A Fleet-Based Machine Learning Approach for Automatic Detection of Deviations between Measurements and Reality.

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Abstract

Deviations between system current measurements and reality can cause severe problems in the power train of electric vehicles (EVs) like inaccurate performance coordination and unnecessary power limitations. In this work, we propose a fleet-based framework to detect such deviations. Our main assumption is that the real value is the mean of all identically constructed EVs' measurements for the same input. Under this assumption, we train individual on-board models to predict the current of the electric machine (EM) and transmit the model parameters to a back-end. There, we compare individual deviations of the predicted current against the fleet in the same scenario. We use the results to classify three fault sources. As models we choose two different Machine Learning algorithms: State Models and Long Short-Term Memory Neural Networks (LSTMs). These are evaluated on an artificial fleet of 34 EVs derived from real drive data containing three different kinds of faults. Results show that our proposed approach correctly classifies major measurement faults. LSTMs are more accurate, whereas state models are less computationally complex, and thus better suited for electronic control units (ECUs).

Motivation

Fig. 1. Electric currents of all HV components in an EV on a test drive. The sum of all currents i_{sum} , which should be constantly 0 according to Kirchhoff's current law, is plotted in black.

Objectives

- Detect deviations between measurements and reality.
- Automated.
 - With Machine Learning methods.
 - Without additional calibration effort.
- Close to series development.
 - Only with data available in production vehicles.
 - Without additional sensors.
 - Efficient and executable on ECUs.

Problem

Fig. 2. If we have two different measurement signals describing the same situation, how can we detect the real values?

Idea

Fig. 3. If we take as many equally constructed EVs as possible, the mean of all measurements tends towards the true value.

Concept

Fig. 4. The classification in the deviation chart is done as follows:
I: Battery measurement fault. II: EM measurement fault.
III: Healthy. IV: Hardware fault.

Models

For the measurement model, we compare two classes of algorithms.

State Models:

$$[A, B, C, D] = N4SID(u(t_0:t_{end}), y(t_0:t_{end})) [1]$$

Fig. 5. Structure of a State Model.

LSTMs:

Fig. 6a. Structure of an LSTM [2].

Fig. 6b. Structure of a neuron [2].

Results

Fig. 7a. Classifier results for our LSTM approach.

Fig. 7b. Classifier results for our State Model approach.

References

- [1] P. van Overschee and B. de Moor, "N4sid: Numerical algorithms for state space subspace system identification", *IFAC Proceedings Volumes*, vol. 26, no. 2, pp. 55–58, 1993.
- [2] P. Wolf, A. Mrowca, T. T. Nguyen, B. Baker, and S. Gunnemann, "Pre-ignition detection using deep neural networks: A step towards data-driven automotive diagnostics", in *IEEE 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 176–183.