On Suitability of the Customized Measuring Device for Electric Motor

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***Abstract*—Setting up a reliable electric propulsion system in the automotive domain calls for a smart condition monitoring device that is able to reliably assess the state and the health of the electric motor. To allow massive integration of such monitoring devices, it is required of them to be low-cost and miniature. Those requirements pose limitations on their accuracy, however, we show in this paper that those limitations can be significantly reduced by suitably processing the sensor data. We used machine learning models (random forest and XGBoost) to transform very noisy measurements of motor winding insulation resistance measured by a low-cost device to the much more reliable value with which we are able to compete with measurements made by the state-of-the-art high-priced measuring system. The proposed methodology represents a crucial building block in future smart condition monitoring system and enables low-cost and accurate assessment of electric motor health connected to the state of its winding insulation.**

***Index Terms*—Electric motors, Electrical resistance measurement, Insulation life, Machine learning**

I. Introduction

The ongoing evolution in road transport and automotive industry allows for the introduction of new technologies, such as in-wheel propulsion systems. Along with changing design and control possibilities and requirements, there is also a demand for increased durability and overall reliability on the system level.

For the in-wheel electric motor system to be massively deployed into electric vehicles, we need to demonstrate its reliability and introduce some technologies to further improve the system reliability and safety by developing a smart condition monitoring system that would increase the reliability of an in-wheel solution.

Based on data analysis, performed with the use of artificial intelligence (AI) algorithms, we can identify what are the critical parameters that impact the durability of motors. This serves as an input to a predictive condition monitoring system to be used in further applications with deployed self-healing algorithms where possible.

This will support the further deployment of innovative in-wheel technology by improving the system with a Smart condition monitoring module which will use state-of-the-art AI approaches to identify critical situations, perform predictive analysis and improve overall durability.

The core of the Smart condition monitoring system is the measurement device of the critical parameters. In order to have a small and low-cost measuring device, a customized device was developed to allow massive integration into the vehicles. While such a device is not state-of-the-art with respect to accuracy, we show in this paper that this accuracy gap can be closed and the accuracy of the device substantially improved by using proper AI-assisted signal processing. By using such methodology the measuring device is small and inexpensive, though fully reliable, and accurate.

Before the Smart condition monitoring system can be used, one needs to learn the insulation aging physics and understand the failure mechanisms and failure modes behind the insulation aging (and/or use AI methods instead). This was done by extensive measurements using a set of electric motors as device-under-test (DUT).

The aim of the paper is to present the suitability of the custom-made measuring device (in-house developed tool ICM) compared to the commercial one (off-the-shelf measuring device from Metrel) – which is used as a reference measurement device in the described use case (as a measurement standard). The work presented in this paper was done as part of the ECSEL JU project iRel40 [1].

The rest of the paper is organized as follows: Section II briefly describes the electric in-wheel motor and the measurement devices; Section III presents the methods used for regression-based predictions; Section IV draws the initial experimentation and results; and Section V summarizes the work and outlines some future steps.

The authors acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0098). This work is also part of a project that has received funding from the ECSEL Joint Undertaking under grant agreement No. 876659 (iRel40).

II. Description of the Measurement Devices

Device under test is an Elaphe L1500 liquid-cooled outer rotor synchronous motor with permanent magnets, designed as in-wheel solution for electric vehicles propulsion, intended for direct-drive applications with high torque requirements [2]. The winding is optimized for a wide operating range with respect to efficiency and speed of typical applications. At voltages different than nominal, the operating area is proportionally scaled to the voltage increase or decrease with respect to the nominal voltage of the given winding configuration. At voltages different than nominal, the speed of the motor will increase or decrease accordingly. Basic specifications of Elaphe L1500 motor are given in Table I [3].

TABLE I
Elaphe L1500 motor specifications.

Nominal supply voltage [V_{DC}]	370
Supply voltage [V_{DC}]	200 - 800
Max torque[1] [Nm]	1500
Max speed[2] [rpm]	1500

[1] At 200 rpm.
[2] With field weakening, 270 Nm load, and nominal supply voltage.

One of the critical parameters of the electric motor is the quality of its insulation (its state of health). The quality of the insulation is assessed by various insulation tests.

- Insulation resistance (IR) measurement is the simplest insulation test. After the test connections are made, the test voltage is applied for a period of time (e.g., one minute). The resistance should drop and remain steady during this period. The acceptable values of IR are learned by experience when measuring the IR on electric motors in service. The normal IRs are in the order of Giga Ohms, and the acceptable values reach down to the order of hundreds of mega Ohms.
- Dielectric absorption ratio (DAR) measurement is a more reliable insulation test. Good insulation shows increasing IR after the test voltage is applied. After the test connections are made, the test voltage is applied, and IR is measured at two different times (e.g., after 1 min and after 10 min). The quotient of the latter and the earlier IR measurement is DAR.

The durability measurement tests are performed in Elaphe environmental chamber where two motors are tested simultaneously. The duration of the test cycle is 30 minutes, after which the measurements are acquired using an ICM and Metrel device. To accelerate the aging of the motors two types of cycles are being repeated, where one cycle is run at a chamber temperature of approx. -30 °C, while the second cycle is run at a chamber temperature of approx. 85 °C.

To have data as realistic as possible the representative real-world usage (load) profiles are used. In our case, the WLTP (World harmonized Light-duty vehicles Test Procedure) driving cycles [4] were used, as standardized for the development of a vehicle and its components.

The main task after each test cycle is the set of measures to detect if a breakdown of the winding insulation or any other failure has occurred.

A. Metrel device

Since the insulation resistance is in the range of Giga Ohms, the insulation leakage current is very low and thus difficult to measure accurately. To increase the measurement accuracy, high voltage sources are used by megaohmmeters. In our study a Metrel megaohmmeter was used to measure insulation resistance as well as the dielectric absorption ratio. While megaohmmeters provide accurate results their cost is relatively high and special test arrangements must be provided hence they are difficult to be integrated into the vehicle.

In Table II, the measurement attributes of the Metrel device are reported. They consist of the temperature and humidity in the chamber at the time of the measurement, the motor temperature, the timestamp and the average measured resistance in GOhm.

TABLE II
Metrel measurements and their description.

Measurements	Description
Chamber temperature [°C]	Temperature in the chamber at the time of the measurement.
Chamber humidity [%]	Humidity in the chamber at the time of the measurement.
Motor temperature [°C]	Motor temperature at the time of the measurement.
Time [date]	Date/time of the measurement.
Ravg [GOhm]	Average measured resistance

B. ICM device

A low-cost impedance measurement circuit (ICM) for monitoring the insulation impedance was developed. It is based on the AD5934 high precision impedance converter system [5]. The AD5934 device consists of a frequency generator, 12-bit Analog-to-Digital Converter (ADC), Discrete Fourier Transform (DFT) engine, and I^2C communication interface. The frequency generator is a voltage source used to excite the insulation impedance with known frequencies. The receiving stage of the AD5934 device receives the current from the insulation impedance. It consists of an adjustable current-to-voltage amplifier, a programmable gain amplifier, an anti-aliasing filter, and 12-bit ADC. The digital data from ADC is passed to the DSP core and a DFT is calculated for each frequency. The results are passed to the micro-controller via I^2C interface. To extend the accurate impedance measurement to higher impedance [6], the voltage source is smoothed and boosted by a low-pass 2^{nd} degree Butterworth filter with a gain of 1.5 and cut-off frequency of 1.5 kHz. Similarly, on the receiving end, the current-to-voltage amplifier and signal amplifier is added to improve the sensitivity.

To measure the unknown impedance, first the system is calibrated using a known resistance. From a known resistance and a measured magnitude of the signal at given frequency a gain is determined. The unknown impedance is then determined using computed gain and the magnitude of the signal of the unknown impedance at the same frequency. Similarly, the phase is determined from the phases of the measurements of the calibration resistance and of the unknown impedance.

While the resistance measurement range of the developed circuit is at the boundary of the insulation resistance range, its cost is significantly lower than the cost of more precise megaohmmeters. Furthermore, it can be integrated into the vehicle which enables continuous monitoring.

In Table III, the measurement attributes of the ICM device are reported. In this case, like in Metrel measurements, the temperature and humidity in the chamber at the time of the measurement, the timestamp and the motor temperature are also reported. Moreover, the resistance, the capacitance and the dissipation factor are measured at 3 different frequencies (1, 1.5 and 2 Hz).

TABLE III
ICM MEASUREMENTS AND THEIR DESCRIPTION.

Measurements	Description
Chamber temperature [°C]	Temperature in the chamber at the time of the measurement.
Chamber humidity [%]	Humidity in the chamber at the time of the measurement.
Motor temperature [°C]	Motor temperature at the time of the measurement.
Time [date]	Date/time of the measurement.
Resistance 1 Hz [MOhm]	Measured resistance at 1 Hz
Resistance 1.5 Hz [MOhm]	Measured resistance at 1.5 Hz
Resistance 2 Hz [MOhm]	Measured resistance at 2 Hz
Capacitance 1 Hz [nF]	Measured capacitance at 1 Hz
Capacitance 1.5 Hz [nF]	Measured capacitance at 1.5 Hz
Capacitance 2 Hz [nF]	Measured capacitance at 2 Hz
Dissipation factor 1 Hz	Measured dissipation factor at 1 Hz
Dissipation factor 1.5 Hz	Measured dissipation factor at 1.5 Hz
Dissipation factor 2 Hz	Measured dissipation factor at 2 Hz

III. METHOD

Because the winding insulation protect the motor from short circuit its resistance is very high and hard to measure. Both Metrel and ICM measurements have large noise levels and their values, due to temperature dependence, span over several orders of magnitude, which is depicted in Fig. 1 for Metrel case. When looking at only resistance there is no correlation between measurements of Metrel and ICM due to before mentioned noise (see Fig. 2). However, as we will show in this paper, if in addition other features measured by ICM are also considered it is possible to model resistance measured by Metrel to sufficient accuracy using machine learning.

A. Prototype Design

The basic overall design of the regression prototype is composed of

- Pre-processing: Algorithms that standardize the input data and perform data linkage.
- Learning regression model: Machine learning regression model trained on Metrel and ICM measurements with ICM measurements taken as features and Metrel resistance measurement as targets.
- Regression model: A model that is able to predict the Metrel resistance measurement value from ICM measurements.

Fig. 3 illustrates the aforementioned prototype.

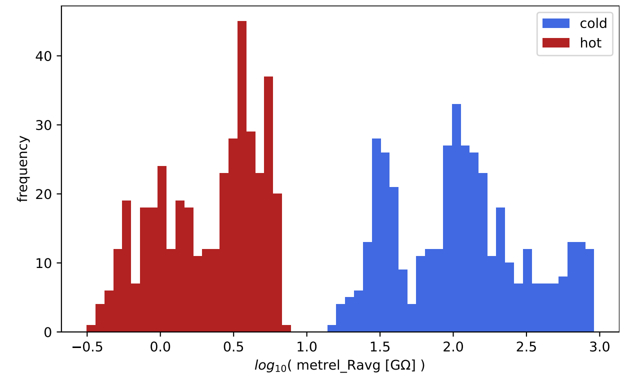

Fig. 1. Distributions of *metrel Ravg [GOhm]* in the cold and in the hot cycles. Due to fat-tailed distributions a logarithm of resistance is displayed.

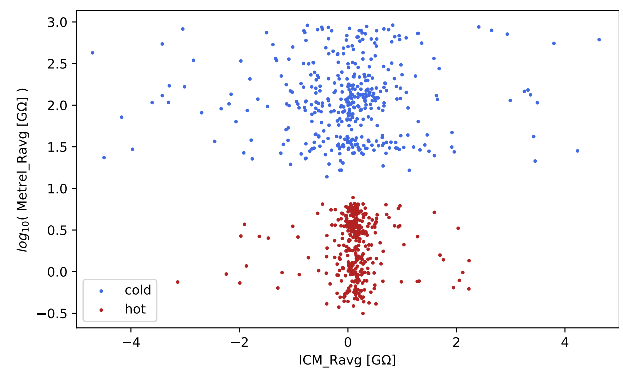

Fig. 2. Depiction of the noisiness and the absence of correlation between average resistance measured by ICM and Metrel.

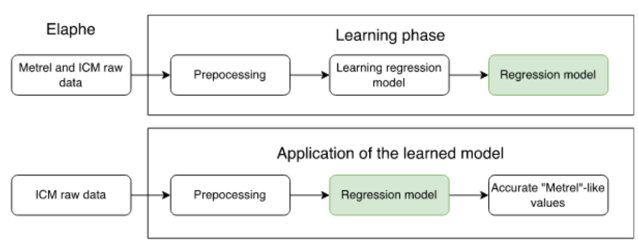

Fig. 3. Diagram of the basic design of the regression prototype.

B. Tested Predictive Algorithms

When mapping from ICM measurements to Metrel measurements we use the following models: *Random forest (RF)* [7] is a machine learning model where multiple simpler trees are built using bagging [8] and combined to form an ensemble learning model; *Extreme Gradient Boosting (XGBoost)* [9] employees a strategy of combining multiple weak learners (models that perform slightly better than random guessing), usually trees, to accurately predict a target variable. The model is trained using a modified version of gradient boosting [10]. Both of the aforementioned methods are common choices for tabular regression problems with low number of training examples [11], [12]. Finally, as a baseline, we are using mean (Mean) prediction where the mean value of the training set is used for all predictions.

To get a better understanding on how prediction models use the features to make the prediction we have applied a method that uses feature permutation to identify their importance. *Permutation feature importance* [13] is a method for evaluation feature importance based on the decrease in a model score when a single feature value is randomly shuffled. Shuffling one feature and observing how the performance of the model changes is indicative of how much the model depends on the shuffled feature. While such technique is a valuable tool when examining the link between model and features, one has to be aware of it downsides such as inability to properly assign importance for correlated feature and being dependant on the model loss function [14].

IV. Experimental environment

All the experiments are being performed in Python v3.10. For Random forest and mean approach we are using RandomForestRegressor and DummyRegressor from sklearn library, respectively. For Extreme Gradient Boosting we are using xgboost library. For all approaches default values were used, so no tuning was performed. Hyper-parameters are available in table IV.

TABLE IV
HYPER-PARAMETERS FOR LEARNING PREDICTION MODELS

Model	Parameter	Value
Random forest	number of trees	100
	bootstrap	true
	max depth	unlimited
XGBoost	learning rate	0.3
	max depth	6

Since the data consists of hot and cold cycles where the resistance/temperature values greatly differ, we have performed three experiments. In the first, we are evaluating the approaches on data from cold cycles only, in the second we are evaluating the approaches on data from hot cycles only, and in the last experiment data from combined cold and hot cycles was used for training the models.

To get a better understanding of the performance of the individual approach a k-fold cross validation was applied, where the data was split into k randomly split groups. This provides us with k different training/validation sets, where one group is in validation set while all the others are used for training the models. The average prediction performance on all folds can be then taken for comparison between approaches. In our experiments we used $k = 10$. Similarly, reported feature importance values are calculated on the validation set and averaged over all 10 folds.

A. Predictive performance results

This section analyzes the performance of different regression models for approximation of the METREL resistance based on ICM measurements. Experiments were conducted in hot and cold chamber environments. Therefore we evaluated the models on data gathered from the cold and hot cycles with 201 and 210 data instances, respectively. Lastly, we combined both cycles and try to model them together with a single regression model.

1) Cold cycles: Firstly we show the performance of the regression models when the motor is in a cold cycle. Figure 4 show the performance of selected regression models.

We can observe that due to the outliers, prediction errors can differ significantly between the folds.

When models are compared, the best performing model is random forest.

Table V describes the most important features. With respect to feature importance the temperature and humidity are the most relevant features that influence the performance of best performing model (i.e., random forest).

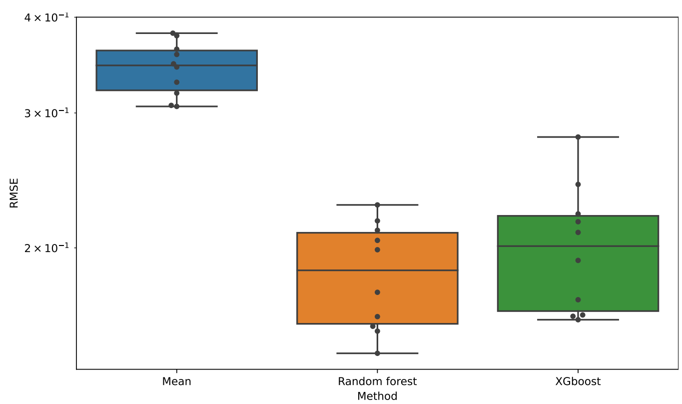

Fig. 4. Models prediction errors for cold cycle across all folds.

TABLE V
FEATURE IMPORTANCE OBTAINED WITH PERMUTATION FEATURE IMPORTANCE ON RANDOM FOREST MODEL TRAINED ON DATA FROM COLD CYCLES.

Feature name	Importance
icm_Motor temperature	0.472118
icm_Chamber humidity	0.1926
icm_Chamber temperature	0.11528
icm_Capacitance [nF] 2 Hz	0.040178
icm_Capacitance [nF] 1.5 Hz	0.030252
icm_Dissipation factor 1.5 Hz	0.018194
icm_Resistance[MOhm] 1 Hz	0.004818
icm_Resistance[MOhm] 1.5 Hz	0.00386
icm_Dissipation factor 2 Hz	0.000296
icm_Resistance[MOhm] 2 Hz	-0.000296
icm_Dissipation factor 1 Hz	-0.004851
icm_Capacitance [nF] 1 Hz	-0.004939

2) Hot cycles: Next, we show the performance of the regression models when the motor is in a hot cycle. Figure 5 show the performance of selected regression models.

Again we can observe that due to the outliers, prediction errors can differ significantly between the folds.

When models are compared, the best performing model is again the random forest. This results indicate that random forest seems to be the most suitable for predicting resistance in all three scenarios.

Table VI describes the most important features. With respect to feature importance again the temperature and humidity are the most relevant features that influence the performance of random forest model. Compared to model trained on cold cycles data, the chamber and motor temperature have now switched places in the feature importance table. We can not offer a definite explanation for this, however, we speculate that the most relevant feature for modeling is the temperature of the insulation which would be somewhere in between the chamber and motor temperature. It seems that in cold cycles insulation temperature correlates more with the motor temperature while in hot cycles it correlates more with the chamber temperature which makes sense when considering the heat transfer in both scenarios.

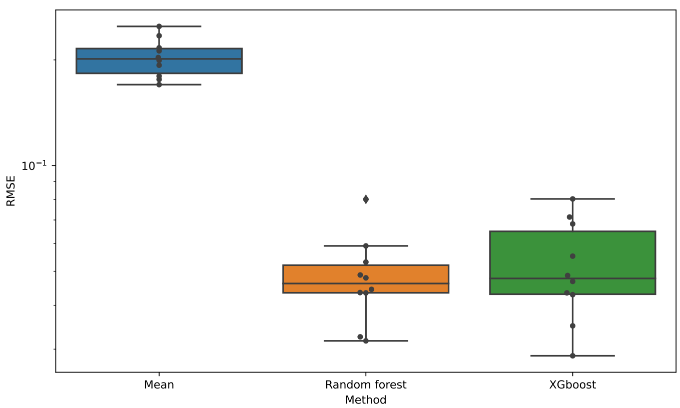

Fig. 5. Models prediction errors for hot cycle across all folds.

TABLE VI
FEATURE IMPORTANCE OBTAINED WITH PERMUTATION FEATURE IMPORTANCE ON RANDOM FOREST MODEL TRAINED ON DATA FROM HOT CYCLES.

Feature name	Importance
icm_Chamber temperature	1.546679
icm_Chamber humidity	0.065118
icm_Motor temperature	0.024514
icm_Resistance[MOhm] 1 Hz	0.002612
icm_Capacitance [nF] 2 Hz	0.002359
icm_Capacitance [nF] 1 Hz	0.001196
icm_Dissipation factor 1 Hz	0.001026
icm_Resistance[MOhm] 1.5 Hz	0.000838
icm_Capacitance [nF] 1.5 Hz	0.000194
icm_Dissipation factor 1.5 Hz	-0.000012
icm_Resistance[MOhm] 2 Hz	-0.000345
icm_Dissipation factor 2 Hz	-0.000519

3) Combined cold and hot cycles: Lastly, we show the performance of the regression models when the motor is in all combined cycles. Figure 6 show the performance of selected regression models.

We can observe that due to the outliers are relatively less noticeable with respect to prediction errors between the folds.

When models are compared, the performances of both random forest and XGBoost models are on average similar, but random forest seems more robust.

Table VII describes the most important features. Here again the temperature and humidity are the most relevant features that influence the performance of random forest model, however, the humidity is now at the top of the table. Since this is to some degree unexpected, this warrant further research with increased number of data instances to confirm or deny such indications.

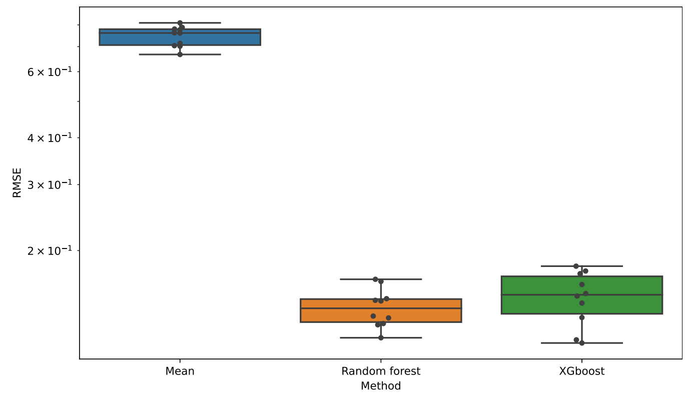

Fig. 6. Models prediction errors for combined cycles on all folds.

TABLE VII
FEATURE IMPORTANCE OBTAINED WITH PERMUTATION FEATURE IMPORTANCE ON RANDOM FOREST MODEL TRAINED ON DATA FROM COMBINED COLD AND HOT CYCLES.

Feature name	Importance
icm_Chamber humidity	0.923603
icm_Motor temperature	0.138452
icm_Chamber temperature	0.074186
icm_Capacitance [nF] 2 Hz	0.010004
icm_Capacitance [nF] 1.5 Hz	0.002758
icm_Dissipation factor 1.5 Hz	0.00239
icm_Resistance[MOhm] 1 Hz	0.000856
icm_Resistance[MOhm] 1.5 Hz	0.000486
icm_Dissipation factor 1 Hz	0.000124
icm_Dissipation factor 2 Hz	0.000026
icm_Resistance[MOhm] 2 Hz	-0.000139
icm_Capacitance [nF] 1 Hz	-0.000314

V. CONCLUSIONS AND FUTURE WORK

The described experiment is part of research that is a work in progress and is being continued. A set of electric motors as DUT have been tested (several series of measurement results have been gathered) in the harsh accelerated aging environment, electric motor exposed to high temperature, high load conditions. Two measurement devices have been used.

The first, an “off-the-shelf” commercial device (Metrel), is considered to be a reference one, having commercially declared accuracy and measurement uncertainty. It is an expensive instrument and not to be used as a “mobile” device. The second one is cheaper, proprietary ICM device, appropriate to be built in quantities and thereby affordable to be deployed into commercially available vehicles.

At first sight of the comparison between the two measurement devices appears to have little to no similarity due to the measuring resistance ranges. But, when applying the described AI algorithm a seemingly strong correlation can be observed though. The random forest algorithm was found to be the most accurate and robust for this task. The correlation indicates that the measurement results obtained using only the simpler, cheaper, and more mobile, of the two tested devices, could be used (after the AI learning phase) as a means for predicting the state of health of the electric motor insulation.

This implies the described methodology as a possible enabler of the future predictive maintenance functionality in electric vehicles - as a part of series equipment. And thus, contributing to a greater (and predictable) reliability of the propulsion system and vehicle.

For future work, much more data from the measuring devices needs to be collected, so the conclusions obtained from initial data instances used in the presented experiments can be validated and confirmed.

Acknowledgment

The authors acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0098 and young researcher grants). The work is also part of a project that has received funding from the ECSEL Joint Undertaking under grant agreement No 876659 (iRel40).

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