

An e-Axle Loss Evaluation Method Using Continuous Measurement, Assuming Machine-Learning-Based Data Analysis

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Improving the energy efficiency of electric vehicles requires identifying vehicle energy losses on a factor-by-factor basis and reducing each of them. Vehicle energy loss is broadly divided into running resistance, e-Axle loss, and auxiliary consumption, and among these the e-Axle loss accounts for about 26% of the battery energy consumption during mode driving, making it one of the dominant factors. To reduce it, the e-Axle loss must be quantified accurately under on-vehicle conditions. However, the e-Axle loss has a multi-dimensional characteristic that varies continuously with several parameters such as gearbox oil temperature, voltage, rotational speed, and torque, so characterizing it accurately is difficult. In conventional measurement, these parameters are fixed and each operating point is measured one at a time, so obtaining loss data across many conditions requires an enormous number of measurement points and time. This study therefore proposes a method that, assuming machine-learning-based loss interpolation, integrates continuous measurement, in which the parameters are varied without being fixed and the loss is acquired together as multi-dimensional data, so that the vehicle-mounted e-Axle loss can be evaluated in a short period.

Here, the e-Axle loss is defined as the combined loss of the inverter, motor, and reduction gear, and is calculated from the difference between the e-Axle input, given by the product of the high-voltage battery voltage and the inverter input current, and its output, given by the product of the drive-shaft torque and rotational speed. The proposed method is an integrated process that combines a continuous-measurement experiment in which the parameters are varied continuously, construction of a machine-learning e-Axle loss estimation model, and generation of condition-specific loss maps by inputting the oil temperature and voltage within the measured range. In the measurement, rather than fixing the voltage and oil temperature as in the conventional approach, the sequence is designed in advance on the premise that both change during the experiment, and the voltage transition accompanying the SOC decrease is predicted beforehand. On this basis, each rotational-speed and torque operating point is traversed in turn while the voltage changes from high to low and the oil temperature from low to high, and only the steady portion excluding the transient immediately after switching is used as training data. Furthermore, by designing multiple measurement sets, nine in this study, with different start/end conditions, the entire oil-temperature and voltage range that a single experiment cannot cover is covered comprehensively.

Using the e-Axle loss as the objective variable and the high-voltage battery voltage, gearbox oil temperature, drive-shaft torque, and drive-shaft rotational speed as explanatory variables, multiple regression methods were compared by automated machine learning (AutoML) using 10-fold cross-validation, evaluated by the mean absolute error (MAE), root-mean-square error (RMSE), and coefficient of determination R^2 . The tree-based nonlinear methods all showed R^2 greater than 0.98, clearly outperforming the linear regressions (MAE $\approx$ 0.45, $R^2 = 0.78$ –0.80). Among them, the Extra Trees Regressor achieved the smallest error (MAE = 0.0473, RMSE = 0.0997) and the highest R^2 (0.9955); the Random Forest Regressor was almost equivalent (MAE = 0.0483, RMSE = 0.1017, $R^2 = 0.9953$) but was slightly surpassed by the Extra Trees Regressor on every metric. This is because linear models cannot capture the nonlinearity and parameter interactions of the loss, whereas tree-based methods represent them by recursively partitioning the input space. Since it gave the smallest validation errors (MAE, RMSE) and the highest R^2 among the candidates, the Extra Trees Regressor was selected as the final model.

The model achieved R^2 greater than 0.99 on the validation data, and a consumption simulation using the generated loss maps reproduced the load-dependent increase of e-Axle loss energy under all SOC and load conditions, with the driving range agreeing with the vehicle test within 1.57%. Hundreds of condition-specific maps were built in only about 15 working days—including experiment preparation through data processing—versus about 60 working days per map conventionally, greatly shortening the e-Axle loss evaluation. Improving accuracy in low-data-density regions remains a future task.

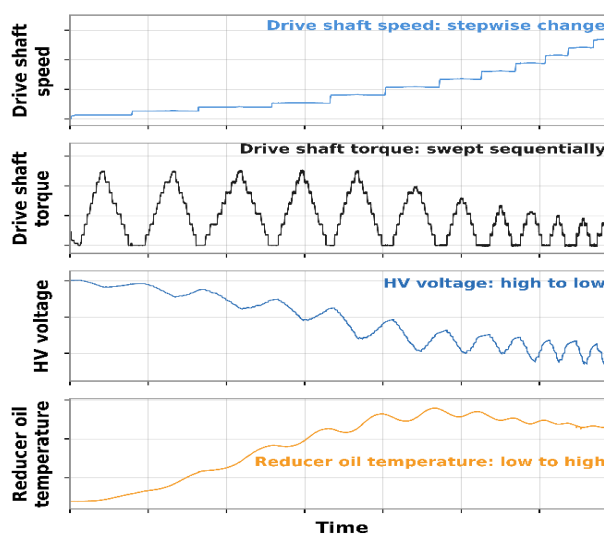


Fig.1 Time histories of parameters during one continuous measurement