Computationally Efficient "Stator-winding" Temperature Predictions for Electric Motors

Anthony Crespo
Operations Research
George Mason University
Fairfax, United States
acrespo4@gmu.edu

Eyan Abel Bantebya
Civil Engineering,
Transportation Engineering
George Mason University
Fairfax, United States
ebanteby@gmu.edu

Joshua Mark Kickhoefer
Systems Engineering
George Mason University
Fairfax, United States
jkickhoe@gmu.edu

Sidney G. Beck
Data analytics engineering
George Mason University
Fairfax, United States
sbeck7@gmail.edu

Abstract— **With the expansion of the electric vehicle (EV) industry, automotive manufacturers are focusing on optimizing electric motor production to ensure competitive performance and cost-effectiveness compared to internal combustion engines (ICEs). Performance metrics such as speed, torque, and power are pivotal in determining the effectiveness of electric motors. The power-to-weight ratio, a crucial indicator of a vehicle's overall performance, can be significantly enhanced by employing machine learning techniques to eliminate the need for stator winding sensors, ultimately making motors lighter, more efficient, and cost-effective[1].**

In this study, we highlight the value of accurate motor temperature predictions and precise classification of stator-winding insulation conditions as key factors in optimizing electric motor production. Two motor types, Induction Motors (IMs) and Permanent Magnet Synchronous Motors (PMSMs) are used in electric vehicles. IMs currently dominate the industry due to their cost-effectiveness and high reliability. At the same time, PMSMs offer increased power and efficiency but face challenges in cost and reliability because of their magnet construction. With increased production, PMSMs can match IMs in cost and reliability, positioning them as the superior motor type in the future [2][3].

Our research underscores the importance of accurate motor temperature predictions and stator-winding insulation condition classification for the electric motor industry. These advancements contribute to the optimization of electric motor production, addressing critical performance and cost factors that drive the rapid growth and evolution of the EV market.

Introduction

Our research aimed to predict stator winding temperatures and classify stator winding insulation overheating in permanent magnet synchronous motors, with a focus on developing a more computationally efficient model compared to previous efforts such as Deep Neural Networks ($R2 = 0.9439$, $RMSE = 0.2368$, Guo et al.) [4] and PCA+ELM ($R2 = 0.9955$, $RMSE = 0.0622$, Dilmi et al.) [5]. The objective was to support cost-effective electric motor manufacturing by providing enhanced temperature predictions. The National Electric Motor Association (NEMA) categorizes stator winding insulation into four temperature rating classes: Class A (105°C), Class B (130°C), Class F (155°C), and Class H (180°C), which serve as the basis for our study. Class B temperature rise refers to an 80°C rise in motor insulation, achievable with a conservative motor design. S.F. stands for Service Factor, representing the motor's ability to handle the extra load.

This increased thermal margin leads to an insulation life of approximately five to six times longer than a motor operating at its rated insulation temperature. It is important to maintain lower operating temperatures because for every 10°C decrease in temperature, the insulation life doubles, allowing the motor to handle higher loads and various operating conditions more effectively [6]:

NEMA MOTOR INSULATION TEMPERATURE RATINGS		TEMPERATURE RISES			
		1.0 SF MOTORS			
Class	Temperature	Ambient	Hotspots	Rise @ 1.0	Rise @ 1.15
A	105°C	+40°C	+5°C	60°C	70°C
B	130°C	+40°C	+10°C	80°C	90°C
F	155°C	+40°C	+10°C	105°C	115°C
H	180°C	+40°C	+15°C	125°C	Not Defind

Fig. 3. This chart shows the NEMA stator winding allowable temperatures by insulation type; our classification analysis will focus on type B [6].

We will use root mean squared error (RMSE) in degrees Celsius and the coefficient of determination (R2) as our stator winding temperature prediction accuracy metric. Temperature predictions within a +10°C margin from the originally observed temperature will be acceptable, and prediction errors closer to 0°C (RMSE) will be considered ideal. According to NEMA, class B is the most common insulation used in 60-cycle motors, so our classification model will attempt to classify overheating with a Boolean value of "Pass or Fail" in relation to temperatures that exceed class B's 130°C rating or not.

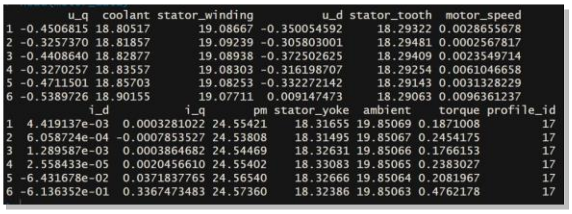
I. Data Selection and Description

A. Selection

Our data was selected from Kaggle.com. Our data is a popular electric motor temperature analysis dataset collected by Paderborn University's Power Electronics and Electrical Drives department, comprising sensor data from a permanent magnet synchronous motor (PMSM) test bench. The dataset, sampled at 2 Hz, contains 185 hours of records from multiple measurement sessions, distinguishable by their "profile id." The motor is excited by hand-designed driving cycles, resulting in various quantities such as motor speed and torque [7].

B. Description

The dataset comprises 13 columns and 1,330,816 samples, with 12 quantitative variables and one categorical. The first six columns consist of temperature measurements for the “coolant,” “permanent magnet,” “stator yoke,” “ambient temperature,” “stator-tooth,” and “stator-winding.” The four electrical measurement columns are “i_q,” “i_d” for the d and q component current measurement in amps, and “u_q,” “u_d” for the q and d component voltage measurements, respectively. The last three columns are the “profile IDs” for each measurement, “motor speed,” and “torque.” We refined our data for both Regression and classification models using unsupervised learning, recursive feature selection/elimination, and feature engineering. To better understand our dataset, please refer to the following sample, which provides a visualization of the data:



```
        u_q  coolant stator_winding         u_d stator_tooth  motor_speed
1 -0.4506815 18.80517       19.08667 -0.350054592     18.29322 0.0028655678
2 -0.3257370 18.81857       19.09239 -0.305803001     18.29481 0.0002567817
3 -0.4408640 18.82877       19.08938 -0.372502625     18.29409 0.0023549714
4 -0.3270257 18.83557       19.08303 -0.316198707     18.29254 0.0061046658
5 -0.4711501 18.85703       19.08253 -0.332272142     18.29143 0.0031328229
6 -0.5389726 18.90155       19.07711  0.009147473     18.29063 0.0096361237
           i_d           i_q       pm stator_yoke  ambient    torque profile_id
1  4.419137e-03  0.0003281022 24.55421    18.31655 19.85069 0.1871008         17
2  6.058724e-04 -0.0007853527 24.53808    18.31495 19.85067 0.2454175         17
3  1.289587e-03  0.0003864682 24.54469    18.32631 19.85066 0.1766153         17
4  2.558433e-05  0.0020456610 24.55402    18.33083 19.85065 0.2383027         17
5 -6.431678e-02  0.0371837765 24.56540    18.32666 19.85064 0.2081967         17
6 -6.136352e-01  0.3367473483 24.57360    18.32386 19.85063 0.4762178         17
```

Fig. 2. This overviews our initial data from an R console.

II. STATOR-WINDING TEMPERATURE PREDICTION

Stator-winding temperature sensors are interlaced with electric motor stator-windings or “copper wires” that feed the current and voltage, ultimately rotating the motor. As mentioned above, machine learning models can be used to predict the “copper wire” temperatures instead of installing slightly larger temperature sensors which can decrease production costs. See the graphic below to visualize the problem and what a stator winding sensor looks like:

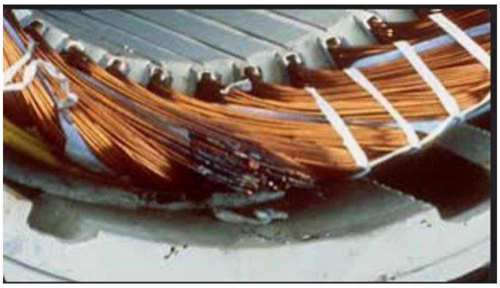


Fig. 3. Overheated stator-winding in an electric motor: A visual representation of the consequences of excessive thermal conditions on the stator-winding insulation, leading to breakdown and unintended electrical arcing [8].

The illustration above shows that the stator-winding insulation has experienced a breakdown due to excessive thermal conditions [8]. This has led to the copper conductor establishing an unintended electrical arc rather than facilitating the designed electromagnetic circuit. It should be noted that the insulation, though not easily visible, can be discerned through a tactile examination of the wires. Upon contact, one can feel a rubbery, plastic-like film, which is the NEMA-rated insulation material referred to previously.

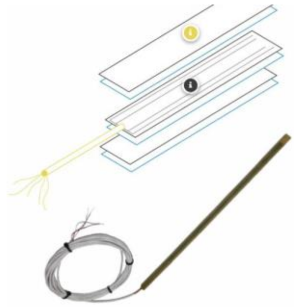


Fig. 4. Image of a stator winding temperature sensor, these devices increase the price of PMSM construction [9].

We trained six Regression models (Linear, Robust, Partial Least Squared [PLS], Ridge, Lasso, and Elastic Net) and successively tested predictions with each model to compare R2 and RMSE performance metrics. The elastic net model performed the best with an R2 of .999 and an RMSE (in degrees Celsius) of 0.859, comparable to, if not better than, the more computationally expensive deep neural network or PCA+ELM mentioned earlier. Additionally, Czerwinski et al. found that the elastic net was the most accurate model for predicting stator-winding temperature without a cooling fan. Czerwinski et al.’s elastic net performance metrics were RMSE = 2.53 °C, and R2 = 0.975 [10], which our elastic net model seems to outperform.

A. Assumptions

There are multiple widely known methods for stator-winding temperature predictions [11]. One common method NEMA uses for insulation analysis utilizes the current and voltage to predict temperatures based on excess resistance produced in the copper wire [7]. Our assumptions are derived from a method that involves using the temperatures of the other motor components, coolant, and ambient temperature measurements to predict the stator winding temperatures. We intuitively selected this method through extensive unsupervised learning methods such as Principal Component Analysis (PCA) and K-means clustering. Eventually, we found a supervised method called recursive feature elimination/section [12] to be the most effective method for selecting our predictors.

B. Preprocessing

- Our data was Centered and Scaled prior to model training using the preprocessing function in the caret package, and the preprocessing method from the “train” function in the caret package was not used. Initial data contained no Null or absolute zero values since it was produced in a lab-type environment. The data did contain 4,625 negative values from the alternating current electrical measurement predictors.

- Skew values in our data ranged from 0.08 to 1.08. Given minimal skewness and the number of negative values, logarithmic transformations such as Box-Cox were not used.

- Unsupervised exploration using K-means clustering identified a clear line of separation for all predictors when clustered against the motor speed variable, which made intuitive sense since any change in electrical voltage would affect motor speed and, ultimately, motor temperatures. PCA conducted on all predictors identified six components to explain the variance in all of our data, but when components were plotted on a scree bar and line chart only four components seem to be the most important after examining the bend in the elbow of the scree line plot. With four components identified and three lines between each component, we used K=3 for our K-means clustering, essentially providing a heuristic that most of our data could be separated into low, medium, and high motor speeds.

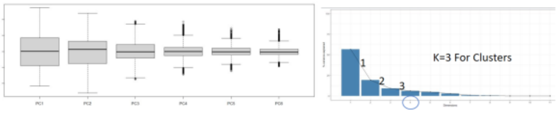


Fig. 5. Depiction of six components that explain 100% of our data on the left. On the right is a screen bar and line plot showing four components that contributed the most, and the 3 lines connecting them are how we selected our K value for K-means clustering.

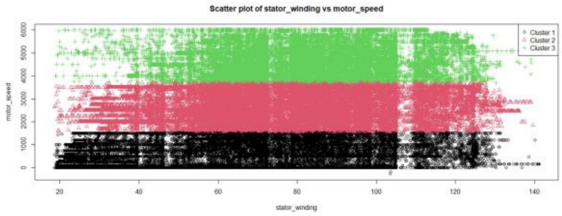


Fig. 6. K-means clustering output for stator winding temperatures verses motor speed utilizing K=3.

- Recursive Feature selection/elimination is a method that uses modeling methods such as linear regression against individual predictors and the response to find the best predictors for predicting the response [12]. Using this method, we identified the five most significant predictors for predicting stator-winding temperatures; Stator tooth, stator yoke, coolant, permanent magnet (pm), and ambient temperatures. These five predictors were used for all six regression models mentioned above, and ultimately, elastic net yielded the best performance.

C. Model Training, Testing and Selection

Our research employed a systematic data sampling strategy to develop an efficient predictive model. Initially, we divided the dataset into two halves (50% subset), from which we further partitioned using a stratified 70/30 train-test split to facilitate the preliminary modeling process. After evaluating various models, we identified Elastic Net as the most suitable option for our study.

Leveraging high-performance computing resources, we retrained the Elastic Net model using the entire dataset. The results utilized 10 Fold cross-validation and yielded a near-perfect prediction R-squared value of 0.999 and a minimal Root Mean Square Error (RMSE) of 0.859 degrees Celsius. This outcome implies that our model exhibits exceptional accuracy in its predictions, with deviations of merely 0.86 degrees when errors occur.

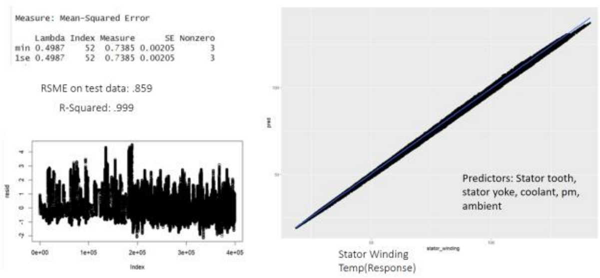


Fig. 7. Elastic net observed versus predicted values on the right, residual plot in the bottom left. Lambda and performance metrics are in the top left.

Notably, our model's performance surpasses the National Electrical Manufacturers Association (NEMA) standard, which permits a +10 degrees margin for stator winding hotspot temperature predictions. Consequently, our approach demonstrates significant potential in improving the reliability and efficiency of temperature prediction models within the engineering community while maintaining simplicity for broader comprehension.

Lastly, it should be noted that since our data was collected from an electric motor in a lab-type environment, model performance may vary on new or real-world data. Further testing on real-world stator-windings will likely be required.

III. NEMA Class B Insulation Overheating Classification

Our secondary objective centered on precisely assessing the thermal condition of Type B stator-winding insulation, which is the most widespread insulation type for 60-cycle motors in the industry, as per the NEMA guidelines. Our study initially developed a Boolean "insulation result" column based on the "stator winding" column. We classified instances with temperatures above 130°C as failures and those at or below 130°C as passes. In a general look at our dataset, 2845 instances were identified as failures, constituting 0.002% of the total data.

A. Assumptions

The type of insulation used on the Paderborn Universities motor (our Data) is not readily available on any website. Therefore, we began our analysis by assuming the most common, according to NEMA, type B insulation for 60-cycle US motors.

B. Model Training,Testing, and Selection

We started by employing a 10-fold cross-validated multinomial logistics regression model (the documentation said either could be used in a binomial logistic regression), using accuracy as the evaluation metric while incorporating all variables. However, the results could have been better, and the computational time was excessive. Furthermore, not a single failure was detected in the test dataset.

A significant improvement was observed when we switched to the Generalized Linear Model (GLM) method for binomial logistic regression, still using accuracy as the training metric. The test dataset achieved a 100% success rate and a kappa value of "one" due to accidentally including the stator winding column (The column used to derive the response) in the calculation.

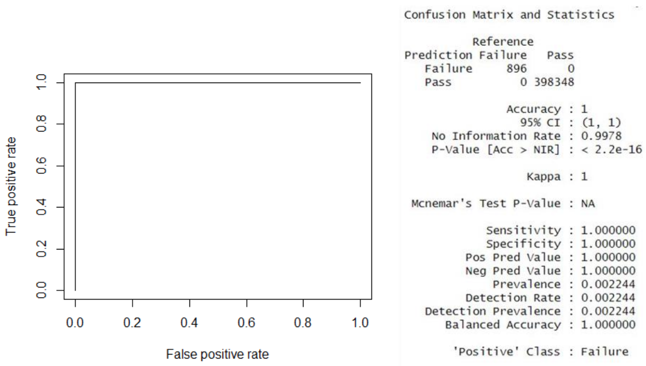
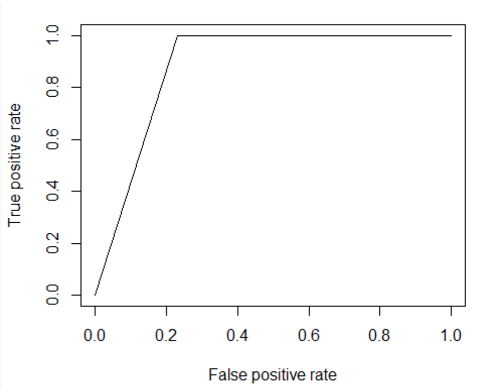


Fig. 8. Unrealistic logistics regression that utilized our five selected predictors and our mistaken inclusion of response-related data in the training processes. ROC curve on the left, performance metrics on the right.

Removing the "stator winding" variable and switching to the general linear model function using accuracy as the training metric attained a kappa value of 0.7898 and a 99.9% accuracy on the test dataset. However, due to significantly more "Pass" values than "Fail" values in the response variable, the model misclassified "failure" 27% of the time. The Kappa value is a more realistic performance metric for this model. With 78% (Kappa) reliability (or agreement between Pass and Fail) for predicting failed class B stator winding insulation, this model will likely need to be coupled with other models to provide the maximum benefit to the motor manufacturing industry and may require further refinement.




```
Confusion Matrix and Statistics

          Reference
Prediction Failure   Pass
   Failure     610     92
   Pass        232 398310

               Accuracy : 0.9992
                 95% CI : (0.9991, 0.9993)
    No Information Rate : 0.9979
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7898

 Mcnemar's Test P-Value : 1.143e-14

            Sensitivity : 0.724466
            Specificity : 0.999769
         Pos Pred Value : 0.868946
         Neg Pred Value : 0.999418
             Prevalence : 0.002109
         Detection Rate : 0.001528
   Detection Prevalence : 0.001758
      Balanced Accuracy : 0.862117

       'Positive' Class : Failure
```

Fig. 9. More realistic logistics regression performance metrics utilizing only our five selected predictors to predict class B stator winding failure on the bottom and the ROC curve for the model above.

IV. CONCLUSION

In conclusion, our research demonstrates machine learning techniques' efficacy in optimizing electric motor production through precise stator winding temperature predictions and stator winding insulation condition classification. The Elastic Net model outperforms existing methods, adhering to NEMA guidelines, and offers benefits in performance and cost factors for the electric vehicle industry.

Additionally, we developed a binomial logistic regression model using the Generalized Linear Model (GLM) method for classifying overheating in NEMA Class B insulation. Despite high accuracy, the kappa value was marginally optimal, and the model necessitates further refinement or potential integration with other models to maximize its utility in manufacturing motor insulation. Future research should focus on the real-world application of these models and investigate improvements to ensure optimal outcomes for the electric motor industry.

REFERENCES

[1] [1] Jape, Swaraj Ravindra, and Archana Thosar. "Comparison of Electric Motors for Electric Vehicle Application." *International Journal of Research in Engineering and Technology*, vol. 06, no. 09, Sept. 2017, pp. 12–17., https://doi.org/10.15623/ijret. Accessed 21 Apr. 2023.

[2] [2] Osmanbasic , Edis. "The Many Types of EV Motors." *Engineering.com*, 25 May 2020, https://www.engineering.com/story/the-many-types-of-ev-motors.

[3] [3] Pronovost, Christian. "10 Things to Consider When Choosing an Electric Motor." *Dana TM4*, 17 May 2016, https://www.danatm4.com/blog/10-things-consider-choosing-electric-motor/.

[4] H. Guo, Q. Ding, Y. Song, H. Tang, L. Wang, and J. Zhao, "Predicting Temperature of Permanent Magnet Synchronous Motor Based on Deep Neural Network," Energies, vol. 13, no. 18, p. 4782, Sep. 2020, doi: 10.3390/en13184782. [Online]. Available: http://dx.doi.org/10.3390/en13184782R.

[5] S. Dilmi, F. Kebaili and M. Ladjal, "A soft sensor of stator winding temperature prediction for PMSMs based on extreme learning machine," 2022 19th International Multi-Conference on Systems, Signals & Devices (SSD), Sétif, Algeria, 2022, pp. 969-975, doi: 10.1109/SSD54932.2022.9955806.

[6] C. Toshiba International, "Tech notes - Toshiba," *toshiba.com*, 2020. [Online].Available: https://www.toshiba.com/tic/datafiles/app_notes/Temperature_Rise_1605749858.pdf [Accessed: 21-Apr-2023]. Fig 1

[7] Kirgsn, "Electric motor temperature," *Kaggle*, 26-Apr-2021. [Online]. Available: https://www.kaggle.com/datasets/wkirgsn/electric-motor-temperature. [Accessed: 21-Apr-2023].

[8] N. A. NA, "Resources," *EASA*, 1985. [Online]. Available: https://easa.com/resources/failures-in-three-phase-stator-windings. [Accessed: 23-Apr-2023]. Fig 3

[9] S. D. L. SDL, "Home," *Sensing Devices*, 2023. [Online]. Available: https://www.sensing-devices.co.uk/products/stator-winding-temperature-sensors. [Accessed: 23-Apr-2023]. Fig 4

[10] D. Czerwinski, J. Gęca, and K. Kolano, "Machine Learning for Sensorless Temperature Estimation of a BLDC Motor," Sensors, vol. 21, no. 14, p. 4655, Jul. 2021, doi: 10.3390/s21144655. [Online]. Available: http://dx.doi.org/10.3390/s21144655 [Accessed: 21-Apr-2023].

[11] F. Magnussen, On design and analysis of synchronous permanent magnet machines for field-weakening operation in Hybrid Electric Vehicles. Stockholm, Sweden: KTH Royal Institute of Technology, 2004.

[12] M. Kuhn, "The Caret package," *Recursive Feature Elimination*, 27-Mar-2019. [Online]. Available: https://topepo.github.io/caret/recursive-feature-elimination.html. [Accessed: 21-Apr-2023].