Machine Learning for Temperature Estimation

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The modern and very effective methods of estimating the temperature of electric motors include machine learning and deep learning. Their unquestionable advantage is that on the basis of the collected measurement data, a function mapping the relationship between the values of the input features and the output is determined. This means that predictive modeling does not require knowledge of the material properties of a given device or having expertise knowledge about its construction.

Keywords: temperature estimation ; machine learning ; BLDC ; electric machine protection

1. Overview

For the purposes of the research, measurements were made for over 160 h of motor operation, and then, they were preprocessed. The algorithms of linear regression, ElasticNet, stochastic gradient descent regressor, support vector machines, decision trees, and AdaBoost were used for predictive modeling. The ability of the models to generalize was achieved by hyperparameter tuning with the use of cross-validation. The conducted research led to promising results of the winding temperature estimation accuracy. In the case of sensorless temperature prediction (model 1), the mean absolute percentage error MAPE was below 4.5% and the coefficient of determination R^2 was above 0.909. In addition, the extension of the model with the temperature measurement on the casing (model 2) allowed reducing the error value to about 1% and increasing R^2 to 0.990. The results obtained for the first proposed model show that the overheating protection of the motor can be ensured without direct temperature measurement. In addition, the introduction of a simple casing temperature measurement system allows for an estimation with accuracy suitable for compensating the motor output torque changes related to temperature.

2. Predicting the Electric Motor Temperature

Permanent magnet electric motors, in particular permanent magnet synchronous (PMSM) and brushless direct current (BLDC) motors, have gained popularity over the past decade. It is visible both in industrial solutions such as servo drives and actuators, but also in household appliances and traction applications. This is due, inter alia, to the fact that the use of permanent magnets allows the miniaturization of devices (due to the much higher power density in motors), which also increases their reliability and energy efficiency. The elimination of one of the most susceptible to damage elements of DC electric motors, i.e., the mechanical commutator and brushes, made it possible to use BLDC motors in applications requiring increased durability. The authors in [1] presented the percentage share of individual failures in induction motors, which shows that more than 40% of failures are caused by bearing failures, while 38% are problems with the machine stator. Therefore, it can be concluded that in DC brushless motors, damage to these elements will also have a significant impact on the reliability of the device. Diagnostics and detection of BLDC motor failures are devoted to many studies, including methods consisting of monitoring the motor current waveform [2][3][4], as well as using built-in Hall sensors [5] or additional vibration measurement [6]. A detailed description of faults occurring in brushless motors and the classification of diagnostic methods can be found in [7]. The authors point out that the detection of damage is also possible by measuring the motor temperature.

The analysis of thermal phenomena in electric motors is important for their proper functioning and the possibility of preventing and detecting faults. Excessive temperature rise can destroy the insulation of the stator winding and lead to a short circuit. The increased operating temperature of the motor causes both the aging of the bearings and the degradation of the rotor permanent magnets, which in turn shortens the remaining useful life of the machine. Zhang et al. in [8] also emphasize that the motor life is reduced by 50% for every 10 °C above the maximum temperature limit set by the manufacturer. One of the methods used by manufacturers of electric motors to protect against long-term operation at the upper operating temperature limit is the oversizing of the device or the use of an additional cooling system in the form of a fan placed on the motor shaft. Another cooling method in the case of high-power traction motors is the forced circulation of the coolant in a casing specially designed for this purpose.

According to [9], there are three basic types of thermal losses in permanent magnet motors. The first of these are the losses in the copper winding, the value of which depends on the flowing current. Another is the core iron losses, which mainly depend on the stator voltage. The last type of losses is mechanical, which is influenced by the motor speed. Stator winding insulation is particularly exposed to the effects of temperature and the thermal aging process. Moreover, if the temperature of the permanent magnet motor winding cannot be effectively controlled, the heat will be transferred to the rest of the components through the casing and the air gap, leading to heating of both the bearings and the permanent magnets. The authors in [10] emphasize that the increase in temperature of permanent magnets causes their partial demagnetization, which leads to a drop in motor output torque. If the critical temperature value characterizing a given permanent magnets material is not reached, the process is reversible. Otherwise, the magnets are permanently and irreversibly damaged, resulting in worse motor performance.

The above-mentioned phenomena show that there is a need to monitor the temperature inside DC brushless motors. Therefore, some BLDC motor manufacturers decided to install factory-built winding temperature sensors. This solution entails an increase in the production costs of the device and constitute another element of the machine that may be damaged. On the other hand, the installation of the temperature sensor by the user requires a lot of time and effort, as well as knowledge about the design of the device itself.

In order to optimize costs and eliminate the need for sensors, scientists have made a number of attempts to estimate the temperature of individual internal components of electric motors, such as stator winding [11], rotor [12], or bearings [13]. These efforts are mainly aimed at protecting these components from excessive temperature rise. However, studies show that it is also possible to compensate the torque pulsations on the machine shaft caused by the influence of temperature on the winding resistance and demagnetization of permanent magnets [14][15][16][17]. The authors in [18] propose using the BLDC motor thermal model to optimize the trajectory of the industrial robot movements, taking into account thermal constraints.

One of the most popular and most effective methods of forecasting the electric motor temperature is lumped parameter thermal networks (LPTN), which simplify the physical model of the motor and allow for temperature estimation based on a set of parameters assigned to network nodes. As described in [19], motor equivalent thermal circuit diagrams can be divided into three basic types depending on the number of nodes in the thermal model. The first is a white box model in which a multi-node network is created that describes the motor based on the theory of heat transfer. In this type of model, there are additional sub-nodes that are designed to even more accurately reflect the actual heat distribution in the machine. Conducting calculations aimed at temperature prediction with such complex network structures requires a lot of computing power and, despite high accuracy, cannot be used for real-time prediction. In addition, creating such accurate models requires knowledge of many parameters and properties of the materials of which the motor is made, as well as expertise in its construction. Therefore, it is obvious that this is difficult to achieve, as manufacturers do not provide complete information about their devices. Light gray box models are another type of thermal equivalent networks. They represent the first degree of simplification compared to the previously described white-box networks and typically have five to fifteen nodes. Thanks to the use of a simpler structure, the complexity of calculations is much lower, although there is still a need for detailed information on the materials and geometry of the motor. In response to the above problems, dark gray box models were created, which have only two to five nodes corresponding to the dominant heat transfer paths and achieve very good prediction accuracy thanks to determining the values of the thermal model parameters based on experimental tests. High efficiency and the possibility of real-time calculations made dark gray box networks popular in the field of thermal modeling of electric motors. However, it is worth noting that they require knowledge of the temperature (application of the sensor) in at least one point in the network, as well as some expertise knowledge of the modeled object. In the literature, a number of publications on temperature estimation based on the created lumped parameter thermal networks of permanent magnet motors can be found [11][20][21].

Another way to predict the temperature of electric motors is to estimate the winding resistance by injecting signals of the appropriate frequency into the stator circuit [12][22][23][24]. Methods of this type allow for real-time temperature estimation and are resistant to changes in motor cooling conditions (damage to the cooling system), because it is assumed that the relationship between winding resistance and temperature is known and does not change with time. However, the introduction of additional signals causes current and voltage distortions, significantly affecting the electromagnetic compatibility of the device. In addition, the injected signals cause torque pulsations that are unacceptable in some applications.

Thermal modeling of electric motors is also carried out in a purely analytical manner using mathematical [25] and finite element (FEA) methods. It is worth mentioning that there are also hybrid estimation methods such as those described in [26]. An interesting issue concerning motors with permanent magnets is the estimation of the rotor temperature on the basis of the flux measurement with the use of built-in Hall sensors, as described in [5]. However, this method requires the knowledge of the thermal demagnetization constant of the material of which the magnets are made. Moreover, the flux measurement is also affected by the influence of the stator flux, which contributes to erroneous predictions at higher loads.

The modern and very effective methods of estimating the temperature of electric motors include machine learning and deep learning. Their unquestionable advantage is that on the basis of the collected measurement data, a function mapping the relationship between the values of the input features and the output is determined. This means that predictive modeling does not require knowledge of the material properties of a given device or having expertise knowledge about its construction. Both neural networks and other machine learning methods have proven their effectiveness in estimating the temperature of induction motors [27], permanent magnets synchronous motors [9][28][29][30], as well as brushed DC motors [31][32]. Many of the articles on PMSM temperature prediction using machine learning available in the literature use the motor coolant temperature as an input variable of the algorithm [9][28][29][30]. Moreover, the authors in [33] emphasize that the stator temperature is strongly correlated with the exponentially weighted moving average of the PMSM motor coolant temperature, and removing this variable from the feature vector results in a significant decrease in the effectiveness of the prediction algorithm.

3. Conclusions

Overheating protection of the motor can be provided using a trained machine learning algorithm without any additional sensors, thus avoiding the cost of installing additional hardware by the manufacturer or the user. In addition, the use of information from the sensor mounted on the BLDC motor casing allows for very good winding temperature prediction results. This means that it is possible to introduce a compensation mechanism for the temperature impact on the motor output torque. It is worth adding that mounting the sensor on the motor casing is an uncomplicated operation that the user who wants to know the exact temperature inside the device can do by himself and at a low cost. In addition, most motor faults, such as interturn short circuits, bearing damage or magnet degradation, cause the motor temperature to rise significantly. Therefore, it can be anticipated that the described temperature estimation method can be used to detect device components damages.

Under laboratory conditions, the ambient temperature was approximately constant and had no effect on the casing temperature and inside the motor. Difficult conditions at the motor site may increase the prediction errors, but a possible solution is to introduce an additional variable informing about the ambient temperature.

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