Data-driven reinforcement learning-based parametrization of a thermal model in induction traction motors

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Abstract

Monitoring the temperature of induction traction motors is crucial for the safe and efficient operation of railway propulsion systems. Several thermal models were developed to capture the thermal behaviour of the induction motors. With proper calibrating of the thermal model parameters, they can be used to predict the motor's temperature. Moreover, calibrated thermal models can be used in simulation to evaluate the motor's performance under different operating conditions and find the optimal control strategies.

Parameterization of the thermal model is usually performed in dedicated labs where the induction motor is operated under predefined operating conditions and calibrating algorithms are then used to find the model's parameters. With the development of digital tools, including smart sensors, Internet of Things (IoT) devices, software applications, and various data collection platforms, operational data can be collected and used later to calibrate the parameters of the thermal model. Nevertheless, calibrating the model's parameters from operational data collected from different driving cycles is challenging as the model has to capture the thermal behaviour from all driving cycles' data.

In this paper, a data-driven reinforcement learning-based parametrization method is proposed to calibrate a thermal model in induction traction motors. First, the thermal behaviour of the induction motor is modelled as a thermal equivalent network. Second, a reinforcement learning (RL) agent is designed and trained to calibrate the model parameters using the data collected from multiple driving cycles. The proposed method is validated by numerical simulation results. The results showed that the trained RL agent came up with a policy that adeptly handles diverse driving cycles with different performance characteristics.

Keywords: Railway, Propulsion system, Traction motor, Induction motor, Thermal model, Parametrization, Data-driven, Reinforcement learning, Calibrating, Optimization

1. Introduction

Traction motors are subjected to varying operating and environmental conditions due to the dynamic loads over the operation cycle. The transient loads may cause overloading of the drive components which causes extra heat load. Operations causing overheating of the motor parts are of significant concern as they may lead to stator winding failure and accelerated ageing. Furthermore, to be able to exploit the motor's maximum utilization, it is essential that its operation is optimized to make it cost-effective.

On the other hand, induction motors (IMs) are the most used motors in railway propulsion applications to date because of their mechanical robustness and high overload capabilities. The added advantages are their low cost and the possibility of employing multiple drives connected to a single converter (Nategh *et al.*, 2020). However, their performance varies nonlinearly with temperature, frequency, saturation, and operating point which makes temperature monitoring essential for the safe and reliable operation of the motor.

The thermal limits of these motors are associated with the winding insulation material which is classified based on its temperature withstanding capacity. There are several established direct or indirect means for estimating the temperature in motor parts. Direct methods such as installing contact-based sensors in the stator, and rotor are the simplest means for measurement. However, the data transmission in the rotating parts has to be carried out with the help of end slip rings, or telemetry means. Regardless, installing sensors requires integration effort and additional cost and adds complexity due to their inaccessibility for replacement in case of failures or detuning. Hence model-based measurement techniques have been rather focused in the past decade (Ramakrishnan *et al.*, 2009; Wilson, 2010). Here the temperatures can be estimated from the temperature dependent electrical parameters both off-line and online

6. Conclusion and Future Work

In the paper, a reinforcement learning framework is proposed for training an agent to find the parameters of the thermal model in induction traction motors. The framework has been applied to find the thermal conductance for the thermal network model from nine driving cycles.

By running different driving cycles, the trained agent came up with a policy that produces the parameters for the different driving cycles. The model with the calibrated parameters showed a good estimation of stator and rotor temperature.

In future work, other structures for the agent and the reward function will be considered to produce better temperature estimation.

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