Vehicle Health Monitoring for Driving Safety using Co-simulation between Dymola and Simulink

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Abstract

A vehicle dynamics model-based health monitoring process is presented to enhance driving safety. The vehicle model can simulate driving by reflecting degradation performance of suspension and tires. The model was developed using Dymola, and driving simulation was performed by integrating the lane keeping assistant system with the vehicle model using Simulink. The degradation behavior was monitored with *k*-nearest neighbor and Gaussian mixture model. The remaining useful life for vehicle components was predicted using Gaussian process regression. The proposed method predicts remaining useful life with a 95% confidence level for vehicle components to improve safety for driving.

Keywords: Vehicle Health Monitoring, Lane Keeping Assistant System, Prognostics and Health Management, Anomaly Detection, Remaining Useful Life

1 Introduction

As driving technology is gradually becoming automated, the functional safety of vehicle is becoming more important. The advanced driver assistance system (ADAS) assists the driver for convenient of driving. However, it is need for a technology to prevent risks caused by vehicle defects that may occur while driving.

Recently, prognostics and health management (PHM) technology for detecting defects in vehicle parts and predicting lifetime has been applied. PHM is an engineering approach that enables real-time health assessment of a system under its actual operating conditions, as well as the prediction of its future state based on up-to-date information, by incorporating various disciplines including sensing technologies, physics of failure, machine learning, modern statics, and reliability engineering. It enables engineers to turn data and health states into information that will improve our knowledge on the system and provide a strategy to maintain the system in its originally intended function. While PHM has roots from the aerospace industry, it is now explored in many applications including manufacturing, automotive, railway, energy and heavy industry (Kim et al., 2017; Sankararaman and Goebel, 2015).

In the automotive area, it is possible to provide vehicle state information to the driver and the maintenance company. This ensures vehicle maintenance efficiency and driving safety. It is necessary to obtain degradation data of components by monitoring the vehicle state. However, it takes a significant amount of time to obtain the degradation data.

This study proposes a vehicle dynamics model-based PHM process. The vehicle modeling, including degradation of suspension and tires, was performed using Dymola. The driving simulation was performed by integrating the lane keeping assistant system (LKAS) with the vehicle model using Simulink. The vehicle model was imported in the Simulink environment using functional mock-up interface (FMI). The LKAS is a control system that aids a driver in maintaining safe travel within a marked lane of a highway. Simulation data-based machine learning was used to determine normal/abnormal vehicle states and to assess the lifetime for vehicle components as shown in Figure 1.

The remainder of this paper is organized as follows. Section 2 explains the degradation modeling for vehicle components and the co-simulation process between Dymola and Simulink. Section 3 explains machine learning algorithms used for vehicle states and lifetime assessment. Finally, Section 4 concludes the study and discusses future study plans.

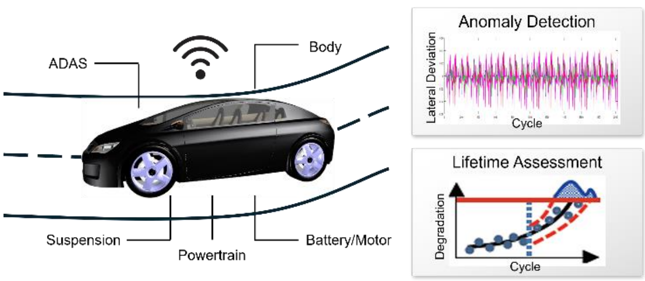


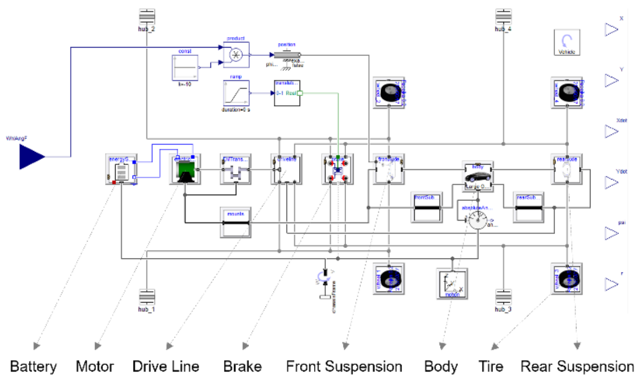
Figure 1. Virtual driving simulation-based vehicle health monitoring.

2 Virtual Driving Simulation

2.1 Vehicle Modeling

The vehicle model was developed using components from Claytex and vehicle systems modelling and analysis (VeSyMA) libraries in Dymola (Deuring et al., 2011; Yoo et al., 2018). The model was comprised of subsystems for vehicle body, suspension, driveline, electric motor, battery, brake, and tires as shown in Figure 2.

The front suspension was designed with a MacPherson strut suspension. The rear suspension was designed with an integral link suspension. The suspension blocks included shock absorber, rubber bush and stabilizer bar components. The tires were designed with 215/50R17 Pacejka model. The electric motor was designed with an AC induction motor on the front wheel, and the maximum torque of the motor was 350 Nm. The battery was designed with a 240 V voltage and 85.5 kWh capacity.



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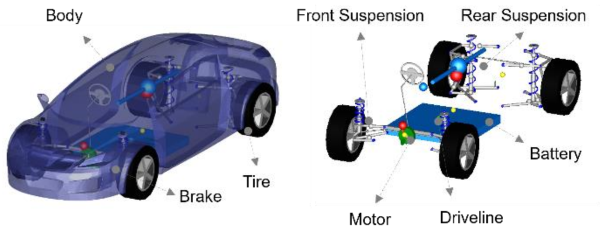

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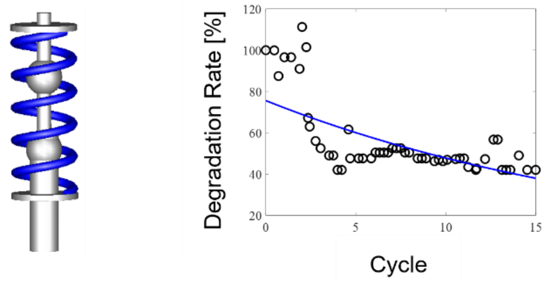
Figure 2. Vehicle model developed using components from Claytex and VeSyMA libraries: (a) graphics and (b) animation views.

2.2 Degradation Modeling

The shock absorber, rubber bush, and tire models were developed for degradation simulation of vehicle driving. The degradation rates for shock absorber damping, rubber bush stiffness, and tire friction coefficients were reflected in the models as shown in Figure 3. As the cycle increases, the degradation rates of the damping and friction coefficients decrease, but the stiffness increases.



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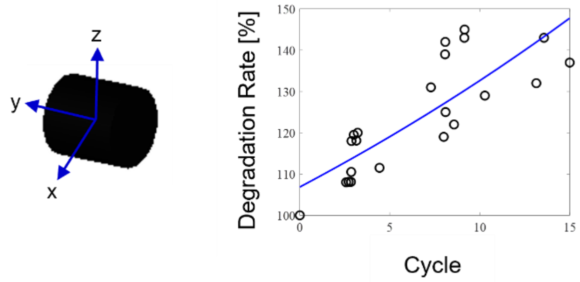

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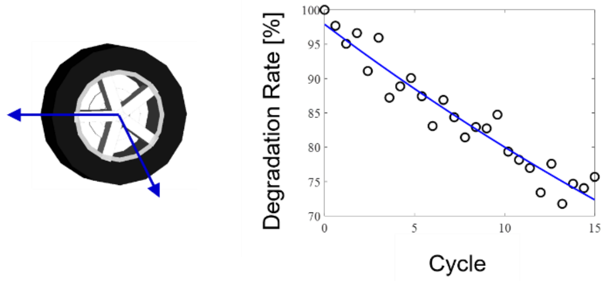

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Figure 3. Degradation models: (a) shock absorber damping, (b) rubber bush stiffness and (c) tire friction coefficients.

The degradation rate data were converted into exponential functions and reflected in the components as shown in Listing 1. D_damping is shock absorber damping. D_stiffness is rubber bush stiffness. D_friction is tire friction coefficient. Param1 and Param2 are coefficients of exponential function.

Listing 1. Degradation equations

```
equation
D_damping=Param2_damping*exp(Param1_damping*cycle) ;

equation
D_stiffness=Param2_stiffness*exp(Param1_stiffness*cycle) ;

equation
D_friction=Param2_friction*exp(Param1_friction*cycle) ;
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2.3 FMI-based Co-simulation

The vehicle model was converted to functional mock-up unit (FMU) to co-simulate with LKAS in Simulink as shown in Figure 4. The input ports of the FMU are steering angle and longitudinal velocity. The output ports are longitudinal position, lateral position, longitudinal velocity, lateral velocity, yaw angle, and yaw rate.

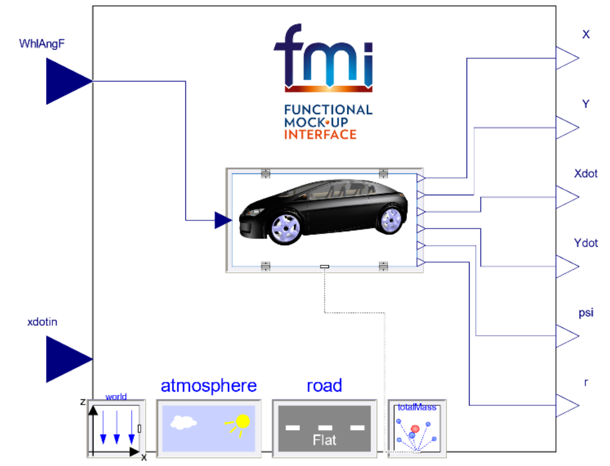
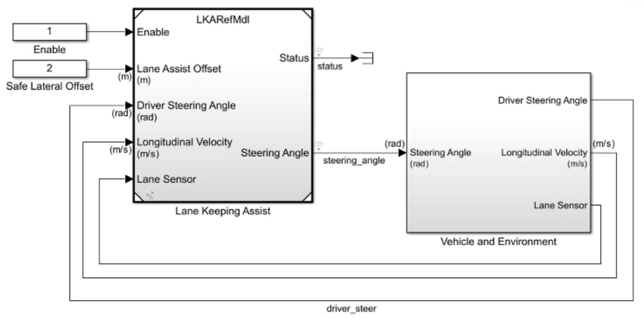


Figure 4. Vehicle model converted to FMU.

The LKAS (Lee et al., 2014) detects when the vehicle deviates from a lane and automatically adjusts the steering to restore proper travel inside the lane without additional input from the driver. The LKAS was constructed as shown in Figure 5.



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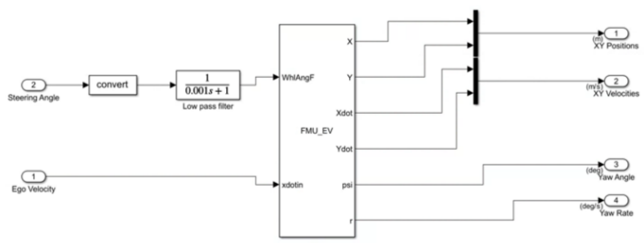

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Figure 5. LKAS in Simulink: (a) LKAS blocks and (b) vehicle dynamics block imported with FMU.

The lane keeping assist block contains lane center estimation, lane keeping controller, lane departure detection, and assist blocks. The lane center estimation block outputs the data from lane sensors to the lane keeping controller. The goal for the lane keeping controller block is to keep the vehicle in its lane and follow the curved road by controlling the front steering angle. The lane departure detection block outputs a signal that is true when the vehicle is too close to a detected lane. The assist block decides if the lane keeping controller or the driver takes control of the vehicle. The switch to assisted steering is initiated when a lane departure is detected.

The vehicle and environment block contains vehicle dynamics, scenario reader, vision detection generator, and driver blocks. The vehicle dynamics block includes the vehicle model converted to FMU. The input and output ports of the block are the same as the FMU. The scenario reader block generates the ideal left and right lane boundaries based on the position of the vehicle with respect to the scenario. The vision detection generator block takes the ideal lane boundaries from the scenario reader block. The driver block generates the driver steering angle based on the driver path.

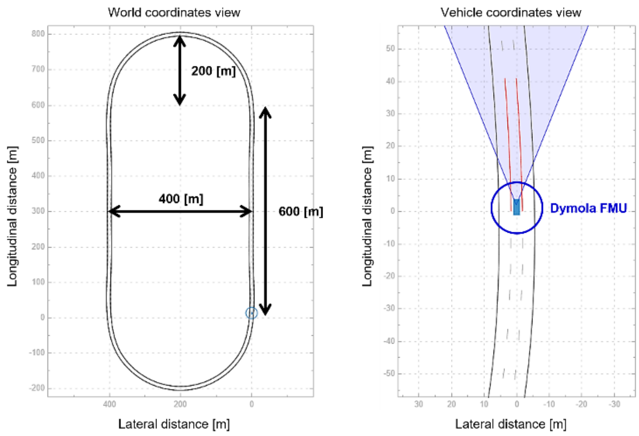


Figure 6. Driving road view.

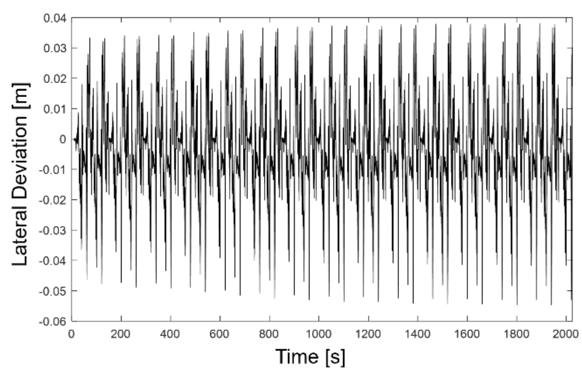


Figure 7. Lateral deviation between road centerline and vehicle for 15 laps of driving.

The driving road was designed with elliptical type as shown in Figure 6. The initial vehicle speed was 15 km/h. It was increased to 60 km/h within 15 seconds, after which it ran 15 laps while remaining constant. The lateral safety distance of the LKAS was set to 1 meter. Figure 7 shows the lateral deviation between road centerline and vehicle for 15 laps of driving. The smaller lateral deviation means better driving safety. However, the lateral deviation increased due to degradation of vehicle components.

3 Vehicle Health Monitoring

3.1 Feature Extraction

The feature extraction was performed to analyze the lateral deviation data. It refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. The eight features were extracted from the lateral deviation data as shown in Figure 8. The features were mean, max, root mean square, skewness, kurtosis, crest factor, impulse factor, and shape factor. It is important to find an effective factor that has consistent tendency to increase or decrease in proportion to vehicle mileage.

Principal component analysis (PCA) was performed for eight features as shown in Figure 9. It is a dimensionality reduction method used to simplify a large data set into a smaller set while still maintaining significant patterns and trends. The data is linearly transformed onto a new coordinate system such that the directions capturing the largest variation in the data can be easily identified. The first principal component is the direction in space along which the data points have the highest or most variance. The larger the variability captured in the first component, the larger the information retained from the original dataset. The second principal component accounts for the next highest variance in the dataset and must be uncorrelated with first principal component. The third principal component is the same way.

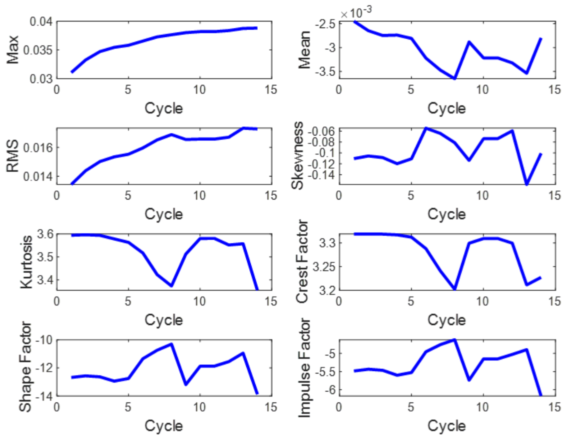


Figure 8. The eight features of lateral deviation data.

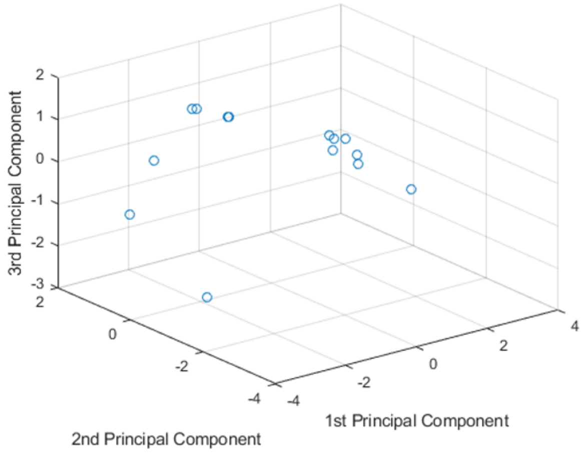
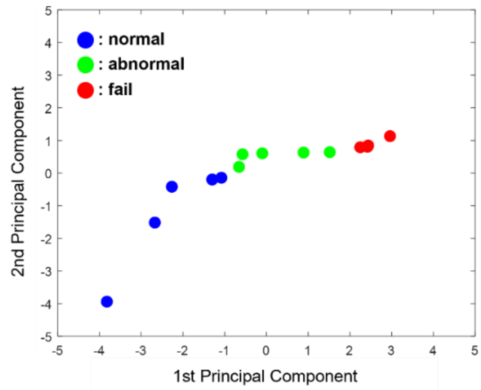


Figure 9. PCA for eight features.

3.2 Anomaly Detection

The lateral deviation data were classified into normal, abnormal, and failure states using machine learning algorithms as shown in Figure 10.



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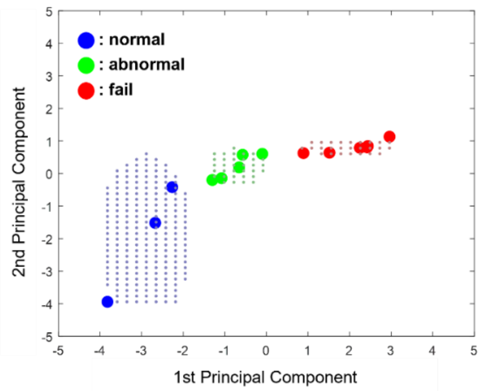

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Figure 10. Classifiers of normal and abnormal: (a) k-NN and (b) GMM.

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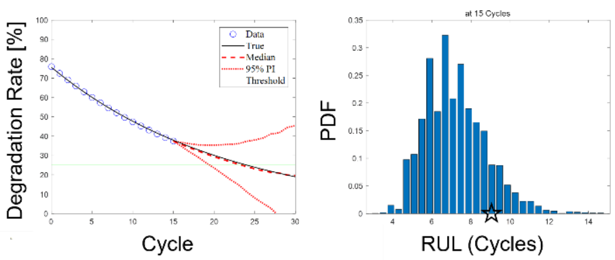
The *k*-nearest neighbor (*k*-NN) is a non-parametric classification method (Cunningham and Delany, 2021). It tries to classify an unknown sample based on the known classification of its neighbors. If the classification of a sample is unknown, then it could be predicted by considering the classification of its nearest neighbor samples. Given an unknown sample and a training set, all the distances between the unknown sample and all the samples in the training set can be computed. The distance with the smallest value corresponds to the sample in the training set closest to the unknown sample. Therefore, the unknown sample may be classified based on the classification of this nearest neighbor. The *k* was set to three for the classification of normal, abnormal, and failure for driving performance.
The Gaussian mixture model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities (Reynolds, 2009). The GMM parameters are estimated from training data using the maximum a posteriori estimation from a well-trained prior model.

3.3 Lifetime Assessment for Components

The lifetime of shock absorber, rubber bush, and tire was assessed using Gaussian process (GP) regression. The GP regression (Schulz et al., 2018) is one of regression-based methods used for data-driven prognostics, which is a linear regression like the least squares method. The difference between GP and ordinary linear regression is whether the correlation in errors between a regression function and data are considered or not. It is assumed that errors are independent and identically distributed in the ordinary linear regression, while they are assumed to be correlated in GP.
As the results, the degradation and remaining useful life (RUL) are predicted as shown in Figure 11. The data point means the average value of degradation datasets, and the true line (i.e., solid line) is a fitting curve for actual degradation data. The median line and the 95% prediction interval (PI) line (i.e., dotted line) are the probabilistic results predicted using the GP regression.
Table 1 shows the percentiles of RUL distribution. It can be confirmed that the 95% PI of the predicted RUL distribution of each degradation component was satisfied with respect to the actual RUL value.



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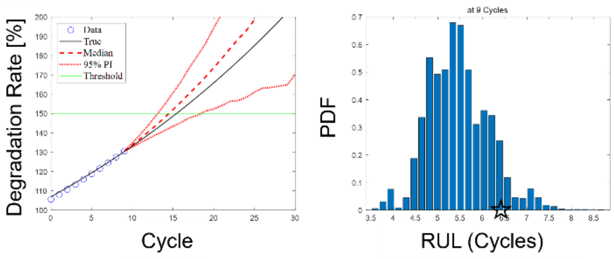

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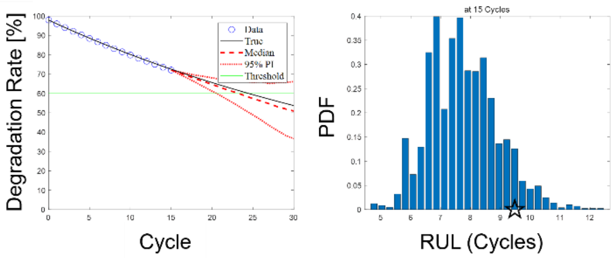

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Figure 11. GP prediction results: (a) shock absorber, (b) rubber bush, and (c) tire.

Table 1. Percentiles of RUL distribution.

Component	True	Estimation	95% PI
Damper	9.04	6.97	4.76~10.69
Bush	6.42	5.41	4.33~7.03
Tire	9.48	7.67	5.77~10.26

4 Conclusions

The health monitoring process using virtual driving simulation based on a vehicle dynamics model was proposed. It takes a significant amount of time to obtain the actual degradation data. To solve this problem, degradation data was obtained using co-simulation between Dymola and Simulink, and anomaly detection and lifetime assessment based on machine learning algorithms were performed. The main results are as follows:

- The virtual driving simulation involving degradation of vehicle components was constructed using Dymola and Simulink.
- The degradation behavior was monitored with *k*-NN and GMM.
- The GP regression predicted RUL with a 95% confidence level for vehicle components to improve safety for driving.

The future study plan is to construct vehicle health monitoring system using virtual driving simulation for battery degradation.

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