## TN, ROM, ML, PINNs – Four Approaches for Real-Time Temperature Estimation in Electric Motors in Comparison

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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) [1],
- Reduced order model (ROM) [2]; automatically derived from a Finite-Element model,
- Data-driven, machine learning (ML) model,
- Physics-informed neural network model (PINNs) [3].

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.

## **REFERENCES**

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