a LIDAR scanner from [17] and extract several street profiles (Figure 1).

To model the degradation of the suspension system, we make the simplified assumption to consider the damping coefficient k_B of the damper as HI. The damping coefficient for an oscillation describes the rate at which the damping decreases. A high damping coefficient means that the oscillation quickly decreases and thus ends quickly. A low damping coefficient means the object still has visible deflections after a long time. It has been shown in [18] that the damping coefficient decays exponentially

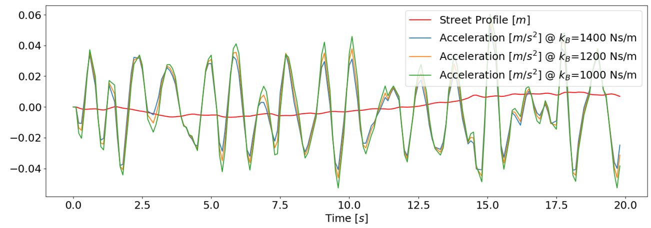

Figure 1: Vertical Acceleration of a car over a street (red) with different damping coefficient values

$$k_B(n) = an^b + c \tag{1}$$

in the number of full cycles n of the shock absorber, i.e., maximal deflections for some constants $a, b, c \in \mathbb{R}$. Let κ denote the damping coefficient value, for which we assume that the component can no longer safely perform its actual functionality. The corresponding ODD is then given as $\text{ODD} = \{n \mid k_B(n) \geq \kappa\}$ and its boundary $\partial\text{ODD} = \{n \mid k_B(n) = \kappa\}$. Then, using the OpenODD notation [4] we can define the ODD by

```
DETERMINE value_degraded WHEN (value <= κ)
SUITABLE * EXCEPT WHEN value_degraded
```

Since $\text{RUL}(n)$ gives the number of cycles until reaching the boundary of the ODD, we get $k_B(n + \text{RUL}(n)) = \kappa$ and therefore an explicit representation for the RUL by

$$\text{RUL}(n) = d(k_B(n), \partial\text{ODD}) = \max\left\{\left(\frac{\kappa - c}{a}\right)^{\frac{1}{b}} - n, 0\right\}. \tag{2}$$

Hence, for a RUL prediction, it is sufficient to estimate a, b, c. For our example of a predictive maintenance recommendation, we use the following procedure (Figure 2). At first, we collect vertical acceleration data z_n for the shock absorber model, which can be assumed to be measured by vehicle sensors.

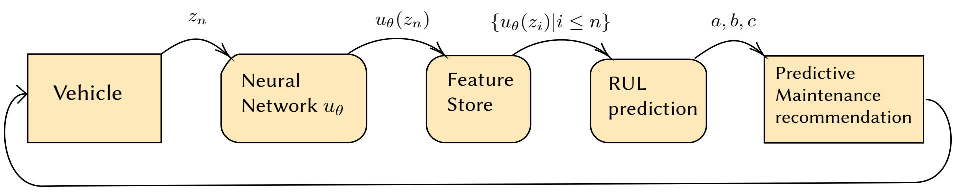

Figure 2: Pipeline for performing a predictive maintenance recommendation from accelerating data

In our simulation environment, we generate this data by solving the quarter-car model for a randomly selected road using a given data set with decreasing damping values over time. Our implementation uses an Euler method [19] to solve the model for a defined input signal z_n. The resulting signal values are transmitted to the cloud. Afterward, the signal is transmitted to a neural network u_θ, with parameters θ, that estimates the current damping coefficient $k_B(n) \approx u_\theta(z_n)$. The network is trained on simulated data of possible roads with different damping coefficients and has learned to interpolate the space of possible damping coefficient values on the known roads. The past determined values for the damping coefficient represent the degradation of the shock absorber. Each time a new damping value is estimated, a new model is fitted to this data that describes the decrease in the damping coefficient by solving the minimization problem

$$\min_{a,b,c} \sum_{i=0}^{n} \left(\left(a i^b + c \right) - u_\theta(z_i) \right)^2 , \tag{3}$$

that we get from comparing the estimated damping coefficients to the general form given in (1). After estimating the parameters, we use them to determine the future behavior. Then, we can check whether this determined value still lies in the ODD and whether to give a predictive maintenance recommendation.

3. Results and Discussion

We use a ResNet18 network [20] for determining the damping coefficient, which achieves an average error of 5.67 on test data with values between 1400 and 1000. For now, we use the mean squared error as training loss. In the future, we also want to test loss functionals that penalize too-high determined damping constants more than too-low ones. In this way, we want to ensure that predictive maintenance recommendations are issued too early rather than too late since we consider a safety-critical domain. For solving the optimization problem in (3) we use the BFGS algorithm (Figure 3). In some of our experiments, a problem occurs when the algorithm gets stuck in a local minimum such as a horizontal best-fit line. In future work, we want to solve this problem by additional regularization terms. In this paper, we assumed that the degradation depends only on the time steps but not the street profile. In future work, we also want to include the absorbed energy by the shock absorber in our degradation model. In our example, we have considered a fixed number of road profiles and used a neural network to interpolate the space of possible damping coefficients on this limited set. Later we want to examine an extended pipeline able to estimate the degradation for roads that are not part of the training data within a realistic vehicle simulator [21]. All in all, we have demonstrated a way to denote the RUL of a shock absorber as a metric to the ODD boundary and estimate it through machine learning. In conclusion, an efficient estimation of the damping coefficient opens many possible use cases.

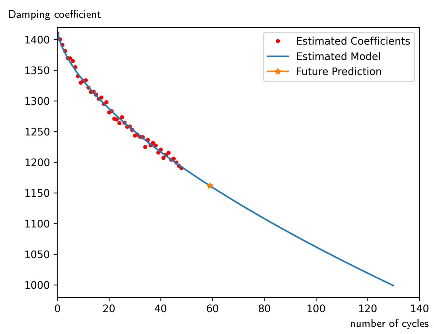

Figure 3: Predicting Damping Coefficients

References

[1] Hiwase, Shrikant Deokrishna and Jagtap, Pramod, Predictive Maintenance of Automotive Component Using Digital Twin Model, in: SAE Technical Paper Series, SAE Technical Paper Series, SAE International400 Commonwealth Drive, Warrendale, PA, United States, 2022. doi:10.4271/2022-28-0075.

[2] Society of Automotive Engineers, Taxonomy & Definitions for Operational Design Domain (ODD) for Driving Automation Systems, 2021.

[3] British Standards Institution, Operational Design Domain (ODD) taxonomy for an automated driving system (ADS) - Specification, 2020.

[4] Association for Standardization of Automation and Measuring Systems, ASAM OpenODD: Concept Paper, 2021.

[5] V. M. Barethiye, G. Pohit, A. Mitra, Analysis of a quarter car suspension system based on nonlinear shock absorber damping models, INTERNATIONAL JOURNAL OF AUTOMOTIVE AND MECHANICAL ENGINEERING 14 (2017) 4401–4418. doi:10.15282/ijame.14.3.2017.2.0349.

[6] C. Ferreira, P. Ventura, C. Grinde, R. Morais, A. Valente, C. Neves, M. Reis, Characterization and testing of a shock absorber embedded sensor, Procedia Engineering 5 (2010) 319–322. doi:10.1016/j.proeng.2010.09.112.

[7] K. Jeong, S. B. Choi, H. Choi, Sensor Fault Detection and Isolation Using a Support Vector Machine for Vehicle Suspension Systems, IEEE Transactions on Vehicular Technology 69 (2020) 3852–3863. doi:10.1109/TVT.2020.2977353.

[8] C. Howard, Sergiienko N., G. Gallasch, Monitoring the age of vehicle shock absorbers, Proceedings of the International Conference on Science and Innovation for Land Power (2018) 1–4.

[9] Guy Edward Gallasch, Nicholas Brealey, On monitoring the health and remaining useful life of vehicle suspension systems, DST Group International Conference on Health and Usage Monitoring Systems 10 (2017).

[10] S. Yin, Z. Huang, Performance Monitoring for Vehicle Suspension System via Fuzzy Positivistic C-Means Clustering Based on Accelerometer Measurements, IEEE/ASME Transactions on Mechatronics 20 (2015) 2613–2620. doi:10.1109/TMECH.2014.2358674.

[11] T. Zehelein, T. Hemmert-Pottmann, M. Lienkamp, Diagnosing Automotive Damper Defects Using Convolutional Neural Networks and Electronic Stability Control Sensor Signals, Journal of Sensor and Actuator Networks 9 (2020) 8. doi:10.3390/jsan9010008.

[12] H. Park, R. Diane Cuebas, K.-S. We, S. Hoon Kim, C.-G. Lee, Oil Leakage Detection in Automobile Shock Absorber using Machine Learning Classifiers, in: 2021 the 5th International Conference on Robotics, Control and Automation, ACM Digital Library, Association for Computing Machinery, New York,NY,United States, 2021, pp. 71–77. doi:10.1145/3471985.3472377.

[13] H. Wang, X. Liu, Q. Wu, X. Wang, Y. Wang, An improved fatigue life prediction model for shock absorber cylinder with surface roughness correction, Engineering Computations 38 (2021) 2713–2732. doi:10.1108/EC-05-2020-0263.

[14] H. Wang, Y. Liu, Z. Liu, Z. Wang, H.-Z. Huang, Remaining useful life estimation for degradation and shock processes, in: 2013 International Conference on Quality, Reliability,

Risk, Maintenance, and Safety Engineering (QR2MSE), IEEE, 2013, pp. 1762–1764. doi:10.1109/QR2MSE.2013.6625917.

[15] G. Xu, M. Liu, J. Wang, Y. Ma, J. Wang, F. Li, W. Shen, Data-Driven Fault Diagnostics and Prognostics for Predictive Maintenance: A Brief Overview, in: 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), IEEE, 2019, pp. 103–108. doi:10.1109/COASE.2019.8843068.

[16] M. Mitschke, H. Wallentowitz, Dynamik der Kraftfahrzeuge, VDI, 4., neubearb. aufl. ed., Springer, Berlin and Heidelberg, 2004. URL: http://digitale-objekte.hbz-nrw.de/webclient/DeliveryManager?pid=1493716&custom_att_2=simple_viewer.

[17] M. Kane, A 3d texture dataset of 27 km road, Data in Brief 35 (2021) 106855. URL: https://www.sciencedirect.com/science/article/pii/S2352340921001396. doi:10.1016/j.dib.2021.106855.

[18] X. Yao, M. Pecht, Performance Degradation of Hydraulic Vehicle Dampers, 2018 Prognostics and System Health Management Conference (PHM-Chongqing) (2018).

[19] P. Balzer, Dynamik eines Viertelfahrzeugs, 2011. URL: https://www.cbcity.de/dynamik-eines-viertelfahrzeugs.

[20] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, 2015. URL: https://arxiv.org/pdf/1512.03385.

[21] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, V. Koltun, CARLA: An Open Urban Driving Simulator, 2017. URL: https://arxiv.org/pdf/1711.03938.