Vehicle Vertical Wearing Index ($\mathrm{V^2WI}$): active monitoring of wearing and aging of vertical-dynamics components in four-wheeled vehicles

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***Abstract*— Being able to assess the state-of-health of a vehicle opens of course many possible applications. All the more so if the ongoing degradation of the monitored components can be provided continuously as the vehicle life extends over time. In modern shared mobility systems, thanks to which migration from ownership to usership models should eventually take place, developing means to actively monitor the state of the vehicle fleet is crucial to improve business models and feasible and predictive maintenance plans. Within this challenging context, the present paper focuses on the monitoring of the vehicle vertical dynamics, to understand, from the analysis of measured data, which is the combined effect of driving-style and introduce road pavement roughness in determining the usage profile of the vertical-dynamics-related components of the vehicle, mostly the suspensions system. The proposed cost function concisely represents such wearing process, with the advantage of not requiring detailed parametric models of the vehicle dynamics and of the components themselves. The approach is tested on more than 9.000 km of trips carried out on four different vehicles, allowing to prove the effectiveness and generality of the approach.**

I. Introduction

Although new vehicles are increasingly equipped with on-board diagnostic systems, the problem of assessing vehicle wear over time remains open today. An online identification of the state-of-health of a car could be very appealing for second-hand car market, as it would offer an objective assessment of the vehicle conditions. Furthermore, the power to demonstrate quantitatively the wear of a vehicle becomes even more relevant if connected to the car-sharing context. In this setting, in fact, a quantification of the impact that each trip has in terms of vehicle usage can both support the driver in adopting a less aggressive driving style and the service provider to develop individual pricing schemes and to actively monitor the fleet.

In the scientific literature, the concept of the so-called health-and-usage monitoring systems (HUMS) has been developed mainly within the aeronautical community, both for aircraft and helicopters, and is being transferred to military ground vehicles, for which maintenance plans are crucial to ensure a correct operation of the fleet, see *e.g.* [1], [2], [3].

In the ground vehicle world, most of the approaches that analyze the consumption of the various parts of a vehicle are based on mathematical models of the involved mechanical components, see *e.g.*, [4], [5], [6] for tire wear models, [7], [8], [9], [10], [11], [12] for suspensions and shock-absorber systems. These methods, while guaranteeing a remarkable precision of the results, are difficult to implement in practice because they require the knowledge of the technical characteristics of the involved individual components as well as the measurement of signals that are often very difficult to access in practice.

In this paper, we address the problem of analyzing the combined effect of driving style and road pavement input on the aging of vertical dynamics components of a vehicle devising a black-box approach that operates on measured signals that can be retrieved from an e-Box, which are telematics sensing units. These devices are commonly used in vehicle telematics applications, thus acting as an add-on with respect to the OEM-based equipment, which we assume not directly accessible. In particular, the proposed method, starting from a minimal set of inertial signals, evaluates the wear of the components linked to the vertical dynamics of the car, specifically those related to the wear of the tires and of the suspension system.

Specifically, the main goal is to develop a wear-assessment approach that is independent of the specific vehicle technology, has low implementation cost, and uses an equipment that can be easily retrofitted on existing cars. Thus, we discuss a method that would apply both to private vehicles (*e.g.*, to assess the state-of-health of potential second-hand vehicles), and to multi-model fleets of shared-vehicles. To do this, a reference behavior of every vehicle in the vertical direction needs to be characterized from data, to build a baseline model. This reference can be used to classify every trip in terms of the vertical stress that it exerts on the vehicle. The initial data gathering can be, in a final implementation, adjusted with some calibration trips to be done upon installation, and periodically checked for updates. In so doing, all the trips are compared to the computed baseline behaviour of the single car and used to monitor the vehicle life to capture the effect that driving style and road state have on the vertical dynamics in an integral sense, *i.e.*, over the vehicle life-cycle. This is different from the existing fault-detection approaches, see *e.g.*, [13], [14], [15], [16] for the suspension system, which of course are tailored to detect individual anomalous events rather than tracking how usage-related wear develops.

The paper is organized as follows. Section II presents the problem statement and the experimental setup used in this paper, whereas Section III concentrates of the design of the proposed monitoring algorithm. Further, Section IV deals with the experimental results with different vehicles traveling on different road types.

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II. Problem Statement and Experimental Setup

The goal of the proposed approach is to provide a metric that accounts for how driving-style and road input influence the vertical dynamics of a vehicle, which is central in the evaluation of safety, comfort, and suspensions aging. This problem is particularly challenging because vertical dynamics is not only influenced by the driving-style but also by the vehicle speed and the vehicle suspension system, which acts as a filter on the dynamics of interest. An example of this phenomenon is shown in Fig. 1, where two very different cars (a Fiat Panda – denoted with Car 5 – and a Mercedes Benz B-class – Car 6) are compared in controlled tests, *i.e.*, while driving on the same road segments. The vertical acceleration variance is higher for increasing velocities for the same road type. However, this trend is quite different for the two vehicles. For this reason, our approach aims to evaluate the relative impact that driver and road have on the vertical dynamics for each different car, using its normal behavior as a baseline with respect to which new trips are evaluated. Furthermore, we assume that suspension aging is characterized by a slow-time dynamics with respect to driving style effects and road inputs variations, thus implying that we work under the assumption that suspensions response does not change within a single journey.

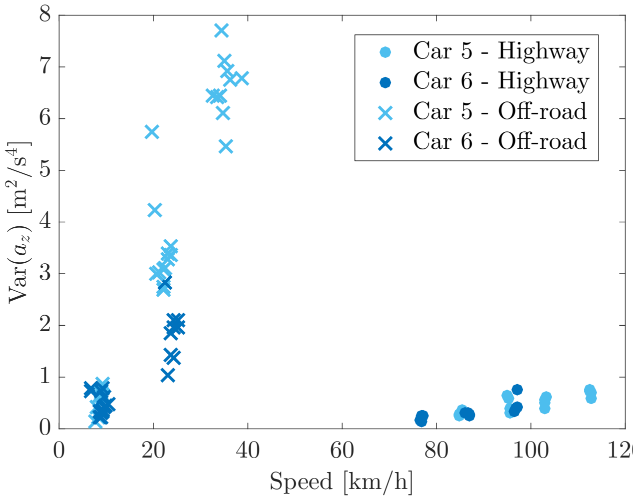

Fig. 1: Analysis of the variance of the vertical acceleration of two vehicles driving on the same roads. As shown, suspensions filter the same road pavement quality (*i.e.* highway vs off-road) differently for different vehicles and longitudinal speeds.

Particular importance is given to the use of a minimal sensor setup, which measures vertical acceleration and speed only. These measurements are already widely available in all modern vehicles through CAN bus. However, relying on embedded sensors would increase the complexity of evaluating the proposed approach unnecessarily. Also, it would be difficult to compare different vehicles because of their non-standard sensor quality. For this reason, in the experimental campaign we equipped all tested vehicles with the same external device, which was a modern, cost-effective, and easy to install telematic e-Box [17]. This apparatus was already employed in different applications [18], [19], [20], proving to be a flexible and reliable device for similar applications. E-Boxes are equipped with an inertial measurement unit (IMU) and a GPS/GNSS receiver. Data are sampled at a sampling frequency of $f_s = 10$ Hz for both the IMU and the GPS/GNSS unit. The external device was mounted close to the vehicles' center of mass to reduce the effect of roll and pitch movements on the vertical acceleration.

The available data were collected during a four-month experimental campaign involving five drivers, driving more than nine thousands kilometers over 441 journeys. An overview of the trips and the vehicles used in these experiments is listed in Table I.

TABLE I: Summary of the experimental vehicles and the recorded trips.

	Vehicle	Trips [-]	Distance [km]
Car 1	Toyota Aygo	115	1640
Car 2	Alfa Romeo MiTo	78	1160
Car 3	Mercedes-Benz A-class	83	2307
Car 4	Jaguar E-Pace	117	3967
Car 5	Fiat Panda	30	133.5
Car 6	Mercedes-Benz B-class	18	83.7
	Total	441	9291.2

III. Algorithm Design

In this section, we illustrate the proposed method and discuss its main parts. First, we investigate the effects of signal windowing on data representation. Then, a reference profile denoting the nominal vehicle response is identified. Finally, the driving-style index that accounts for vertical wearing is discussed.

A. Signals windowing

To extract the needed information from data, the first step is to understand how to process them online looking at a time window that is representative of the phenomenon under investigation. Specifically, we first aim to tune a sliding window that can well characterize the road profile in terms of its statistical distribution. This tuning parameter plays a key role, to trade-off responsiveness with completeness of information.

In Fig. 2, an overview of some road sections are analyzed for different windows lengths w (*i.e.*, from 5 up to 60 seconds). In this analysis, the sample variance of each signal is computed and represented with its 95% confidence interval, denoted with the error bars. In these tests, the same vehicle (*i.e.*, *Car 6*) was driven at steady state on a high-quality reference profile. We assumed the vehicle to be in stationary motion when the speed variance was below 7 km^2/h^2.

As shown, larger buffers provide an estimate with lower uncertainty, *i.e.*, smaller error bars. However, it should be remarked that such reduced uncertainty is obtained looking at a large amount of data collected on significantly long road sections. Because of this, distributions are no longer able to

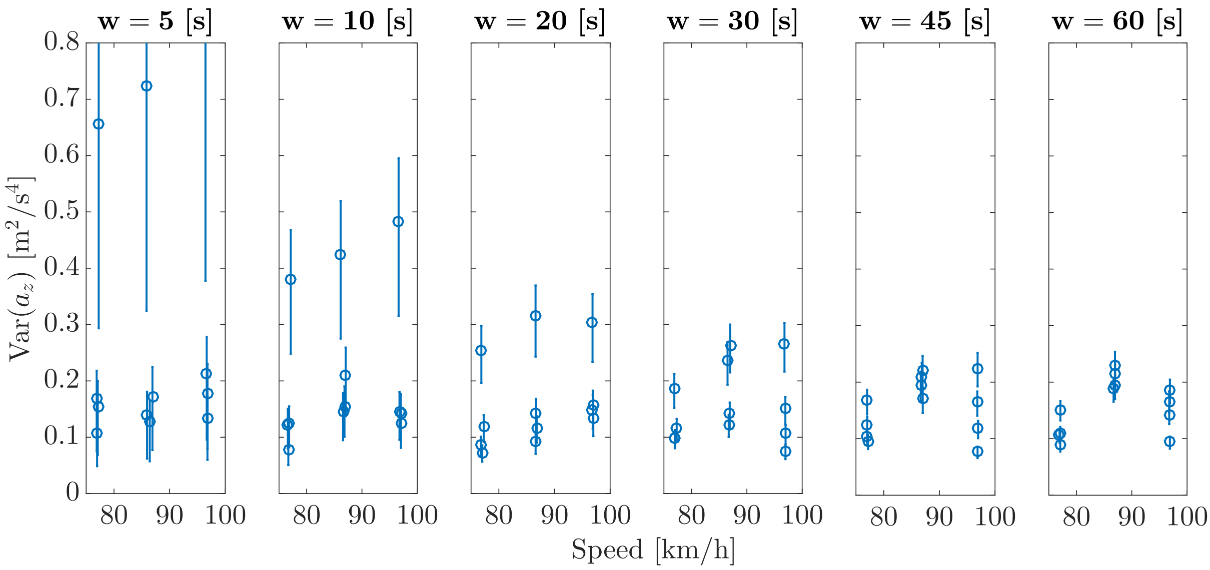

Fig. 2: Vertical acceleration sampling variance distributions for different velocities and window lengths. Shorter windows (*e.g.*, $w \leq 10$ s) result in less accurate estimates. Instead, too long windows (*e.g.*, $w \geq 45$ s) provide accurate estimates, though over long road sections. A good trade-off is $w = 20$ s.

capture interesting, yet short events, as they populate only a small portion of the entire buffer. As shown in Fig. 2, three events with large variance are captured only for $w \leq 20$ s. For larger windows (*e.g.*, $w \geq 45$ s), these anomalies no longer stand out, and all the distributions lie in a small range.

For a qualitative analysis of vertical aging, we consider these anomalies particularly important as they point out to stressful events, which impact on the suspensions system more than on average. Thus, in this application we select $w = 20$ s.

B. Identification of the baseline vertical behavior

Once the buffer size and the sampling frequency are set, vertical acceleration measurements can be buffered in the sliding window and its sampling variance computed. The analysis of the variance of the vertical acceleration has been already widely used in similar applications, in particular for road pavement quality assessment, see, *e.g.*, [21]. However, to define a metric that accounts for vertical wearing, a reference profile needs to be defined for each vehicle. To this end, we created a database containing a set of tuple $s = \{\mathbb{E}\left[v(t-k,\ldots,t)\right], \mathrm{Var}\left(a_z(t-k,\ldots,t)\right)\}$ for each vehicle, in which $\mathbb{E}\left[v(t-k,\ldots,t)\right]$ is the averaged speed, and $\mathrm{Var}(a_z(t-k,\ldots,t))$ the vertical acceleration sampling variance computed on the window w, so that $k = \frac{w}{f_s}$.

When the database is sufficiently populated, the collected data represent a large exploration of different road profiles and different driving behaviors. Then, such points are used to define a lower bound, which is a set of samples that characterize the best use of the vehicle, *i.e.*, that with lower stress on the vertical dynamic, within the monitored period. These points are clustered using DBSCAN, a non-parametric density-based clustering algorithm that groups together points with many nearby neighbors and marks as outliers those points whose nearest neighbors are sufficiently far from them [22]. It is worth noting that a meaningful clustering with DBSCAN is possible only if the database is populated with continuity on the entire velocity range (*e.g.*, one sample every 2 km), otherwise some samples could be marked as outliers.

As clustered points may be affected by noise and may not cover all velocity values, a compact representation that averages the cluster profile is necessary. To this end, we leverage what proved in [21]: The power of the vertical acceleration sensed in a vehicle moving with constant horizontal speed can be approximated as

$$P_{a_z}(v) = \widehat{q} v^{\gamma}, \tag{1}$$

with $\widehat{q} \in \mathbb{R}$ and $\gamma \in \mathbb{R}$ parameters to be identified. Assuming the vertical acceleration to be a stationary process, the power of the vertical acceleration is equivalent to its variance. Thus, (1) can be turned into

$$\mathrm{Var}(a_z) = \widehat{q} v^{\gamma}. \tag{2}$$

By fitting the model in (2), the lower bound is generalized into a reference profile that can be used as a benchmark, against which all subsequent trips can be evaluated. Moreover, this benchmark is described by only two parameters that are directly learned from data, and are characteristic of every vehicle. Since we assume to have a large database covering multiple roads and driving conditions, it is worth to point out that the identified curve represents the vehicles' heave dynamics at different velocities on a smooth surface. Furthermore, parameters $\widehat{q}$ and γ are a compact representation of the vehicle's vertical response, in particular:

- $\widehat{q}$ represents the vehicle filtering capabilities. The smaller its value, the smoother the vehicle response.

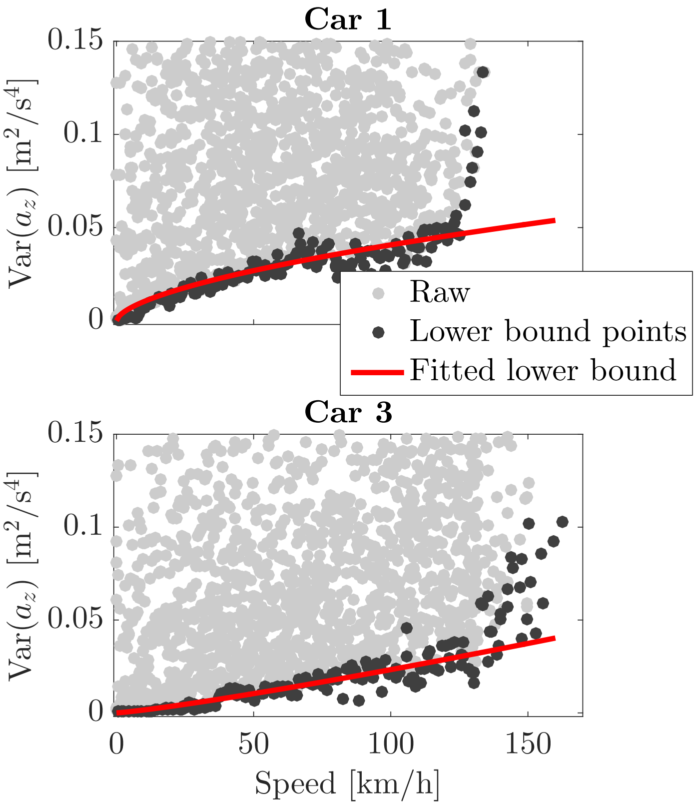

Fig. 3: An overview of the datasets created for each vehicle. Darker points are the lower bound clustered with DBSCAN, representing the vehicle response in the best driving conditions. Model (2) is fitted with the curve in red.

- γ accounts for the loss of filtering action due to higher velocities.

We evaluated this fitting step on experimental data, as shown in Fig. 3. Within the experimental campaign, we obtained a dense cluster of points for each vehicle. The lower bounds group together all the samples closest to zero, highlighted with the darker shade. It is possible to notice that every lower bound depends on the specific vehicle. As mentioned before, these differences are due to the specific vehicle suspension system. In fact, *Car 1*, which is an affordable, compact hatchback, smooths the vertical road profile less than other tested vehicles, especially at low-medium speed. Instead, more expensive, heavier cars, *e.g.*, *Car 4*, provide a more comfortable driving experience, shown in the data with a lower bound closer to zero.

In Table II, vehicles are further compared in terms of their baseline reference model parameters $\widehat{q}$ and γ. As the table shows, *Car 1* is characterized with the highest value of $\widehat{q}$, which confirms what qualitatively stated before. Moreover, *Car 1* has the lowest value of γ, meaning that the filtering action degrades less at higher speed with respect to the other vehicles. Instead, the two sedans (*i.e.*, *Car 2* and *Car 3*) have different responses: The less expensive *Car 2* provides a less smoothing suspension system; on the other hard, *Car 3* becomes less effective at higher speed. Parameters identified for *Car 4*, the high-end SUV, lie in between what obtain for the sedans: The filtering action is slightly worse than *Car 3*, but it is less sensitive to the effects of speed.

Finally, it is worth to point out that the relation in (2) has proved to lose its modeling capabilities when driving at a speed above 130 $\mathrm{km/h}$, which is generally the maximum speed legally accepted in many countries. This should not surprise: Vehicles are designed to provide the most comfort for the range of speed in which the car is supposed to drive most of the time, while the poorly fitting area is outside the design range. For what follows, we kept the identified model as valid for all speed values, assuming that aging increases non-linearly outside the main speed range commonly explored.

We now have a methodology for defining a reference profile that can be used to normalize every vehicle behavior regardless of the road profile. Driving style is then assessed with respect to both vertical acceleration and speed. In the next section, we define a metric for the evaluation of the vertical wearing on the basis of the obtained baseline.

TABLE II: Identified parameters for the vehicles used in tests.

	$\widehat{q}$	γ
Car 1	$4.9 \cdot 10^{-3}$	0.5972
Car 2	$1.5 \cdot 10^{-3}$	0.8089
Car 3	$0.5 \cdot 10^{-3}$	1.1665
Car 4	$1 \cdot 10^{-3}$	0.7505

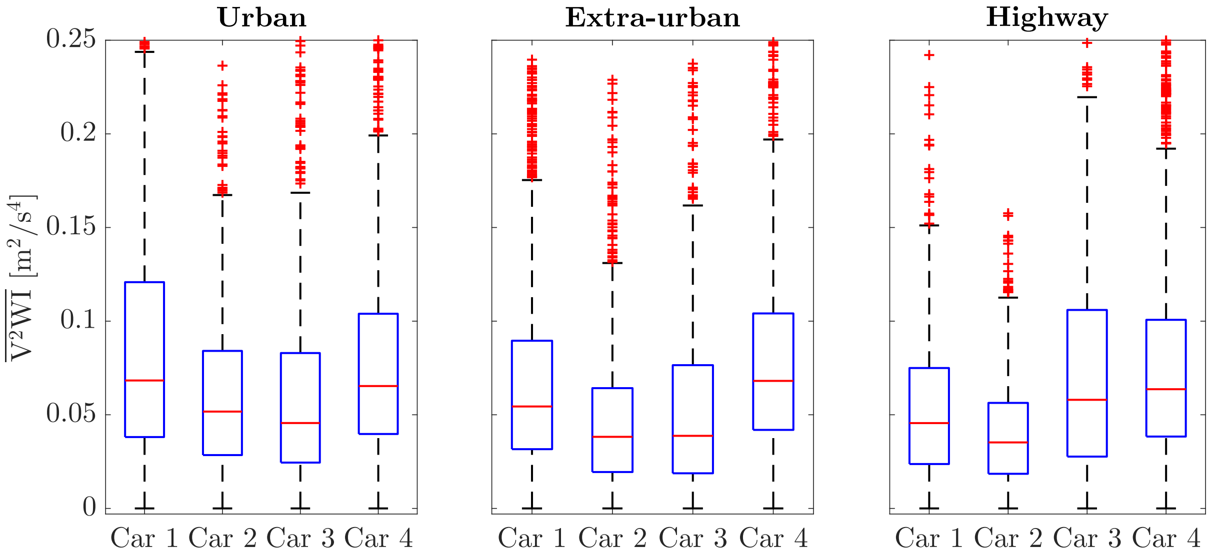

Fig. 4: Analysis of the average $\mathrm{V^2WI}$ for different vehicles based and different road types. As shown, the influence of driving-style on aging is dependent on the environment.

C. *Definition of the* $\mathrm{V^2WI}$ *cost function*

The last step of the proposed algorithm consists in the definition and computation of the vertical wearing metric. To compute this quantitative indicator, it is necessary to have a database and a reference profile, as discussed in the previous section. We first define

$$d(t) = \mathrm{Var}\left(a_z(t-k,\ldots,t)\right) - \widehat{q}v(t)^{\gamma} \tag{3}$$

as the distance between the variance of the vertical acceleration and the identified benchmark evaluated at the actual speed $v(t)$. This distance represents how intense the driving-style and road profile are impacting on the vertical wearing more than in the best baseline conditions.

Then, the proposed cost function $\mathrm{V^2WI}$ is defined as

$$\mathrm{V^2WI}(t) = \begin{cases} d(t) & d(t) > 0 \\ 0 & d(t) \leq 0. \end{cases} \tag{4}$$

For every new sample of vertical acceleration and speed, the index is computed and updated. As suspension aging has a slow-time dynamics, a suitable and compact representation of our indicator is obtained by averaging its values over an entire journey

$$\overline{\mathrm{V^2WI}} = \frac{1}{T}\sum_{t=k}^{T} \mathrm{V^2WI}(t), \tag{5}$$

where T is the journey duration.

IV. Experimental results and discussion

In this section, the proposed method is analyzed on experimental data. In this analysis, we grouped together the computed cost functions based on the main road type driven during each journey. This overview allows to consider the impact of the environment on the aging assessment. At the end of the experimental campaign, we interviewed the drivers in order to find correlations with what obtained computing the index.

The goal of this analysis is to assess whether the proposed method is capable of discriminating both different behaviors of the same driver, and among different drivers. As shown in Fig. 4, the proposed method seems to be consistent for each driver. In particular, the following remarks are in order:

- *Car 1* shows to have had a very aggressive driving. In particular, at least 50% of the journeys in the urban and extra-urban areas are above the average, stressing the suspension system particularly. When interviewed, the driver reported to commute in a poorly maintained road. Nevertheless, the driver revealed not to have adapted their driving practices considering the low-quality pavements.
- *Car 2*, instead, proved to have been the most conservative driver of the four, especially at high-speed.
- *Car 3* achieved the worst performance on highways, while the driving behavior is similar to *Car 2* in the other environments. In high-speed roads, the driver uses the cruise control frequently, not adapting the speed when approaching lower quality road sections.
- *Car 4* was driven by the most consistent driver. Despite the quite-aggressive behavior, the range spread by $\overline{V^2WI}$ is comparable for the three scenarios. For this car, suspensions age uniformly regardless where the car is driven. To explain this behavior, it is important to remark that the high-quality suspension system provide a lower bound very close to zero for almost all velocities, shrinking the differences due to the driving environment.

Experimental data prove the effectiveness of the proposed approach. The obtained metric is an absolute index of how the use of the vehicle increases vertical wearing. In particular, the benefit of using such metric is twofold: First, $\mathrm{V^2WI}$

analyzes vehicle wearing accounting for each specific vehicle response, which is vehicle-dependent. Thus, the obtained metric can be used to compare driving-style and suspension aging regardless of the vehicle used. Second, the method automatically learns from data without any manual calibration. Moreover, the output is physically explainable, which allows to extend this qualitative analysis for a quantitative assessment of how driving-style influences suspension aging.

Finally, it is also worth discussing the limitations of the current version of the presented algorithm. The first one is that, to compute a meaningful lower bound, a large amount of data is required. Only a high-volume of measurements guarantees to properly characterize the vehicle vertical dynamic response together with the condition of having driven on high-quality pavements roads for a kind of initialization phase. We believe that this limitation cannot be overcome; however, the data collection is rather simple, and one may start from an array of baselines already computed for different classes of vehicles which then needs only to be adapted to the single one, thus probably implying a shorter training phase. Further, to be able to compare the impact of vertical dynamics on two different vehicles, it is necessary to assume that the lower bound values have been collected in correspondence of similar road profiles. Thus, in case of a fleet which needs to be monitored, the training phase should be consistently performed. Finally, in its present form the algorithm is not adaptive. The identified lower fitting curve is kept fixed, while vehicle usage may in principle lead to a natural degradation of its performance. For this reason, consideration should be given to the possibility of adaptively shifting the distribution of the $\mathrm{V}^2\mathrm{WI}$ index towards larger values by means of a triggering decision logic that accounts for the stage of the vehicle life-cycle.

V. Final remarks

In this paper, an innovative data-driven approach for the active monitoring of the combined effect of driving-style and road pavements in the degradation of the vehicle components acting on the vertical direction has been proposed. The resulting $\mathrm{V}^2\mathrm{WI}$ index can be employed both in the second-hand vehicles market and in shared fleets to profile the wear and tear of those components related to the vertical dynamics. The results showed that we are able to provide a vehicle-independent assessment of the impact each trip has in the excitation of the vertical vehicle dynamics with respect to a predefined baseline. Ongoing work is being devoted to map the $\mathrm{V}^2\mathrm{WI}$ index onto a real wearing function of the suspensions system, which of course requires some input data from the suspensions manufacturer, but it will allow employing the proposed index for predictive maintenance plans. Further investigations will also extend the investigation of the proposed index to a larger range of vehicles at different level of vehicles age, which is something that this study has not characterized. Also, it will be explored the use of nonlinear relationships to better evaluate the effects of suspension aging at high speed.

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