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TN, ROM, ML, PINNS – FOUR APPROACHES FOR REAL-TIME TEMPERATURE ESTIMATION IN ELECTRIC MOTORS IN COMPARISON

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Key words: thermal network, reduced order model, machine learning, electric motor, physics-informed neural network.

Summary *One of the major trends in electrical machines for automotive applications is towards higher power-densities and more integrated components. With that, accurate thermal management of the machine and capable cooling systems are of great significance to the safety and reliability of the traction system. Thermal simulations are an integral part in the design process of electrical drives. However, recently thermal models are also more frequently used in the context of machine control. The latter demanding for fast, yet accurate, temperature estimations.*

This work is comparing different approaches towards real-time, spatially resolved, temperature estimation of a direct oil cooled permanent magnet synchronous machine:

- *Spatially resolved lumped parameter thermal network (SLPTN),*
- *Reduced order model (ROM) automatically derived from a Finite Element model,*
- *Data-driven, machine learning (ML) model and*
- *Physics-informed neural network model (PINN).*

The techniques are systematically evaluated in terms of the effort in setting up the model, their accuracy compared to experimental data and their suitability for real-time predictions.

1 INTRODUCTION

Permanent magnet synchronous machines (PMSMs) are one of the most common topologies for tractions motors in electric vehicles. PMSMs offer high efficiency, small size, and full torque starting from low rotation speeds. One of the major technical challenge of PMSMs lies in the sensitivity of the permanent magnets to high temperatures, leading to irreversible demagnetization in the worst case. Therefore, accurate temperature control and capable cooling of the machine is of great significance to the safety and reliability of PMSMs. Likewise, the continuous power output of an electric machine is typically restricted by its thermal limits (cf. Fig. 1).

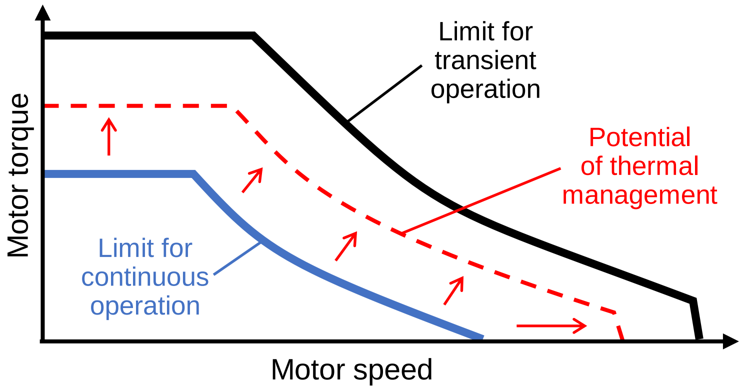

Figure 1: Thermal management effect on motor operating limits [1].

Flexible and accurate thermal management allows expanding the continuous operating limit of a machine without running into thermally critical conditions [1]. As a result, higher continuous output power can be obtained, or smaller machines can be used to achieve the output target. The application of model-based thermal control has also demonstrated good energy savings in terms of overall vehicle energy management [2].

Fast and accurate computational models found the basis for robust model-based control approaches. [3] and [4] provide comprehensive overviews of the state-of-the-art thermal monitoring techniques of electric machines. Lumped parameter thermal networks (LPTN) present a common approach for thermal monitoring of electric machines [5, 6]. LPTNs represent heat flows by equivalent circuit diagrams, defining a system of ordinary differential equations. Alternatively, model-order reduction techniques can be employed to reduce the number of degrees of freedom of high-fidelity models, e.g. Finite Element models [7]. Furthermore, attempts have been made to generate black-box models for electric machines by applying deep-learning techniques to large amounts of experimental data [8].

The paper is structured as follows: Section 2 introduces the studied electric machine and the measurement setup. Section 3 summarizes the fundamentals of heat conduction problems, before the different thermal monitoring approaches are discussed in Section 4. Finally, a summary and conclusions are given in Section 5.

2 ELECTRIC MACHINE AND EXPERIMENTAL SETUP

The PMSM considered in this work features a conventional cooling jacket in the frame and direct cooling of the end windings, as schematically depicted in Figure 2.

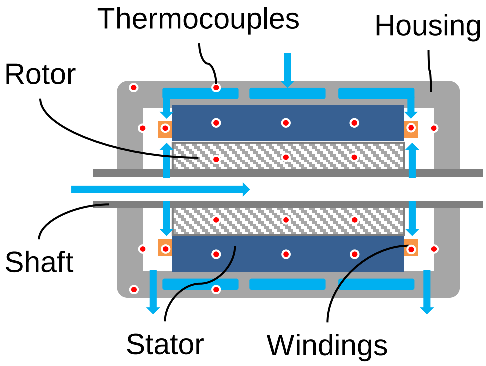

Figure 2: Schematic of the motor oil cooling concept and the qualitative arrangement of thermocouples.

Additionally, oil is flowing through the hollow shaft of the rotor. Channels in the shaft further guide the oil to the end windings by centrifugal forces. Due to the rotating oil jets a homogeneous cooling of the end-windings can be achieved. Oil outlets are located at the bottom on both sides of the machine. Throughout this work, a fixed oil flow rate and oil temperature is considered.

In total, the motor is equipped with 70 thermocouples distributed all over the machine as schematically depicted in Figure 2. The locations were chosen according to internal best practice and K-type thermocouples with an accuracy of about 2-4°C are employed.

This work is focusing on the continuous operation area of the machine (cf. Figure 1). Prior to each measurement, the machine is conditioned for several hours to assure a uniform temperature distribution within all components. Thereby, similar initial conditions for each operating point are assured. Subsequently, the measurement is carried out at a given motor speed and load. The operation points are run until a steady state temperature in all parts of the machine is reached after about 30 minutes.

3 HEAT TRANSFER THEORY

The thermal behaviour of the electric machine is treated as a pure heat conduction problem in this work, neglecting influences of radiation. In general form, the governing heat equation is given by:

$$\rho c_p \frac{\partial T}{\partial t} - \nabla \cdot (k \nabla T) = \dot{q}_V, \tag{1}$$

with the temperature T and volumetric heat source $\dot{q}_V$. The material parameters, thermal conductivity k, specific heat capacity c_p, and density ρ, are typically well defined. Power losses of the electric machine are considered as volumetric heat sources in equation (1). The losses can be obtained from Finite Element Analysis (FEA), measurements, or empirical correlations [3]. This work is focusing on the thermal modelling aspects and therefore the losses are assumed to be given as maps depending on torque and speed of the machine. Thermal contact resistances between different materials and heat transfer coefficients on cooling surfaces are typically modelled based on empirical assumptions [9] or identified with the help of experimental data. Details on the latter are provided in the Section 4.

4 MODEL-BASED THERMAL MONITORING OF ELECTRIC MACHINES

Sensor-based temperature monitoring in electric machines is typically limited due to the costs and integration efforts. Conventional simulation approaches, like Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD), commonly used during design phase of the machine are unsuitable for monitoring purposes due to their high computational complexity. In this work, four approaches for real-time thermal monitoring are discussed in the following.

4.1 Thermal Network (TN)

Thermal networks are modelling the heat transfer by thermal nodes and thermal interfaces without explicitly resolving the motor geometry. Therefore, only average temperatures of each component are obtained. As an extension, a space-resolved lumped parameter thermal network (SLPTN) [10] allows to represent each part of the machine with several thermal nodes. Thereby, local hot spots can be identified rendering SLPTNs particularly suitable for the application in thermal management.

For the given machine, the abstracted geometry of the SLPTN is depicted in Figure 3. The computational costs are reduced by considering only a section of the whole geometry and assuming also axial symmetry. Finally, the SLPTN used in this work consists of 164 thermal nodes also resolving six sensor locations of the actual machine that are used for parameter identification of the model.

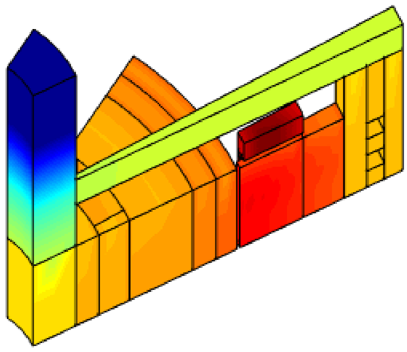

Figure 3: SLPTN geometry of the shaft, rotor, endcap, housing, stator, and windings.

Due to the geometric abstraction with the SLPTN model, defining the model parameters based on empirical correlation may lead to poor approximations. Therefore, the underlying model parameters, namely thermal resistances, conductances and heat transfer coefficients are identified with the help of experimental data. Essentially, a least squares optimization problem is solved using the time series data from six sensors and six operation points.

Figure 4 summarizes the maximum difference between the steady state temperature predicted by the tuned SLPTN and the experiments. Except for one operation point, the model accuracy is within the set target of 10 K.

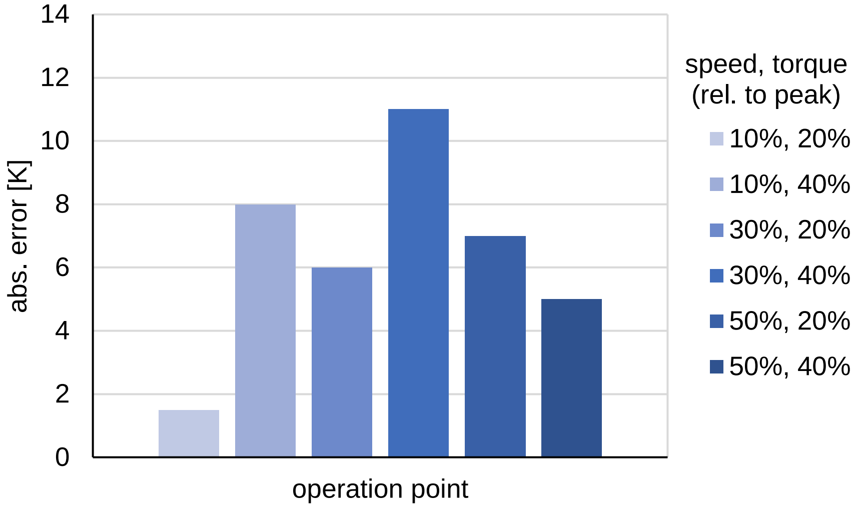

Figure 4: Maximum error between the SLPTN model and the experiment for six operation points.

In [10] it is shown that SLPTN models are basically real-time capable. A mathematical reduction approach (e.g. balanced truncation) can subsequently reduce the degrees of freedom of the SLPTN without affecting the model accuracy significantly (cf. [10]).

4.2 Reduced Order Model (ROM)

One drawback of SLPTN models is the need to perform the geometry abstraction and implementation of the thermal network manually. With the target of a more automated workflow, a reduced order model (ROM) of the full electric machine is investigated. Here, the Craig-Bampton method is employed. For details on the methodology, it is referred to e.g. [11]. This ROM approach is based on a Finite Element Analysis (FEA) model, assumed to be available from the design phase of the machine. The ROM is derived based on randomly selected boundary nodes and the same six sensor locations that were used in the Section 4.1. In total, the ROM features 227 degrees of freedom for the full machine.

The thermal model parameters are identified in a similar manner as for the SLPTN by solving a least-squares optimization problem. Overall, a similar accuracy level is achieved as with the SLPTN model, see Figure 5.

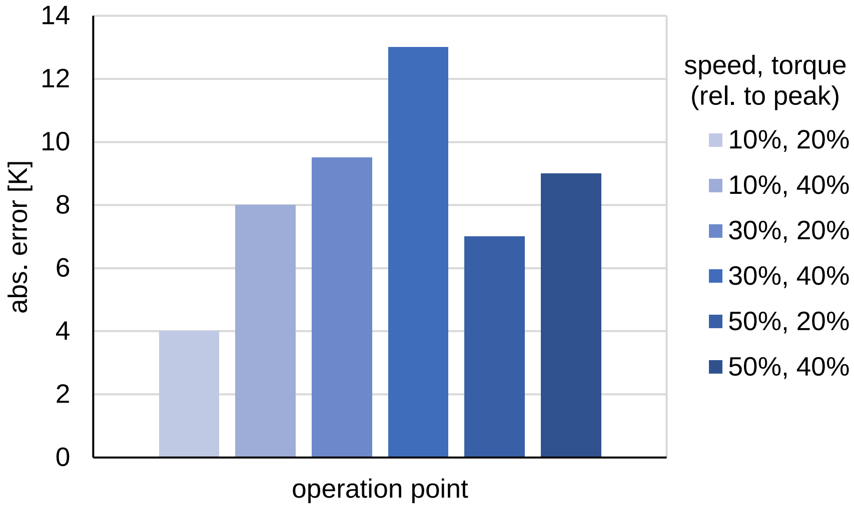

Figure 5: Maximum error between the ROM and the experiment for six operation points.

The major advantage of the given ROM over the SLPTN lies in the reduced model preparation effort. Assuming the availability of a high-fidelity FEA model, the described model order reduction and parameter identification steps can be automated.

Initial trials on embedded hardware could also demonstrate the real-time capability of the resulting ROM.

4.3 Data-driven machine learning model (ML)

Recalling that the time-series of 70 thermocouples is available for the discussed electric machine, the question arose how a purely data-driven approach would perform for thermal monitoring. Therefore, an in-house developed, generic, supervised machine learning pipeline is employed (Figure 6).

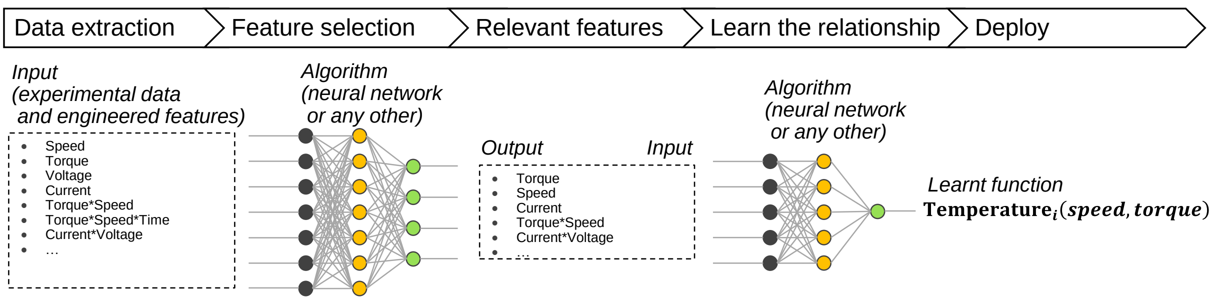

Figure 6: Generic machine learning pipeline used to train a data-driven thermal model.

The pipeline automatically extracts the most relevant features of the input data and the most suitable algorithms. Herein, also combinations of multiple algorithms, like XGBoost, Lasso, etc. are considered. In contrast to the approaches from Section 4.1 and 4.2, all data from the experiments, including electrical features such as voltages and currents are feed into the training pipeline. Furthermore, some additional features are engineered through linear combinations of individual features. Still, it should be noted that the overall approach, including the feature engineering remains rather generic. This contrasts with e.g. [8] where features are engineered based on physical considerations. In total, 24 features per sensor and time step are entering the model training. The transient character of the dataset is accounted for by applying a sliding window method with one-step forecasting [12].

The accuracy of the trained model is evaluated with the same metric as for the SLTPN and ROM in Figure 7.

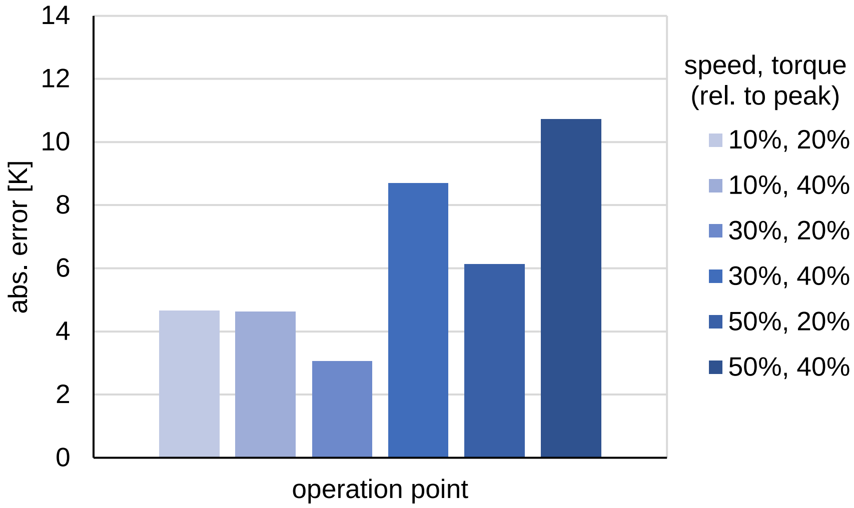

Figure 7: Maximum error between the machine learning model and the experiment for six operation points.

These results are obtained through a cross-validation to avoid overfitting of the model. Like SLPTN and ROM, the data-driven approach achieves good accuracies staying mostly below the set target of 10 K.

Once trained, inference of these models is fast. Therefore, the purely data-driven approach is also considered suitable for real-time applications [13].

4.4 Outlook: Physics-Informed Neural Network Model (PINN)

While the purely data-driven approach achieves good accuracies, the amount of data available in the given case, especially in terms of the number of temperature sensors, is exceptional for conventional machines. In that regard, a more data-efficient approach is desirable. Physics-informed neural networks can be seen as a mid-way between the data-driven approach from the Section 4.3 and the physically motivated approaches from Section 4.1 and 4.2. Raissi et al. introduced the concept of physics-informed neural networks in [14]. Figure 8 depicts the concept of PINNs schematically for the steady state heat equation.

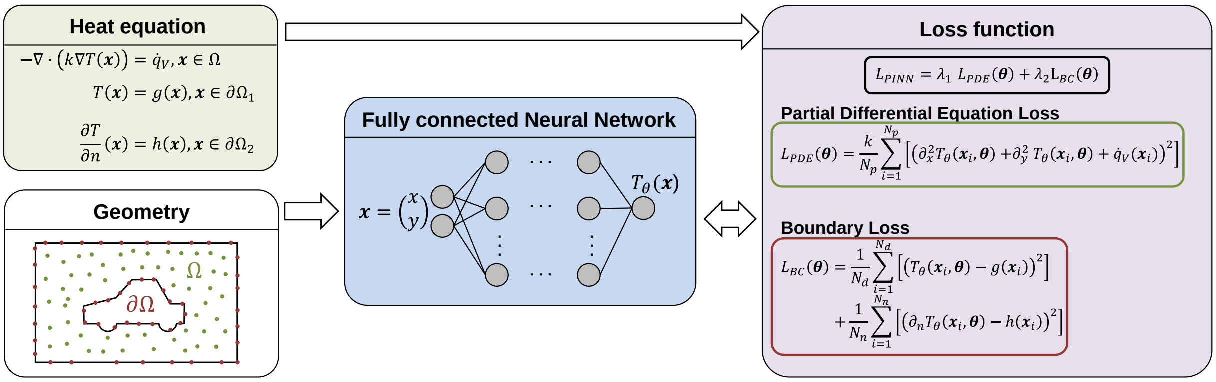

Figure 8: Schematic of a physics-informed neural network for the steady-state heat equation.

A standard fully-connected neural network is considered. The key idea is to train this network to comply with the differential equation and boundary conditions governing the given physical problem. Therefore, a loss function L_{PINN} is defined to regularize the neural network output accordingly during training. Here, the partial derivatives contained in the loss function are obtained through automatic differentiation of the neural network. The proper choice of the weighing factors λ in the loss function (cf. Figure 8) is an active field of research [15]. Upon minimization of the loss function during training, effectively, an approximation T_θ to the solution of the given differential equation is obtained. The geometry information is entering the training through randomly sampled points in the interior and on the boundaries.

Initially, very promising results could be obtained with PINNs for simple heat conduction problems. However, translating the initial findings with PINNs to a more complicated problem, like the thermal modelling of electric machines, remains challenging. At the current state, the training of a PINN for the electric machine fails to converge. Yet, results of other authors [16] motivate to investigate and resolve these issues as part of our future work. Furthermore, in contrast to the SLTPN and ROM of this work, parameterized and inverse problems can be treated with PINNs in a straightforward manner. These features make PINNs especially attractive for building digital twins [17].

5 CONCLUSIONS

In this work, four different modelling approaches for thermal monitoring of electric machines are discussed. Table 1 summarizes the findings of this work with respect to our requirements.

Table 1: Summary of the findings for the discussed approaches for thermal monitoring.

	SLPTN	ROM	ML	PINN
Physical	✓ Yes	✓ Yes	✗ No	✓ Yes
Geometry	✗ Needs abstraction	✓ Full	Sensor locations	✓ Full/segment
Preparation time	✗ High	✓ Low (from FEA model)	✓ Low	Medium
Tuning/training time	✗ Slow	✗ Slow	Medium	✗ Slow
Real-time capability	✓ Yes	✓ Yes	✓ Yes	TBD
Accuracy	✓ Good	✓ Good	✓ Good	TBD
Bottlenecks	Model preparation	FEA model	Data inefficiency	Training time

SLPTN, ROM, and ML achieve the target accuracy and are basically assumed to be real-time capable, that is, our fundamental requirements are full filled. While LPTNs are a very well-established methodology, the herein discussed SLPTNs requires additional, manual, effort in preparing the model and the abstracted geometry (cf. Figure 9).

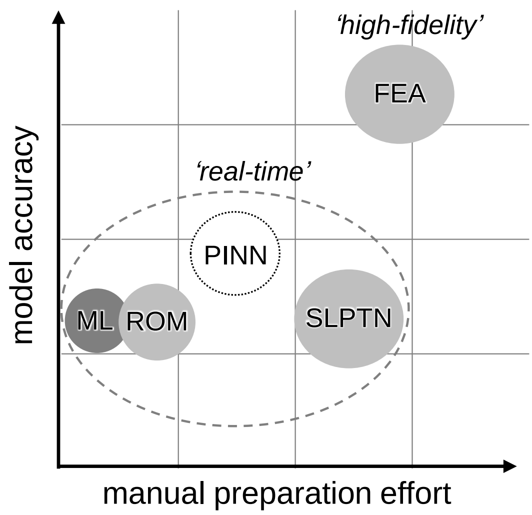

Figure 9 Qualitative manual preparation effort and accuracy for each approach of this work[1].

Assuming the availability of a FEA model, the ROM allows to circumvent this limitation by essentially allowing for a fully automated model reduction and identification workflow. The

[1] Tentative accuracy for PINN.

data-driven (ML) approach achieves good accuracies and is straightforward to set up. Yet, the inherent data-inefficiency and unawareness of physics present decisive factors limiting the deployment of purely data-driven approaches to series applications. The application of PINNs is only briefly outlined in this work. Yet, PINNs are considered a promising compromise between data-driven and physics-based approaches. Preliminary investigations clearly highlight that training duration for PINNs will be a major bottleneck. Furthermore, the suitability and accuracy of this approach still needs to be proven for real application scenarios.

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