DSA/ISE - 5013

Fundamentals of Engineering Statistical Analysis

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Final Project

Temperature Analysis of Electric Motor

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***Abstract*—With climate change problems on the rise, one way to help reduce the carbon print on earth is to use electric vehicles. As widely known, the efficiency of motors in any vehicles is critical for the life of the vehicles [3]. Using the data set that was created in Kirchgässner, Wilhelm & Wallscheid, Oliver & Böcker, Joachim on their research titled *Empirical Evaluation of Exponentially Weighted Moving Averages for Simple Linear Thermal Modeling of Permanent Magnet Synchronous Machines*, an analysis using linear regression model to predict Permanent Magnet Synchronous Machines (PMSMs) surface temperature (its rotor temperature) is able to be conducted. A linear regression model and non-linear regression model for profile ID #4 was conducted to predict the rotor temperature (pm). The Root Mean Square Error (RMSE) of its linear regression model is as low as 0.23 by only using four predictors (*stator_winding, stator_tooth*, *u_q*, *motor_speed*) while a non-linear model Multivariate Adaptive Regression Splines (MARS) using those same four predictors resulted in RMSE of 0.059.**

Introduction

With the rising of the electrical automotive industry today, it is important to analyze the temperature behavior of the core component of that technology, its electric motor. Since a heat build-up will cause problems, finding the ideal torque and motor speed without causing it to overheat will help the motor to last longer while giving its best performance; whether it is a car, a motorcycle, or a scooter. By using a linear model regression, we will train the data to analyze the temperature behavior from the sensor data of the motor and see if we can predict how it will perform based on its torque, motor speed, and voltage components. To be able to do so, a reliable linear model to predict PMSM's rotor or stator temperature will be very insightful in finding those data. By preventing the overheating problem, the life span of the motor will increase and safety issue regarding the overheating problem will also be solved [4]. It is benefiting for both automotive industry companies and also for their customers.

Problem Definition and Formulation

The data set from https://www.kaggle.com/wkirgsn/electric-motor-temperature is used in this project. The data set has been normalized by the author. The attributes for this data set are as follow [2]:

ambient – Ambient temperature as measured by a thermal sensor located closely to the stator

coolant – Coolant temperature

i_d – Current d-component

i_q – Current q-component

motor_speed – Motor speed

pm – Rotor temperature of PMSM surface temperature

profile_id – unique ID for each measurement

stator_tooth – Stator tooth temperature

stator_winding – Stator winding temperature

stator_yoke – Stator yoke temperature

torque – Torque induced by current.

u_d – Voltage d-component

u_q – Voltage q-component

The prediction on rotor temperature on Profile ID #4 is then conducted in this data set. Since the data has been normalized already, the next thing to do is to find the outliers in the data. It was done by using the Rostner Outlier test in R. From that test, there are only two variables with outliers, *coolant* and *i_q* attributes. Since there is only one outlier in coolant, using the Grubbs Outlier test in R, the outlier was removed while *i_q* attributes was transformed by taking its log function. A Principal Component Analysis (PCA) was used to see the correlation of all of the attributes before going into the modeling. The PCA plot of PC1 and PC2 which represented 75% of the data, is shown below:

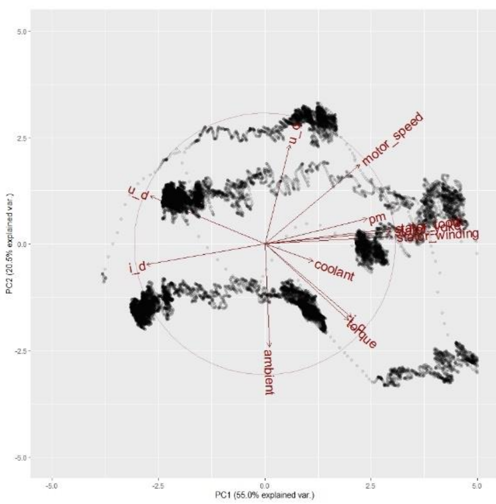

Figure 1 PC2 vs PC1 of the Data Set for Profile ID #4

From **Figure 1**, it shows that *pm* is highly correlated with the stator related attributes. By assuming that the attributes has linear relationship with the predicted variable, *pm*, the vectorized form of linear regression model formula below is used [1]:

$$\hat{\boldsymbol{y}} = \boldsymbol{h}_{\boldsymbol{\theta}}(\boldsymbol{x}) = \boldsymbol{\theta} \cdot \boldsymbol{x}$$

Where $\boldsymbol{h}_{\boldsymbol{\theta}}$ is the hypothesis function, $\boldsymbol{\theta}$ is the linear model's parameter vector, and $\boldsymbol{x}$ is the instance's attribute vectors. The linear model is the dot product of $\boldsymbol{\theta}$ and $\boldsymbol{x}$.

Solutions and Discussion

For the first linear model, all the attributes, beside the *profile_id*, were used to predict *pm*, which resulted in RMSE of 0.240. The behavior of the first linear model is shown below:

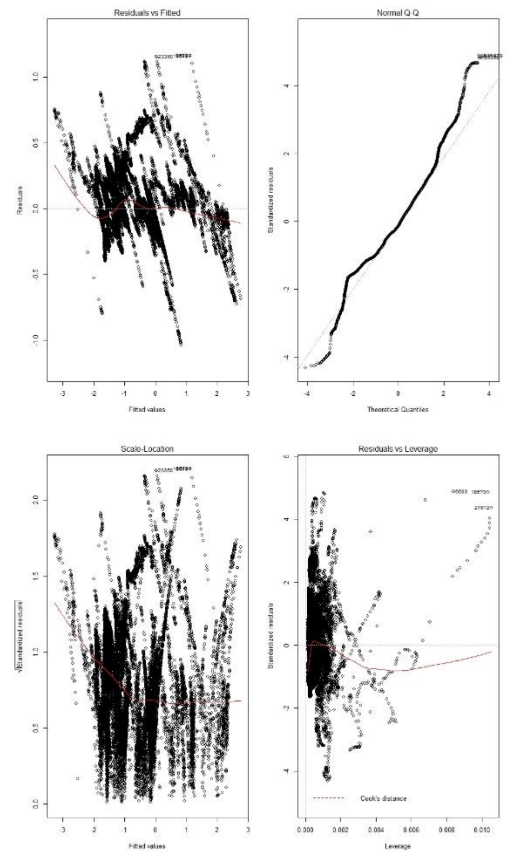

Figure 2 The Linear Model Behavior by Using All Attributes as Predictors

Figure 2 shows:

- The Residuals vs Fitted plot: a better result would have resulted in the data to be as close to zero as possible,
- The Scale-Location plot: needs to be equally spread across the predictors,
- The Normal Q-Q plot: is close to normal distribution, which is indicated by a positive slope linear trend line, and
- The Residuals vs Leverage: help indicates if there are still cases with high leverage data, which shows that it does.

From that linear model, variables importance was conducted by using the varImp function in R.

The result is shown below:

```
> varImp(lm1)
                   Overall
ambient           9.714527
coolant           4.112022
u_d               2.006341
u_q              84.146264
motor_speed      30.688636
torque           28.648295
i_d              22.223750
i_q              27.933229
stator_yoke      11.590619
stator_tooth    104.116910
stator_winding  118.879930
```

Taking the top four important variables of that result as predictors, a second linear model was conducted. It resulted in a better RMSE, which is 0.228.

Conclusions

The data set of the temperature of electric motor would be very useful in designing future electric motor that is not only efficient, cost effective, and safe for the road. Finding more predictors and/or creating a precise and reliable predictive model will be the key to success for achieving this goal. Using a non-linear model is a better option since precision in this matter is very important. Although RMSE of 0.24 is not awful, in automobile industry, a higher precision that that is preferable since it involves a moving vehicles and people's life. A non-linear model of the profile ID #4 by using Multivariate Adaptive Regression Splines (MARS) model using the same first linear model predictors and the second linear model predictors resulted in RMSE of 0.0450 and 0.0593, respectively. Which shows that it is even more precise than the linear models. An analysis on other profile ID should also be conducted in this data set since they are independent from each other [2].

References

[1] Géron, A. (2017). Hands-on machine learning with Scikit-Learn and TensorFlow : concepts, tools, and techniques to build intelligent systems. Sebastopol, CA: O'Reilly Media. ISBN: 978-1491962299

[2] Kirchgässner. (June 2019). Electric Motor Temperature, Version 2. Retrieved 29 October 2019 from https://www.kaggle.com/wkirgsn/electric-motor-temperature/.

[3] Kirchgässner, Wilhelm & Wallscheid, Oliver & Böcker, Joachim. (2019). Deep Residual Convolutional and Recurrent Neural Networks for Temperature Estimation in Permanent Magnet Synchronous Motors.

[4] Kirchgässner, Wilhelm & Wallscheid, Oliver & Böcker, Joachim. (2019). Empirical Evaluation of Exponentially Weighted Moving Averages for Simple Linear Thermal Modeling of Permanent Magnet Synchronous Machines.