Honda Research Institute EU
Honda Research Institute Europe GmbH
https://www.honda-ri.de/

Modelling and Prediction of Remaining Useful Lifetime for Maintenance Scheduling Optimization of a Car Fleet

Duc Nguyen, Steffen Limmer, Kaifeng Yang, Markus Olhofer, Thomas Bäck

2019

Preprint:

This is an accepted article published in International Journal of Performability Engineering. The final authenticated version is available online at: https://doi.org/10.23940/ijpe.19.09.p4.23182328

Modelling and prediction of remaining useful lifetime for maintenance scheduling optimization of a car fleet

Duc Van Nguyen
LIACS
Leiden University
Leiden, The Netherlands
d.v.nguyen@liacs.leidenuniv.nl

Steffen Limmer
Honda Research Institute Europe GmbH
Offenbach, Germany
Steffen.Limmer@honda-ri.de

Kaifeng Yang
LIACS
Leiden University
Leiden, The Netherlands
k.yang@liacs.leidenuniv.nl

Markus Olhofer
Honda Research Institute Europe GmbH
Offenbach, Germany
markus.olhofer@honda-ri.de

Thomas Bäck
LIACS
Leiden University
Leiden, The Netherlands
t.h.w.baeck@liacs.leidenuniv.nl

Abstract

Remaining useful lifetime (RUL) is the time remaining until an asset no longer meets operational requirements. An accurate estimation of the RUL is central to prognostics and health management systems. However, the RUL of an asset is usually very difficult to estimate and to achieve in any industry. This is because the RUL strongly depending on manufacturing, the operating environment, and the observed condition monitoring. Here, we use physics-based approaches and data-driven approaches to predict the RUL of four essential components of a passenger car, namely engine, brake pads, springs, and tires. Our results show a good agreement of both approaches. In addition, we develop a hybrid framework to generate a data set of RULs of a car fleet. This framework can be used for establishing an optimal maintenance schedule for a car fleet, such as the fleet of a taxi company.

Index Terms

Remaining useful lifetime, prognostics, automotive, maintenance scheduling optimization

I. Introduction

Operational safety, maintenance cost efficiency and asset availability have a direct impact on the reduction of the overall operation costs in any industry. Today's complex and advanced industry systems demand highly sophisticated and costly maintenance strategies. High maintenance cost and unwanted downtime in industries are often caused by system fault problems. Therefore, there is a pressing need to continuously develop and improve current prognostics and health management (PHM) systems so that any system's fault can be early detected and system's remaining useful lifetime (RUL) can be accurately predicted. Detecting system's fault soon enough can help to avoid catastrophic failure events while knowing the RUL is essential to establishing an optimal maintenance schedule [1]. The early fault detection capability seeks to detect, isolate and estimate the severity of faults based on models that include cross-subsystem fault propagation effects and relate detected degradation. In contrast, RUL prediction provides the system residual life for a given future operation profile from its current age (condition) and the past operation profile [2]. It is a bottleneck issue for the implementation of PHM activities [3] and has grown recently as a popular issue to researchers.

Commonly, approaches used in prognostics and predicting RUL are classified into three types [4], namely i) physics-based approaches, ii) data-driven approaches, and iii) hybrid approaches. Readers who are interested more in these approaches can find more details in following review papers [4]–[7]. Each approach has its own merits and limitations. For example, physics-based approaches are deterministic methods and allow the estimation and the prediction of the dynamic states [4]. In these approaches, physical/mathematical models for the system or component are developed. These models are physical/mathematical representations of the systems that are able to predict the system degradation and failures. Physics-based methods do not require a large amount of data and especially the data of the failure events. However, to establish this model, a thorough understanding of the physics of the system/component is required and such a model's reliability often decreases as the system complexity increases.

In contrast to physics-based approaches, data-driven methods are much easier to be developed and applied in practical applications [4]. The low cost of algorithm development and little knowledge required about physics of the studied system,

make this approach preferable by prognostics system developers [8]. In addition, data-driven methods provide a high reliability and an effective computation, in spite of system complexity. Nonetheless, compared to the physics-based methods, the data-driven methods require a large amount of data, including both historical observation and current condition monitoring data.

Hybrid prognostics approaches, which are newly developing approaches, aim at integrating the merits of the above mentioned methods while minimizing their limitations. They are promising methods because they can compensate the lack of knowledge about the system's physics and the lack of data [9]–[11].

Generally speaking, the complexity, cost, and accuracy of prognostics techniques is usually inversely proportional to its applicability. Increasing prognostics algorithm accuracy with low cost and complexity is a big challenge. A number of works on RUL prediction in industries are reviewed in Jardine et al. [12], Si et al. [1], Tsui et al. [6] and Sutharssan et al. [7].

However, in automobile industry, except for battery, there has not been much successful work on predicting the RUL of vehicle's assets. In this paper, we present an application of physics-based and data-driven approaches to predict damage percentage and RUL of four essential components of a passenger car, namely engine, brake pads, springs, and tires. Explicitly, we use the physics-based models to estimate the damage percentage and build-up the ground truth data of these components. We then use machine learning algorithms such as Lasso, Ridge, polynomial, decision tree (DT) and random forest (RF) to predict these damage percentages. Our results show a good agreement of both methods. In addition, we develop a hybrid framework to generate a data set of RUL of a car fleet. This framework is a primary input for users/researchers to establish an optimal maintenance schedule for a car fleet, such as a fleet of a taxi company.

The remainder of this paper is organized as follows; section II give an overview of sensor types and their functions in automotive industry. In section III, we show damage and prediction models for estimating damage and RUL of car components. Section IV describes our simulation and prediction algorithms. We show and discuss about the results in section V. In section VI we conclude this paper and discuss the future work.

II. Classification of Automotive Sensors

Vehicles have very complex mechatronic structures consisting of systems and subsystems. Normally any subsystem comprises electromechanical processes, actuators, and sensors [13]. The sensors and actuators are associated and controlled with an engine control unit (ECU) which manages and screens the procedure. Knowing the types, functions and applications of sensors is required to predict the RUL of an asset or an entire vehicle. On the basic level, the primary sensors in use today in automotive systems are reviewed and classified according to their three major areas of automotive systems application, including powertrain, chassis, and body [14]. The powertrain encompasses every component that converts an engine's power into movement. This includes the engine, transmission, the driveshaft, differentials, axles; basically anything from the engine through to the rotating wheels. Chassis, also known as a vehicle frame, is the main supporting structure of a motor vehicle, to which all other components are attached. The chassis is considered to be the most significant component of an automobile, considering the fact that it gives strength and stability to the vehicle under different conditions. The main elements involved in chassis are steering, suspension (tire, springs, shock absorbers and linkages), vehicle breaking and stability. Anything that is not powertrain or chassis is included as a body systems application. It contains main elements such as occupant safety, security, comfort and convenience.

If we classify automotive sensors according to their functions, we can do it as follows [14]: there are engine speed (rotational motion) sensors, pressure sensors, position sensors, and temperature sensors, mass air flow sensors, exhaust gas oxygen sensors, engine knock sensor, linear acceleration sensors, angular-rate sensors, force sensors, torque sensors, near-distance obstacle detection sensors, far-distance obstacle detection sensors, and emerging sensors. Knowing sensor types and their functions is required to study and analyze a health condition of a vehicle asset.

Here, in this work, we use engine speed sensors to predict the RUL of the engine. Force sensors are used for predicting the RUL of the springs and tires and torque sensors are used to predict the RUL of the brake pads.

III. Damage models and remaining useful lifetime prediction models

An important task in PHM systems is to clarify and identify failure mechanisms. Failure mechanisms can be physical, chemical, thermodynamic or other processes that result in a failure [15]. Knowing the failure mechanisms is a must to develop physics-based methods and is crucial to identify and select features in the data-driven methods. Failure mechanisms are categorized as either overload or wear-out mechanisms. An overload failure arises when a single load condition exceeds a fundamental strength property. A wear-out failure arises as a result of cumulative damage related to loads applied over an extended time. The wear-out failure includes deformation, corrosion, fatigue, creep, wear, melting, thermal degradation, electric failures, and radiative failures [15]. Knowledge on these mechanisms, and especially the effect of the governing loads on failures, are essential to understand why, how and when components fail and how to prevent this failure [16]. This work focuses on analyzing the fatigue and wear mechanisms of four car components, namely helical springs, brake pads, tires, and engine.

A. Damage models

Fatigue damage analysis of helical springs: Besides tires, springs are the main components in the suspension system which help to reduce road shocks and vibration of a vehicle [17]. Depending on vehicles, different types of springs are used and they can be classified as: leaf spring, helical/coil spring, torsion bar, rubber spring, or hydro-pneumatic spring. Springs that are too hard or too soft cause the suspension to become ineffective because they fail to properly isolate the vehicle from the road. The helical spring is the most common type of spring used in passenger cars [17].

For a helical spring, fatigue is the main mechanism that reduces its lifetime and it is often analyzed using the fatigue limit or the S-N curve (fatigue curve, Wöhler curve) [15]. A S-N curve describes the relation between cyclic stress amplitude and number of cycles to failure. Figure 1 shows a typical S-N curve. The vertical axis shows the stress amplitude, whereas the horizontal axis indicates the corresponding number of cycles to failure at a given stress amplitude [15], [18]. In Figure 1, the upper and lower dashed lines are the tensile limit and the endurance limit, respectively. The tensile limit and the endurance limit values strongly depend on the spring materials. An applied stress that is stronger than the tensile limit will lead to a direct spring's failure, while any stress that has an amplitude smaller than the endurance limit will have no impact on the spring's lifetime.

Damage percentage of a spring is estimated using the Paris-Erdogan's [19] and Palmgren-Miner's laws [20] and can be formulated as:

$$d_s = \sum_{i=1}^{p} \frac{n_i}{N_i} \times 100\% \tag{1}$$

where d_s is the percentage of life consumed, p is the blocks of number of cycles n_i with stress amplitude S_i and cycles to failure N_i at this stress. The number of cycles is counted using the Rainflow model [21]. For example, if a spring experiences 30 stress cycles with an amplitude S_1 and 20 stress cycles with an amplitude S_2. The corresponding number stress cycles to failure for these stress amplitudes are $N_1 = 10^3$ and $N_2 = 10^4$, respectively. The damage percentage of the spring will be:

$$d_s = (\frac{30}{10^3} + \frac{20}{10^4}) \times 100\% = 3.2\% \tag{2}$$

If $d_s \geq 100\%$, the spring's lifetime ends and a spring failure occurs.

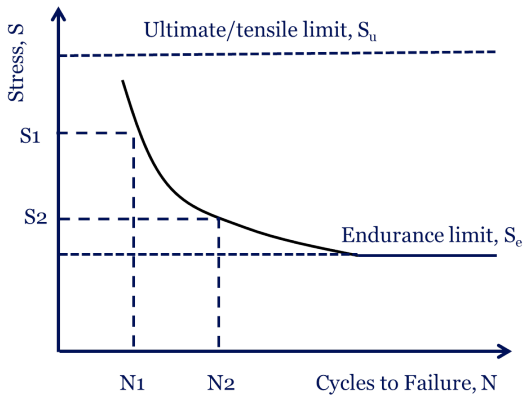

Fig. 1. A typical S-N (Wöhler) curve.

Wear damage analysis of brake pads and tires: In the process of braking, due to friction between the surfaces of the friction couple, the zones of contacts are destroyed after each braking event, resulting in worn-out material. The reduction of the brake lining/pad volume due to worn-out material of the ith braking event can be represented as follows [22], [23]:

$$\Delta V_{bi} = I_i \times W_i \tag{3}$$

where I_i and W_i are the wear energy intensity and the work of the friction forces of the ith braking event, respectively. The wear energy intensity represents for the quality of the brake pad material and depends on the temperature. The work of the friction is simply a multiplication of the friction force and the relative displacement between the brake pad and the brake rotor. If we assume that the wear energy intensity is a constant, Eq. (3) can be re-written as:

$$\Delta V_{bi} = C_{brake} \times F_i \times \Delta d_i \tag{4}$$

where C_{brake} is a brake constant. Normally, brake constant is a function of the brake pad material's strength and the friction coefficient between the brake pad and rotor. F_i and Δd_i are the friction force and the relative displacement between the brake

pad and the brake rotor of the ith braking event, respectively. The overall reduction of the brake lining/pad volume (ΔV_b) is a sum of the reduction of individual braking events.

$$\Delta V_b = \sum_{i=1}^{n} \Delta V_{bi} \tag{5}$$

If V_{b0} is the maximum volume which the brake lining/pad can reduce before a failure might occur, damage percentage of the brake lining/pad (d_b) is estimated by the following equation:

$$d_b = \sum_{i=1}^{n} \frac{\Delta V_{bi}}{V_{b0}} \times 100\% \tag{6}$$

While a car is running, tire's surface is in contact with the road surface. Friction results in worn-out material of the tires. Two force components that cause the tire worn-out are Fx and Fy. The vertical force component Fz is only considered for pressure (overinflation, underinflation) damage of the tires. Similar to the brake pad, a volume reduction of the tire due to worn-out material is formulated as:

$$\Delta V_{ti} = C_{tire} \times (|Fx_i| + |Fy_i|) \times \Delta d_i \tag{7}$$

where C_{tire} is a tire constant and represents for the tire quality. Δd_i is the relative displacement between the tire surface and the road surface and it is simply the car travel distance.

The overall reduction of the tire volume also follows Eq. (5). If V_{t0} is the maximum volume which the tire can reduce before a failure might occur, damage percentage of the tire (d_t) is computed by the following equation:

$$d_t = \sum_{i=1}^{n} \frac{\Delta V_{ti}}{V_{t0}} \times 100\% \tag{8}$$

Engine damage analysis: The engine is the heart and the most complex part of a car. The lifetime of a car engine depends on many variables such as temperature, vibration, oil quality, environmental condition, etc. Establishing a model to estimate the lifetime of a car engine is a big challenge. In our work, we establish a rough model that can estimate the consumption lifetime of the car engine from the travel distance and the engine rotation speed. The equation is:

$$d_{ei} = C_{engine} \times \Delta d_i \times R_i \tag{9}$$

where C_{engine} is a constant and represents for the engine quality. Δd_i and R_i are the car travel interval, and the engine rotation speed corresponding to this travel interval, respectively. The consumed lifetime percentage of the engine is:

$$d_e = \sum_{i=1}^{n} d_{ei} \times 100\% \tag{10}$$

The engine need to be maintained if the d_{ei} sum up to 1.

B. Remaining useful lifetime estimation model

Based on a damage percentage, we can easily compute the remaining useful lifetime (RUL) of a component. For instance, if we want to estimate the RUL as a unit of week, we use the above damage models to compute the sum damage percentage D_i of each week i. The total damage percentage after the wth week is calculated as follows:

$$D = \sum_{i=1}^{w} D_i \tag{11}$$

where D_i is the sum damage percentage of the ith week, and w is the total week number. Based on the definition of D, the RUL after week w can be estimated by:

$$RUL = \frac{100\% - D}{D/w} \tag{12}$$

Here, 100% means that, at the beginning, the component is absolutely new. If the distribution of the sum damage percentage of each week has a standard deviation σ, then the lower bound of the one standard deviation confidence interval of RUL is:

$$RUL_{-} = \frac{100\% - D}{D/w + \sigma} \tag{13}$$

and the upper bound of the one standard deviation confidence interval of RUL is:

$$RUL_{+} = \frac{100\% - D}{D/w - \sigma} \tag{14}$$

C. Future remaining useful lifetime forecasting models

Forecasting of the future remaining useful lifetime of components is important for maintenance scheduling. It can be done by using the historical data and the machine learning techniques. Autoregressive Integrated Moving Average (ARIMA) model [24] and Prophet forecasting model[1] are suitable for this purpose since they allow us to forecast the future values of a time series based entirely on the historical data. Tuning ARIMA method requires a thorough understanding of how the underlying time series models work, for instance, the maximum orders of the differencing, the auto-regressive components, and the moving average components [25]. In contrast, the Prophet forecasting model provides intuitive parameters which are easily to tune [25]. Even someone who lacks expertise in forecasting models can use this to make meaningful predictions for a variety of problems in a business scenario. It uses a decomposable time series model with three main model components: trend, seasonality, and holidays. Using time as a regressor, Prophet fits several linear and non linear functions of time as components. Modeling seasonality as an additive component is the same approach taken by exponential smoothing in Holt-Winters technique [26].

IV. Simulation and prediction algorithms

A. Car fleet simulation using CarMaker

CarMaker simulation is developed by IPG Automotive for testing driving scenarios of passenger cars and light-duty vehicles[2]. It is an open integration and test platform and can be applied throughout the entire development process-from model-to software-to hardware-to vehicle-in-the-loop. The powerful and real-time capable models for vehicles, roads, drivers and traffic guaranty flexibility, productivity and precision for all simulation tasks in realistic driving scenarios. Using CarMaker ensures significant savings in cost and time for testing driving scenarios and development of a desired vehicle.

In this work, we developed Python scripts to automatically run CarMaker simulations to simulate driving scenarios for a car fleet in New York City. Demo car model and default driver are selected and unchanged during the simulation. We used the origin and destination coordinates from Green Taxi Company in January 2015 that we downloaded from NYC Open Data[3]. These coordinates were converted into taxi routes using Google API. In each trip, extra loads were added to all passenger seats of the car. For each position a load between 0 and 100 kg is randomly chosen with an equal probability. A simulation of 4000 trips was performed.

We simulated a fleet of 200 cars. In the car fleet simulation, we assumed that a car can take uniformly from 5 to 15 trips per day. Trips are randomly selected from the 4000 trips of the Carmaker simulation. Car can be used from 4 to 7 days per week with an equal probability.

B. Analyzing of CarMaker sensors

There are 1868 variables as an output of a CarMaker simulation. These variables include sensor data for all three major areas of automotive systems application such as powertrain, chassis, and body. In this work, we use forces to estimate the damage percentage and the RUL of springs and tires. We use brake torque and engine rotation speed for estimating the damage percentage and the RUL of brake pads and engine, respectively. In Figure 2, the top graph shows a representative example of the forces of the springs and tires of four wheels during a trip. The bottom graph shows the corresponding engine rotation speed and brake torques. We observe that, in general, the forces of front springs are higher than that of the rear springs. It is because, in our simulation, all cars have a front-engine layout. In addition, we also observe force peaks with different amplitudes during the trip. A similar pattern was found for tire forces and brake torques. This pattern is in a good agreement with a car which has a front-wheel drive layout. We also observed a good agreement between the brake torques and the engine rotation speed and the forces. Whenever a torque applied on the brake, the engine rotation speed starts to reduce and force peaks also appear. We indicated a representative example by the vertical dashed lines in Figure 2.

V. Experimental results and discussions

A. Component damage percentage

In order to use the S-N curve to compute damage of springs, we need to convert force F to stress τ. It can be done by using the following equation [18]:

$$\tau = K\frac{8 \times F \times D_{coil}}{\pi \times d_{wire}^3} \tag{15}$$

where D_{coil} and d_{wire} are the diameter of the mean coil and the wire, respectively. $C = D_{coil}/d_{wire}$ is the spring index. $K = 1 + 0.5/C$ is so called the Wahl factor. The spring lifetime strongly depends on these parameters. Following the work of Shevale et al. [18], the diameter of the coil is 88 mm in this paper. The wire diameter of the front springs and rear springs are 10.3 mm and 9.75 mm, respectively. Since the car model has a front-engine layout, front springs experience stronger forces

[1]https://research.fb.com/prophet-forecasting-at-scale/

[2]https://ipg-automotive.com/products-services/simulation-software/carmaker/driver

[3]https://data.cityofnewyork.us/Transportation/2015-Green-Taxi-Trip-Data/gi8d-wdg5/data

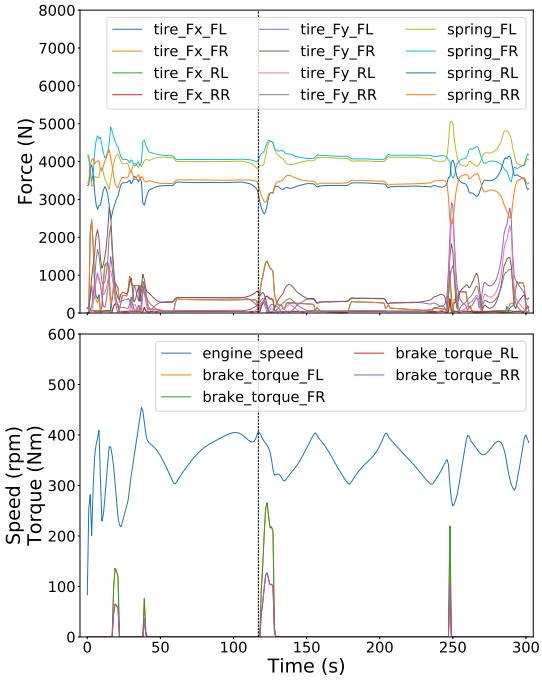

Fig. 2. Top: forces applied on springs and tires. Bottom: engine rotation speed, and brake torques. Vertical dash line indicates a time when a brake torque is applied and the engine rotation speed starts to reduce. FL, FR, RL, RR represent front left, front right, rear left, and rear right, respectively.

in comparison to the rear ones. Damage percentage of a spring is estimated using Eq. (1). In this calculation, the number of the stress cycles in each trip is counted using the Rainflow model [21]. The resulting damage percentage for all springs in all 4000 trips is shown in the inset of figure 3. The result shows that the distributions of the damage percentage of all springs look more or less similar; most of the trips have a damage percentage smaller than 0.05%. However, we also see that some trips result in a large damage percentage, which is an order of magnitude larger in comparison with the other one.

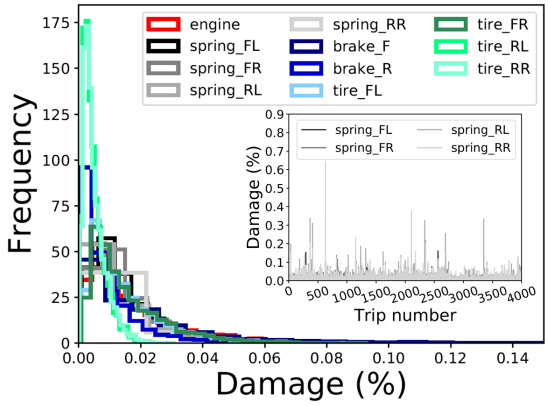

Fig. 3. Main: damage percentage histogram, inset: damage percentage of car springs in all trips

In order to compute damage of brake pads, we need to convert brake torque to brake force. Force is obtained by dividing torque by the length of the level arm. For a certain car, this length is fixed. Therefore, brake force depends linearly on the brake torque. By replacing brake force with brake torque in Eq. (4), damage percentage of the brake pads in each trip can be calculated by using Eq. (6). Where the relative displacement between the brake pads and the brake rotors depends linearly on the car braking distance. We use identical brake pads for all wheels. The brake constant in our calculation is $C_{brake} = 1.8 \times 10^{-5}$.

Damage percentage of tires is calculated directly from tire forces and travel distance using Eq. (7) and Eq. (8). We also use the same tires for all four wheels. In our work, the tire constant is $C_{tire} = 5 \times 10^{-8}$. Similarly, damage percentage of the car engine is calculated directly from the engine rotation speed and the travel distance using Eq. (9) and Eq. (10). In this

TABLE I
The prediction accuracies of all models on the test data set of all springs.

Methods	FL		FR		RL		RR	
	$R^2(\%)$	RMSE	$R^2(\%)$	RMSE	$R^2(\%)$	RMSE	$R^2(\%)$	RMSE
Polynomial	96	0.0027	93	0.0048	95	0.0076	93	0.0041
DT	95	0.0029	90	0.0057	92	0.0094	89	0.0097
RF	95	0.0029	86	0.0065	89	0.0107	88	0.0102
Lasso	93	0.00435	85	0.0068	71	0.0166	72	0.015
Ridge	93	0.00435	85	0.0067	71	0.0166	72	0.0149

calculation we use $C_{engine} = 10^{-7}$. Figure 3 shows the histogram of damage percentage of springs, brake pads, tires, and engine of the 4000 trips.

B. Damage prediction

We used machine learning technique to predict the damage percentage of springs of the car directly from the corresponding forces and the travel distance. For example, to predict the damage percentage of the front left spring, we used the front left force of the spring and the travel distance. From the force curve we created the following features: mean value, sum value, minimum value, maximum value, and number of peaks. A peak is defined as its value is either smaller than 0.95 or larger than 1.05 of the initial value. We first normalized the features then we divided the data set into a training set and a test set with a size of 75% and 25% of the sample population, respectively. Lasso, Ridge, polynomial, decision tree (DT) and random forest (RF) models from Scikit-learn module [27] were used to predict the damage percentage of all springs. For all models, the best hyperparameters were found by using a GridSearchCV technique[4]. A 10-fold cross-validation splitting strategy was used to train the model to minimize the learning bias. Then the models were used to predict the damage percentage on the test data set. We show the best prediction accuracies including R-square score (R^2) and the root mean squared error (RMSE) of all models achieved on the test data set of all springs in Table I. We observed that, for all springs, a fourth polynomial model gave us the best prediction accuracies. It follows by the two decision-tree based machine learning algorithms such as decision tree and random forest. The two linear regression models(Lasso and Ridge) gave us the lowest prediction scores. In addition, for all models, the prediction on the front left spring gave us the best scores. We attribute this highest prediction scores to the lowest variance of the forces on the left spring. In our simulation the driver position was front left and the driver was unchanged. In contrast, each trip, random loads were added to the other positions. Therefore, the standard deviation of the damage percentage is expected to be lowest on the front left spring. Indeed, it is confirmed by the data. The standard deviation of the damage percentage of the front left spring is 0.0105, while these of the front right, the rear left and the rear right springs are 0.0113, 0.0196 and 0.0197, respectively.

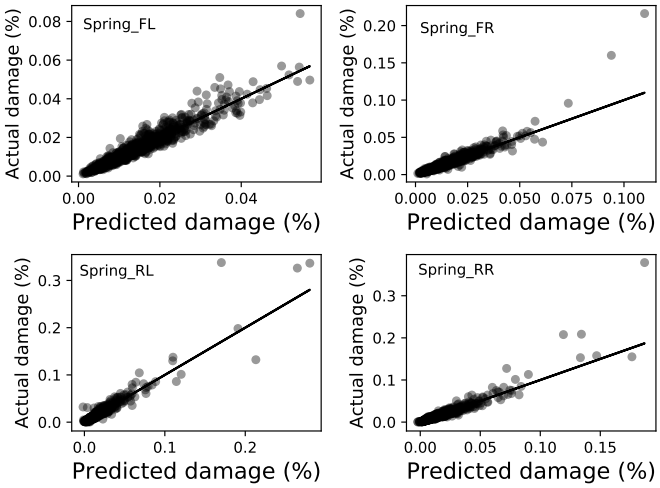

Fig. 4. Comparison of actual spring damage (dots) and prediction spring damage (solid lines) using a fourth degree polynomial model

Figure 4 shows a comparison of the actual damage of springs to the prediction value that comes from the best model. We observed that, except for some outliers, the predicted damage is in a good agreement with the actual damage. We attribute

[4]https://scikit-learn.org/stable/modules/generated/sklearn.model$_s election.GridSearchCV.html$

these outliers to rare events. In some rare occasions, a car might run over a big obstacle resulting a large damage on the springs. An accurate prediction of outliers and rare events is a big challenge in machine learning.

We used the fourth degree polynomial model to predict the damage percentage of brake pads, tires, and engine. In all cases,the model gave us $R^2 \geq 99\%$ on the test data set. The prediction accuracies of these components are much better than that of the springs. This is because the physics-based model for the damage percentage of the springs has the highest complexity. We did not try any other algorithm to predict the damage percentage of brake pads, tires, and engine, considering high prediction accuracies of a fourth degree polynomial model.

C. Remaining useful lifetime simulation

Estimating the RUL is the heart of any PHM system. We used Eq. (12) to compute the RUL of springs, brake pads, tires, and engine for each car in the car fleet. Its confidence interval was estimated by using Eq. (13) and Eq. (14). We show the simulation results of the RUL of a representative car in figure 5. The solid lines indicate the mean values while the shade areas represent for the confidence intervals. For all components, we observe a large fluctuation of the RUL in the first few weeks. It is because of a high fluctuation of the mean damage value (D/w) of all weeks during a short period. The fluctuation becomes smaller with increasing of the simulation time. After about 10 weeks, for all components, the RUL decreases more or less linearly with time.

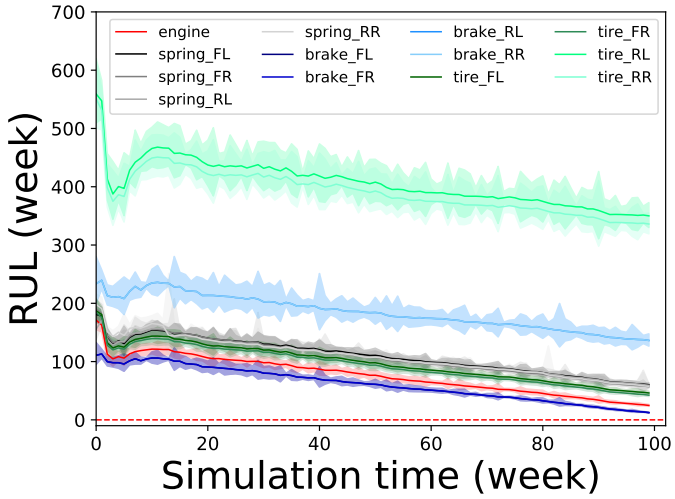

Fig. 5. Simulated remaining useful lifetime of car's engine, springs, brake pads, and tires.

In our simulation, we intended to select parameters so that the car engine needs a major maintenance with a frequency of about two years. To balance the RUL of the front and rear springs, we used large springs in the front wheels and small springs in the rear wheels. In contrast, we used the same tires, and brake pads for all wheels. Our simulation results show that, for tires and brake pads, the lifetime of the front components is much shorter than that of the rear ones. It is consistent with a car that has a front-engine and front-wheel layout. In reality, in comparison with the rear brake pads, the front brake pads are normally thicker. In addition, car experts recommend rotating the car wheels every oil change or every 5,000 to 7,500 miles to balance the lifetime of the car tires[5]. Lastly, we note that the two front brake pads have an almost identical RUL curve, because they experience the same force. A similar observation is found for the rear brake pads.

We show the histogram of the RUL of the engine, the front and rear brake pads, the springs, and the tires of the four wheels after simulating 95 weeks of a car fleet that has 200 cars in figure 6. In all cases, we observe a Gaussian distribution of the histogram.

D. Future remaining useful lifetime forecasting

We used the simulation result of the RUL of the car fleet as historical data to forecast the future remaining useful lifetime. Data from week 10 to week 99 was selected to train our prediction model since it shows a clear trend. The first data point was set to October the 1st, 2017. Prophet forecasting model was used in our work because of its simplicity. Seasonality and holidays parameters were set to False, while other parameters were kept as default values. We compare the forecasting results with the actual values of RUL of a representative car in figure 7. The vertical dashed line divides the graph into two parts. The left hand side of the vertical dashed line shows the historical data (dots) and the model fitting values (solid lines). We see that

[5]https://cars.usnews.com/cars-trucks/how-often-should-you-rotate-your-tires

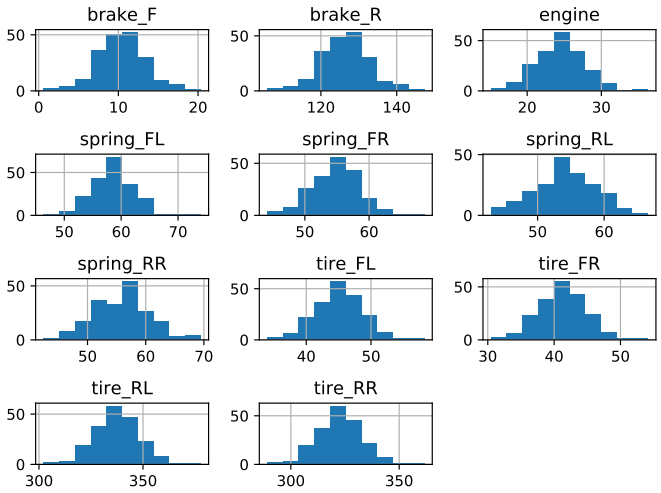

Fig. 6. RUL histogram of the engine, the front (F) and the rear (R) brake pads, the springs, and the tires of the four wheels after 95 weeks of simulated usage of a car fleet that has 200 cars.

the fitting values are in very good agreement with the actual values. In contrast, the right hand side of the vertical dashed line shows the forecasted future RUL. The solid lines represent for the mean values, while the shade areas show the forecasting confidence intervals. As expected, the mean forecasting RUL curves follow a linear trend and the confidence intervals broaden with time.

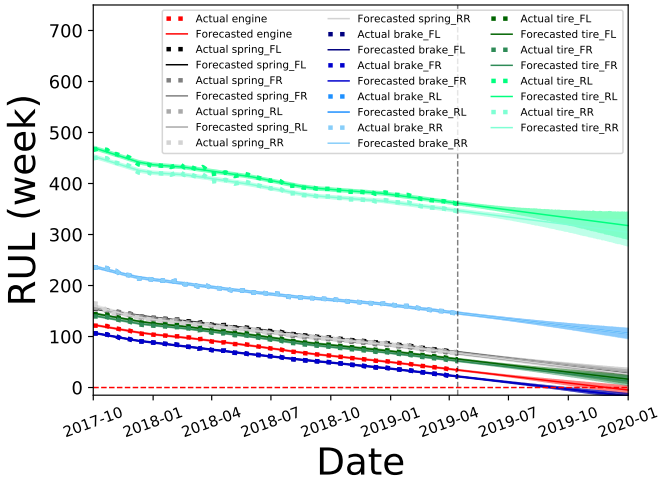

Fig. 7. Forecast remaining useful lifetime of car's engine, springs, brake pads, and tires.

VI. Conclusions

In this paper, we used physics-based approaches to estimate damage percentage of four essential components of a passenger car, namely engine, brake pads, springs, and tires. We then used the fourth-degree polynomial model to predict the damage percentage based on the car travel distance, the mean-, the sum-, the maximum-, the minimum values and the number of peaks of the corresponding sensor data. For all components, the prediction results were in very good agreement with the actual damage percentages.

For car springs, besides the fourth-degree polynomial model, we also used different machine learning algorithms such as Lasso, Ridge, decision tree, and random forest. For all springs, the fourth-degree model gave us the best prediction scores. It follows by the decision-tree and random forest models. The two linear regression models (Lasso and Ridge) gave us the lowest prediction scores. We note that, all models showed the best prediction performance on the front left spring due to the lowest damage uncertainties.

In addition, we showed a modelling method to generate a data set of RUL of the above-mentioned components of a car fleet. In our simulation, the actual RUL was computed directly from the actual damage percentages. We then used the actual RUL to forecast the future RUL using the Prophet model. We found a consistence between the actual RUL and the forecasted values.

As described above, in this work, we combined physics-based methods and data-driven methods to predict the damage percentage and forecast the RUL. Our method can be considered as a hybrid framework for simulating the RUL of a car fleet. We are going to use this hybrid framework to develop a dynamic optimization maintenance scheduling platform for a car fleet. Our platform will serve as a theoretical optimization maintenance scheduling framework for a health management system of a car fleet. This framework has a potential application in the real-world industry. For example, it can be used as a standard platform to optimize the maintenance scheduling of a car fleet of a taxi company.

ACKNOWLEDGMENT

This work is part of the research programme Smart Industry SI2016 with project name CIMPLO and project number 15465, which is partly financed by the Netherlands Organisation for Scientific Research (NWO).

REFERENCES

[1] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation A review on the statistical data driven approaches," *European Journal of Operational Research*, vol. 213, pp. 1–14, Aug. 2011.
[2] G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, and B. Wu, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems: Vachtsevanos/Intelligent Fault Diagnosis*. Hoboken, NJ, USA: John Wiley & Sons, Inc., Sept. 2006.
[3] Z. Wang, C. Hu, W. Wang, Z. Zhou, and X. Si, "A case study of remaining storage life prediction using stochastic filtering with the influence of condition monitoring," *Reliability Engineering and System Safety*, vol. 132, pp. 186–195, 2014.
[4] H. M. Elattar, H. K. Elminir, and A. M. Riad, "Prognostics: a literature review," *Complex & Intelligent Systems*, vol. 2, pp. 125–154, June 2016.
[5] J. Sikorska, M. Hodkiewicz, and L. Ma, "Prognostic modelling options for remaining useful life estimation by industry," *Mechanical Systems and Signal Processing*, vol. 25, no. 5, pp. 1803–1836, 2011.
[6] K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang, "Prognostics and Health Management: A Review on Data Driven Approaches," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–17, 2015.
[7] T. Sutharssan, S. Stoyanov, C. Bailey, and C. Yin, "Prognostic and health management for engineering systems: a review of the data-driven approach and algorithms," *The Journal of Engineering*, vol. 2015, pp. 215–222, July 2015.
[8] Z. Zhao, B. Liang, X. Wang, and W. Lu, "Remaining useful life prediction of aircraft engine based on degradation pattern learning," *Reliability Engineering and System Safety*, vol. 164, pp. 74 – 83, 2017.
[9] J. B. Alia, B. Chebel-Morello, L. Saidi, S. Malinowski, and F. Fnaiech, "Accurate bearing remaining useful life prediction based on weibull distribution and artificial neural network," *Mech Syst Signal Process*, pp. 150–172, 2015.
[10] W. He, N. Williard, C. Chen, and M. Pecht, "State of charge estimation for li-ion batteries using neural network modeling and unscented kalman filter-based error cancellation," *International Journal of Electrical Power and Energy Systems*, vol. 62, pp. 783 – 791, 2014.
[11] P. Baraldi, M. Compare, S. Sauco, and E. Zio, "Ensemble neural network-based particle filtering for prognostics," *Mechanical Systems and Signal Processing*, vol. 41, no. 1, pp. 288 – 300, 2013.
[12] A. K. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing*, vol. 20, pp. 1483–1510, Oct. 2006.
[13] J. Jeong, N. Kim, W. Lim, Y.-I. Park, S. W. Cha, and M. E. Jang, "Optimization of power management among an engine, battery and ultra-capacitor for a series HEV: A dynamic programming application," *International Journal of Automotive Technology*, vol. 18, pp. 891–900, Oct. 2017.
[14] W. Fleming, "Overview of automotive sensors," *IEEE Sensors Journal*, vol. 1, pp. 296–308, Dec. 2001.
[15] T. Tinga, *Springer Series in Reliability Engineering*. London, Heidelberg, New York, Dordrecht: Springer, 2013.
[16] M. Pecht and Jie Gu, "Physics-of-failure-based prognostics for electronic products," *Transactions of the Institute of Measurement and Control*, vol. 31, pp. 309–322, June 2009.
[17] E. S. Dishant, Er.Parminder Singh, "Suspension systems: A review," *International Research Journal of Engineering and Technology (IRJET)*, Apr. 2017.
[18] D. V. Shevale and N. D. Khaire, "Review on failure analysis of helical compression spring," *International Journal of Science, Engineering and Technology Research*, vol. 5, pp. 892–898, 2016.
[19] K. Sobczyk and B. Spencer, *Random Fatigue: From Data to Theory.* San Diego, USA: San Diego, CA: Academic, 1993.
[20] M. Miner, "Cumulative damage in fatigue," *Journal of Applied Mechanics*, vol. 12, pp. A159–A164, 1945.
[21] M. Matsuishi and T. Endo, "Fatigue of metals subjected to varying stress," *Japan Soc. Mech. Engineering*, 1968.
[22] Y. A. Golubev, "Theoretical and experimental procedure for determining the service life of automotive brake linings," *Journal of Friction and Wear*, vol. 30, pp. 337–340, Oct. 2009.
[23] Y. A. Golubev and V. V. Ivanenko, "A calculation method of energy intensity of brake lining wear as related to temperature," *Journal of Friction and Wear*, vol. 30, pp. 258–260, Aug. 2009.
[24] J. L. M. Saboia, "Autoregressive integrated moving average (arima) models for birth forecasting," *Journal of the American Statistical Association*, vol. 72, no. 358, pp. 264–270, 1977.
[25] A. Subashini, K. Sandhiya, S. Saranya, and U. Harsha, "Forecasting Website Traffic Using Prophet Time Series Model," p. 8.
[26] C. Chatfield, "The Holt-Winters Forecasting Procedure," *Applied Statistics*, vol. 27, no. 3, p. 264, 1978.
[27] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, and D. Cournapeau, "Scikit-learn: Machine Learning in Python," *MACHINE LEARNING IN PYTHON*, p. 6.