Machine Learning Engineer Nanodegree

Capstone Proposal

Niranjan P Salimath

July 14th, 2019

Proposal

Domain Background

In most automotive applications, a high power and torque density as well as efficiency is required for any given motor, which makes the permanent magnet synchronous machine (PMSM) the preferred choice. In order to exploit the machine's full capabilities, high thermal stress on the machine's potentially failing components must be taken into account. A sensor-based temperature measurement would yield rather precise knowledge regarding the machine's thermal state, yet for the rotor part, it is technically and economically infeasible due to an electric motor's sophisticated internal structure and the difficult accessibility of the rotor. Hence, direct rotor monitoring techniques such as infrared thermography [1], [2] or classic thermocouples with shaft-mounted slip-rings [3] fall short of entering industrial series production. In contrast, stator winding temperature monitoring is measured on a sensor basis nowadays, yet in case of faults, these sensors cannot be replaced due to being firmly embedded in the stator. In addition, sensor functionality may deteriorate during the motor's life cycle. Taking into account the ever increasing importance of functional safety especially in the automotive industry, redundant temperature information becomes obligatory.

In this project, it will be shown that a supervised machine learning models, namely linear regression and support vector regression circumvents any kind of electric motor modeling by being fitted on measured test bench data with minor preprocessing directly and still achieves high estimation performance with time invariant properties. This approach ignores domain knowledge and, hence, does not require any conventional engineering expertise in electric machine thermal management.

Problem Statement

Permanent magnet synchronous machines (PMSMs) are a popular choice in many traction drive applications due to their high energy and power density and moderate assembly costs. However, electric motor thermal robustness in general is harmed by the lack of accurate temperature monitoring capabilities such that safe operation is ensured through oversized materials at the cost of its effective utilization. Classic thermal modeling is conducted through lumped parameter thermal networks (LPTNs), which help to estimate internal component temperatures rather precisely but also require expertise in choosing model parameters and lack physical interpretability as soon as their degrees of freedom are curtailed in order to meet the real-time requirement. It will be shown that, as an alternative to LPTNS, supervised learning algorithms like linear regression, logistic regression and support vector regressor achieve similar predictive performance with low computational complexity as long as input representations are preprocessed with exponentially weighted moving averages. Thus, domain knowledge becomes neglectable, and estimation performance depends entirely on collected data and considered input representations.

Datasets and Inputs

Kaggle Datasets link: pmsm_temperature_data.csv.

Dataset of Electric-Motor-Temperature Project (https://www.kaggle.com/wkirgsn/electric-motor-temperature)

Input fields of data:

1. Ambient – Ambient temperature as measured by a thermal sensor located closely to the stator.
2. Coolant - Coolant temperature. Motor is water cooled. Measurement is taken at outflow.
3. u_d - Voltage d-component
4. u_q - Voltage q-component
5. motor_speed - Motor speed
6. torque - Torque induced by current.
7. i_d - Current d-component
8. i_q - Current q-component
9. pm - Permanent Magnet surface temperature representing the rotor temperature. This was measured with an infrared thermography unit.
10. stator_yoke - Stator yoke temperature measured with a thermal sensor.
11. stator_tooth - Stator tooth temperature measured with a thermal sensor.

12. stator_winding - Stator winding temperature measured with a thermal sensor.
13. profile_id - Each measurement session has a unique ID. Make sure not to try to estimate from one session onto the other as they are strongly independent.

Data organization:

ambient	coolant	u_d	u_q	motor_speed	torque	i_d	i_q	pm	stator_yoke	stator_tooth	stator_winding	profile_id
-0.75214	-1.11845	0.327935	-1.29786	-1.2224282	-0.250182	1.029572	-0.24586	-2.52207	-1.8314217	-2.0661428	-2.0180326	4
-0.77126	-1.11702	0.329665	-1.29769	-1.2224293	-0.249133	1.029509	-0.24583	-2.52242	-1.8309687	-2.0648587	-2.0176313	4
-0.78289	-1.11668	0.332772	-1.30182	-1.2224278	-0.249431	1.029448	-0.24582	-2.52267	-1.8304	-2.064073	-2.0173435	4
-0.78094	-1.11676	0.3337	-1.30185	-1.2224301	-0.248636	1.032845	-0.24695	-2.52164	-1.8303328	-2.0631368	-2.0176322	4
-0.77404	-1.11678	0.335206	-1.30312	-1.2224286	-0.248701	1.031807	-0.24661	-2.5219	-1.8304977	-2.0627947	-2.0181448	4
-0.76294	-1.11695	0.334901	-1.30302	-1.2224286	-0.248197	1.031031	-0.24634	-2.5222	-1.8319309	-2.0625494	-2.017884	4

Target feature: Rotor temperature [“pm”]

Solution Statement

- Rotor temperature of a Permanent magnet synchronous machines is predicted using supervised machine learning algorithms based on other important features affecting it.
- Supervised learning algorithms like support vector regression is helpful in achieving the good prediction of rotor temperature with less mean squared error.
- In this project as input data is a time series, group the data based on profile IDs.
- To reduce time taken to fit the model and predict the rotor temperature, preprocess the input data before feeding to algorithm.

Benchmark Model

The benchmark model will be a simple linear regressor trained on the train data. Then I will try to fit and predict using different supervised learning algorithms like logistic regression and support vector regressor with preprocessing of input data.

Evaluation Metrics

The evaluation metric to be used is mean squared error to quantify the performance of both the benchmark model and the solution model.
If y_i is the predicted value of the i-th sample, and y_i is the corresponding true value, then the mean squared error (MSE) estimated over $n_{samples}$ is defined as

$$\text{MSE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} (y_i - \hat{y}_i)^2.$$

Project Design

The project workflow as below,

- Read the datasets and remove NAs.
- As input data for this project is a time series, whole of the data needs to be visualized, trained and tested by grouping.
- Identify important features which are influencing the rotor temperature by visualizing the input data using "matplotlib" or "seaborn".
- Transform the input data using Principal component analysis technique for benchmark model.
- Split the input data into training and testing set in every group of data.
- Prediction of "Rotor Temperature" is always floating numbers. Hence Regression algorithms need to be used to predict rotor temperature.
- Use support vector regressor algorithms to fit and predict.
- Fit the model.
- Validate the results and calculate mean squared error produced during prediction of rotor temperature.

References

[1] M. Ganchev, B. Kubicek, and H. Kappeler. Rotor Temperature Monitoring System. The XIX International Conference on Electrical Machines - ICEM 2010, 2010.
[2] S Stipetic, M Kovacic, Z Hanic, and M Vrazic. Measurement of Excitation Winding Temperature on Synchronous Generator in Rotation Using Infrared Thermography. IEEE Transactions on Industrial Electronics, 2012.
[3] C. Mejuto, M. Mueller, M. Shanel, A. Mebarki, M. Reekie, and D. Staton. Improved Synchronous Machine Thermal Modelling. In 2008 18th International Conference on Electrical Machines, 2008.