Predicting rotor temperature for a permanent magnet synchronous machine using Neural Networks and Recurrent Neural Networks

Nadhir BOUZIANE Imed Eddine BOUKHARI

Ecole Nationale Polytechnique
Laboratoire de Recherche en Electrotechnique (LRE)
Département d'Electrotechnique
Avenue des Frères Oudek, Hassan Badi, B.P.182, El-Harrach, 16200 Alger, ALGERIE
nadhir.bouziane@g.enp.edu.dz imed_eddine.boukhari@g.enp.edu.dz

Abstract

This paper presents a study on temperature prediction in Permanent Magnet Synchronous Machines (PMSMs) using Artificial Neural Networks (ANN). It explores the shortcomings of existing methods and investigates the usage of both traditional Neural Networks (NN) and Recurrent Neural Networks (RNN) for temperature prediction. The study includes training, testing, and performance evaluations of the NN and RNN models, followed by a performance comparison. The findings provide insights into selecting the most effective temperature prediction method for PMSMs.

Keywords : Permanent magnet synchronous machine, Temperature prediction, Neural networks, Recurrent Neural Networks.

1. Introduction

Permanent Magnet Synchronous Motors (PMSMs) play a vital role in various industries and applications due to their significant advantages. PMSMs offer high power density, exceptional efficiency, precise control, and quick response times. Their permanent magnets eliminate the need for field winding, resulting in reduced size, weight, and maintenance requirements. They however are not immune to malfunctions. It can be affected by electrical or mechanical faults in the stator, rotor, or both simultaneously.

Several factors can contribute to the malfunction of a Permanent Magnet Synchronous Motor (PMSM). Electrical causes include issues such as short circuits, open circuits, insulation degradation, or excessive current flow. Mechanical causes can include bearing wear, misalignment, unbalanced loads, or excessive vibrations. Environmental factors like temperature extremes, humidity, or contamination can also impact motor performance. Additionally, improper maintenance practices or manufacturing defects can lead to PMSM malfunctions. Predicting these causes is crucial to ensure the reliable and efficient operation of PMSMs.

In this paper we explore a rotor malfunction prediction method based on temperature prediction using traditional neural networks (NN) and recurrent neural networks (RNN).

2. Permanent Magnet synchronous machines

A. Construction

Permanent Magnet Synchronous Motors (PMSMs) consist of several key components. The stator, which is the stationary part, contains a laminated core with slots for winding copper coils. The coils are arranged in a specific pattern and connected to an external power source. The rotor, the rotating part, is equipped with permanent magnets that create a magnetic field. This magnetic field interacts with the magnetic field generated by the stator's coils, resulting in the motor's rotational motion. The stator and rotor are carefully designed and assembled to ensure precise alignment and minimal air gap for efficient power transfer. The motor housing protects the internal components and provides structural support.

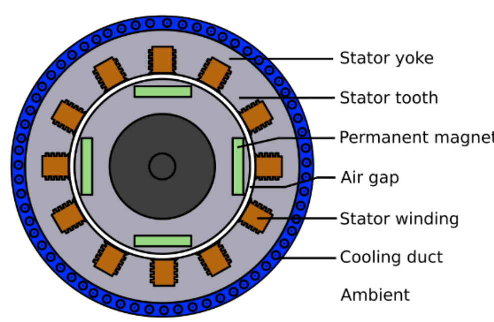

FIGURE 1 – Construction of a permanent magnet synchronous machine (PMSM).

B. Temperature measurement in PMSMs

Thanks to the appearance of new magnetic materials, the power density of PMSMs is increasing day by day. Meanwhile, the density of losses generated inside the machine is also increasing, hence the temperature of a PMSM changes rapidly. In many applications, the temperature of the winding is measured with a sensor to prevent melting of the winding insulator. However, using temperature sensors leads to extra space and cost and becomes an additional candidate for mechanical faults – detachment. Additionally, a temperature sensor embedded in the stator is hard to replace, although its functionality deteriorates over time. Since the rotor spins, usually an IR (infrared) sensor is used to measure the magnet temperature to prevent irreversible demagnetization. There have also been studies using a sensing board that rotates with the machine and sends the measured rotor temperature with wireless communication. However, these methods are hard to apply in mass-production ; the side of the rotor should be covered with low-reflective paint to use an IR sensor, and the attached sensing board limits the speed of a PMSM due to mechanical safety. Hence, there has been a need to estimate the temperature in a PMSM.[3]

C. Temperature prediction in PMSMs

Conventional temperature prediction models can be categorized into two main classes. The first class employs electrical parameters that vary with temperature [4].

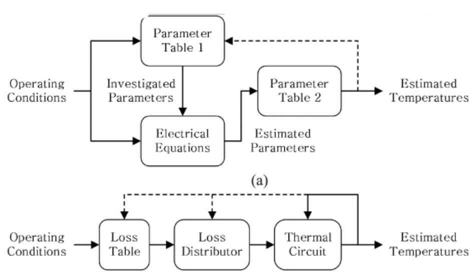

FIGURE 2 – Conventional temperature prediction method.

The second class of temperature estimation models involves finding the temperature distribution of a PMSM using a thermal circuit [1]. In previous studies, a thermal circuit was created by modeling each component of the PMSM as thermal elements (resistors or capacitors) and considering losses as heat sources. However, determining the amount and dispersion of losses becomes challenging for temperature estimation, even when investigating the total machine loss based on operating conditions.

Therefore, this paper proposes a temperature prediction model based on Neural Networks and Recurrent Neural Networks that can be directly generated from experimental results, specifically targeting rotor temperature estimation.

3. Artificial Neural Networks

A. Neural Networks

Neural networks have emerged as valuable tools for predicting the characteristics of electrical machines. By training on experimental data, neural networks can uncover the underlying patterns and relationships within the machine's characteristics. This enables them to make accurate predictions about future performance, efficiency, fault probabilities, or other relevant metrics. By analyzing input features such as operating conditions, electrical parameters, or sensor data, neural networks can generate valuable insights and predictions regarding the behavior and condition of electrical machines. This application of neural networks in electrical machines enhances decision-making, facilitates condition monitoring, and aids in optimizing machine performance and reliability.
An ANN is composed of an input layer, hidden layer(s), and an output layer. Each layer has neuron(s) in it, and an FNN is a type of an ANN in which the layers are connected sequentially. A neuron calculates the linear combination of all output values of the neurons in the previous layer. After being added to a bias value, the calculation result is passed to an activation function [3]

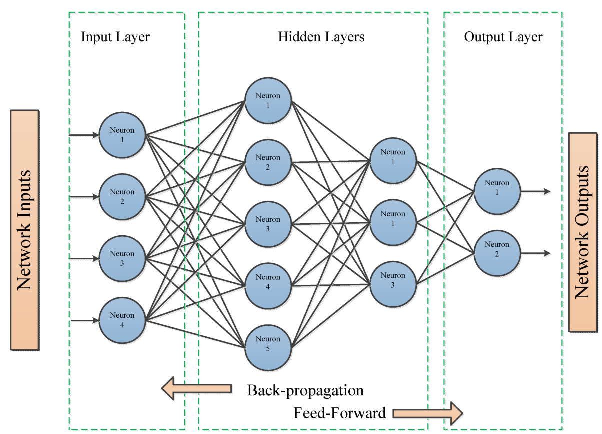

FIGURE 3 – Artificial neural networks

B. Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are a specialized type of neural network that excels in modeling sequential data, making them particularly useful for analyzing time-dependent characteristics in electrical machines. Unlike traditional feedforward neural networks, RNNs have feedback connections that allow information to be propagated not only forward but also backward in the network. This enables RNNs to capture the temporal dependencies and dynamic patterns present in electrical machine data, such as time-varying voltages, currents, or sensor readings. RNNs are well-suited for tasks like sequence prediction, anomaly detection, and time-series forecasting in electrical machines. By leveraging their ability to retain memory of past information, RNNs can contribute to more accurate and sophisticated predictions, enabling better understanding and control of the dynamic behavior of electrical machines. [2]

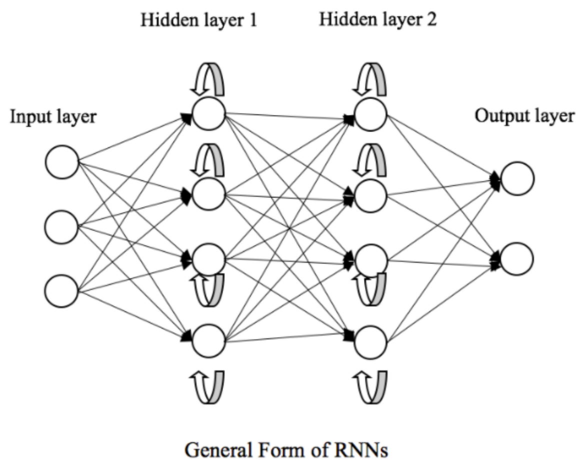

FIGURE 4 – Recurrent neural networks

4. Methodology

A. Dataset Used

The data set comprises several sensor data collected from a permanent magnet synchronous motor (PMSM) deployed on a test bench. The PMSM represents a german OEM's prototype model. Test bench measurements were collected by the LEA department at Paderborn University. This data set is mildly anonymized.
All recordings are sampled at 2 Hz. The data set consists of multiple measurement sessions, which can be distinguished from each other by column "$profile_{id}$". A measurement session can be between one and six hours long.
The motor is excited by hand-designed driving cycles denoting a reference motor speed and a reference torque. Currents in d/q-coordinates (columns "i_d" and i_q") and voltages in d/q-coordinates (columns "u_d" and "u_q") are a result of a standard control strategy trying to follow the reference speed and torque. Columns "$motor_{speed}$" and "torque" are the resulting quantities achieved by that strategy, derived from set currents and voltages.
The most interesting target features are rotor temperature ("pm"), stator temperatures ("$stator_*$") and torque. Especially rotor temperature and torque are not reliably and economically measurable in a PMSM.

B. Conventional Neural Networks

The initial steps involve importing the necessary libraries and obtaining the dataset. Subsequently, the data is partitioned into features and target variables, further divided into testing and training subsets. StandardScaler is employed to ensure standardized features. Four distinct neural networks are then constructed and compiled with unique architectures, promoting diversity among the models. Bagging is applied by assigning random samples from the training data to each network. A combiner network is created to merge the outputs of the constituent networks, with the individual networks set as non-trainable. Finally, the results are visualized through plotting, enabling the evaluation of training performance and the model's ability to capture the underlying trends within the training data [5].

C. Experimental results

The used method for testing the training history of our neural network is to analyze and visualize the loss and accuracy metrics during the training process. By plotting these metrics against the number of training epochs, we can observe the model's performance and determine if it is learning effectively and generalizing well. This helps in identifying overfitting or underfitting issues as well.

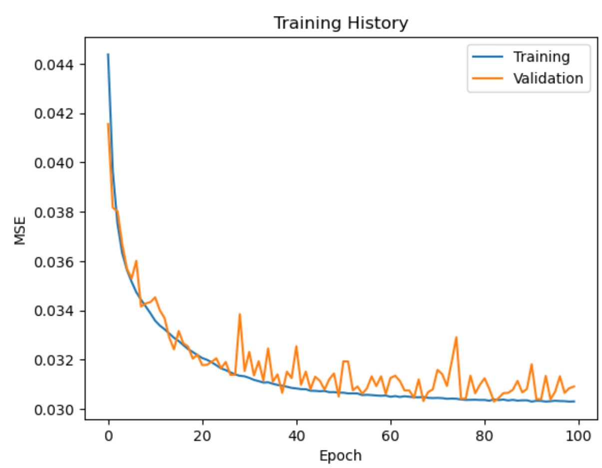

FIGURE 5 – Training history of our Neural Network

We tested the inference on one of our training set

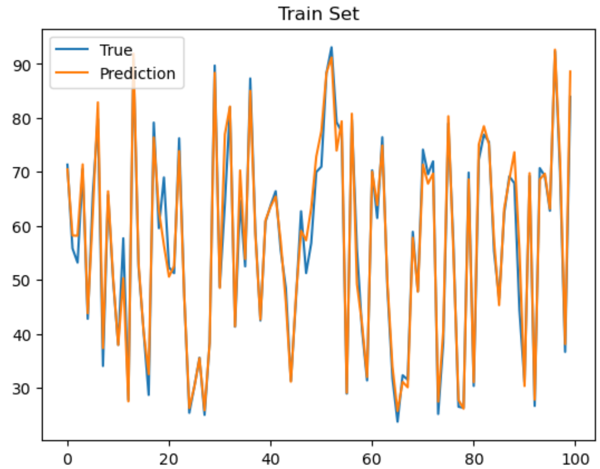

FIGURE 6 – Inference test on of our training sets

We got the final results of inference on one of the test sets.

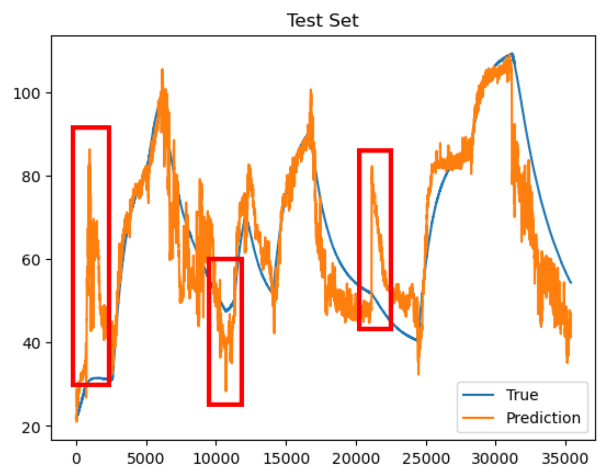

FIGURE 7 – Inference results on a test set

Our performance on the test set exhibited satisfactory results, although significant spikes were observed during periods where they should not have occurred. To enhance our ability to accurately capture the underlying trends in the data, we intend to incorporate a Recurrent Neural Network (RNN) into our existing model. The utilization of an RNN is particularly beneficial in handling time series data, enabling us to effectively address the sequential nature of our dataset. By leveraging the contextual information provided by the RNN, we anticipate mitigating the occurrence of these undesired spikes and improving the overall accuracy of our predictions.

D. Recurrent Neural Networks

To account of the shortcomings of the traditional neural networks we constructed an RNN architecture that incorporates the output of the ensemble NNs and trains the model using the provided training data, aiming to optimize the mean squared error loss. The training history is stored in the history variable for further analysis or visualization

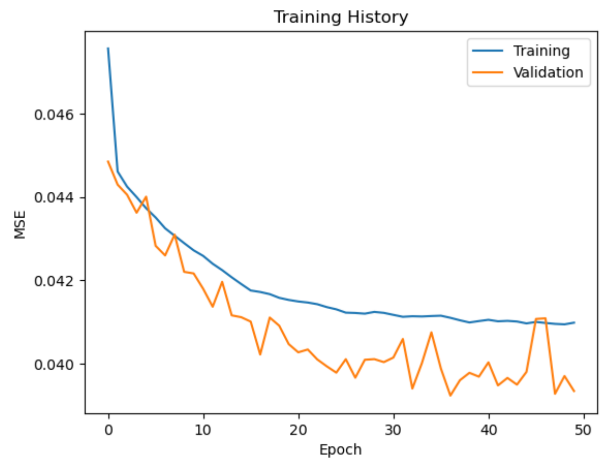

FIGURE 8 – Inference results on a test set

We tested the inference on one of our training sets

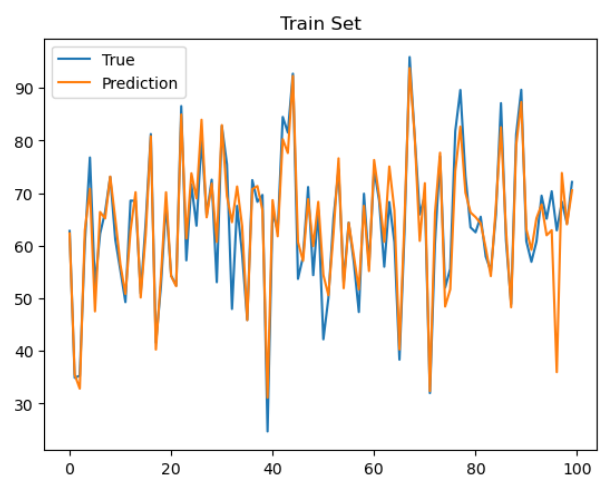

FIGURE 9 – Inference results on a test set

We got the final results of inference on one of the test sets.

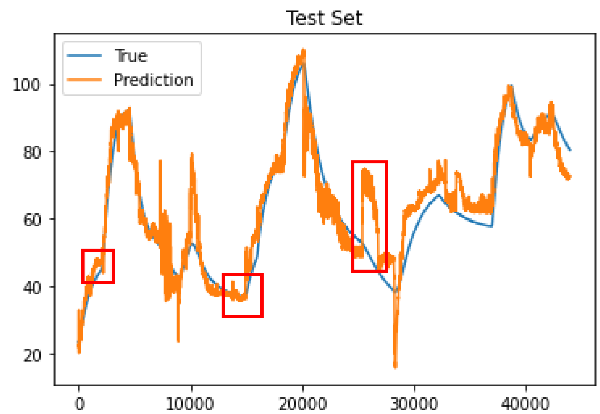

FIGURE 10 – Inference test on of our training sets

In general, the incorporation of the Recurrent Neural Network (RNN) resulted in a modest enhancement, especially when it comes to the temperature peaks artifacts ; however, it should be noted that this improvement was achieved at the cost of significantly increased computational time.

5. Conclusion

This article has presented a comprehensive investigation into the implementation of Neural Networks (NNs) and Recurrent Neural Networks (RNNs) for temperature estimation in Permanent Magnet Synchronous Machines (PMSMs). By leveraging the capabilities of NNs and RNNs, significant advancements have been achieved in accurately predicting and monitoring the temperature of PMSMs. The integration of NNs enables capturing complex nonlinear relationships between input features and temperature outputs, while RNNs excel at handling sequential and time-dependent data patterns. This combined approach showcases promising results in enhancing temperature estimation accuracy, facilitating proactive maintenance, and mitigating potential risks associated with temperature-related faults in PMSMs. As further research progresses, the adoption of NNs and RNNs in temperature estimation for PMSMs holds substantial potential for improving the performance and reliability of electrical machines in various industrial applications.

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