Neural Network-Based Estimation implemented in a particular Dielectric Oil Spray Electric Motor Cooling Technique

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Abstract. Accurate thermal modelling is critical for optimizing the cooling system's performance and reliability of electric motors. A promising cooling method is the direct spray cooling of stator end windings using dielectric oil. A key parameter in such cases is the heat transfer coefficient (HTC), which depends on complex interactions between surface characteristics, material properties, and coolant fluid behaviour. Traditional methods for HTC evaluation such as empirical functions have limited accuracy, as they fail to capture time variations. Computational Fluid Dynamic techniques (CFD) combined with 3D finite elements analysis (FEA), provide increased accuracy but necessitate very important computational means, rendering them practically inapplicable in real-time and iterative design processes. This paper introduces a novel Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) framework for estimating the HTC of direct spray cooling on end windings of electric motors. The neural network is trained on a sequential dataset that integrates appropriate parameters to capture transient phenomena. Training labels are derived from CFD simulations and experimental data from literature. The model's predictions are given as input to a distributed Lumped Parameter Thermal Network (LPTN) for temperature calculation enabling fast and efficient thermal modelling of PMSMs.

1. Introduction

In recent years, transportation is undergoing a rapid transformation toward electrification, replacing fossil fuels targeting a sustainable, carbon-neutral future. Traction electric motors are characterized by high-power density, which require effective heat dissipation. The most advanced motors have efficiencies greater than 97% thus thermal management is one of few ways to increase efficiency further. Overheating in critical components, such as the end windings, can lead to insulation degradation and diminished motor performance, making precise temperature estimation very important.

EVs operate transiently with high peaks at acceleration and braking. Spray cooling directly on end windings is an emerging and highly effective cooling technique, capable of achieving heat removal fluxes as high as 1000 $\frac{W}{cm^2}$ using water, as demonstrated in recent studies [1],[2]. El-Refaie et al. [3] developed a motor for traction applications and compared three cooling designs including (i) stator cooling jacket, (ii) cooling tubes inside slots and (iii) end-winding spray cooling. They concluded that the spray cooling was the most effective and relatively simple in terms of design complexity. This method has already been successfully applied in the cooling of power electronic devices used in electric vehicles (EVs) and more electric aircraft (MEAs). Implementing a closed-loop system for spray cooling, it is also possible to maintain a continuous high heat removal flux. Extensive parameter studies in the spray cooling field have explored factors such as nozzle positioning, coolant volumetric flow rate, surface roughness of the heated area and spraying frequency [4],[5]. These investigations have been conducted through both experimental approaches and numerical simulations and their results are promising.

Heat transfer coefficient governs the heat exchange between the winding surfaces and the coolant. HTC is influenced by complex factors like surface smoothness, material properties, and coolant behaviour (e.g., flow rates, spray angles). Furthermore, HTC varies dynamically in different operating conditions (i.e. surface temperatures), which affect fluid properties like viscosity and thermal

conductivity. Traditional approaches to HTC estimation such as empirical formulashave limitations. While computationally efficient, they are inherently static and fail to capture the transient phenomena associated with end winding cooling, such as the temporal variations in HTC due to temperature changes or dynamic flow behaviour. In contrast, CFD simulations provide detailed insights into thermal and flow dynamics but require significant computational resources and time, making them impractical for iterative design processes. Lumped Parameter Thermal Network (LPTN) models offer a more computationally efficient alternative for electric motor thermal analysis. However, the predictive accuracy of LPTNs depends heavily on the quality of input parameters, particularly the HTC for convective heat flux estimations. The limitations of static empirical formulas and the computational intensity of CFD simulations highlight the need for a faster, more adaptive method to estimate HTC, especially under transient operating conditions.

This paper introduces a novel approach to overcome these challenges by leveraging a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) unit, which are emerging in many research areas like fluid flow analysis [6] and image processing. The training dataset includes geometric configurations, material properties, and coolant parameters. The RNN accurately predicts the HTC of directly oil cooled end windings, accounting for transient phenomena and bypassing the need for time-intensive CFD simulations for every design case. RNN's also perform well in understanding non-linearities. The main target is to integrate these predictions into an LPTN (figure 1) simulating a radial flux Permanent Magnet Synchronous Motor (PMSM) designed for electric cars. To validate this approach, we will juxtapose the results with the ones already acquired from 3D FEA-CFD combined simulations and LPTN with empirical calculations of HTC. To decrease the time complexity of our analysis, we simulate a linear stator part equivalent to half of one phase of the complete motor. By addressing the limitations of traditional HTC estimation methods and demonstrating the effectiveness of the proposed model, this work aims to establish a faster, more reliable way for thermal modelling directly oil cooled PMSMs.

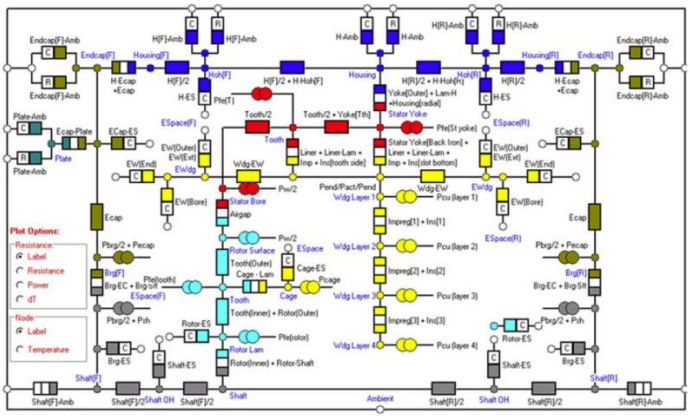

Figure 1. Distributed Lumped Parameter Thermal Network

2. Methodology

Traditionally, the HTCs of spray cooling electric motors are calculated via empirical formulas as the one proposed in [7] and reported in equation (1):

$$h = k_1 * \left(1 + k_2 * v^{k3}\right), \tag{1}$$

where k_1, k_2, k_3 are constants and v denotes the fluid velocity. Recently, following the rise of machine learning models, there are many neural networks formulated for estimating fluid flow and fluid spraying characteristics [8],[9] and thermal properties. The proposed framework for predicting the HTC employs an artificial neural network trained on a dataset derived from CFD simulations for the same simulation time (steady state reached). The final train and validation data also contain already acquired data from literature and will be incrementally updated with experimental data. Note that the data fed to the model are sequential, meaning for each different operating condition the data are

captured in chronological order, so that the model could extract the time dependency of the transient phenomena.

2.1 3D FEA and CFD

An axisymmetric model for CFD analysis is employed to minimize simulation time, capturing the interaction between fluid and solid surface as shown in figure 2. The target is to monitor heat transfer between sprayed oil droplets and motor's end winding copper region, using the Volume of Fluid method (Eulerian model) for air and oil phases, the Energy Equation for incompressible flow as formulated in equation (2) and k-e SST model for turbulence modelling.

$$\rho C_p \left[\frac{\partial T}{\partial t} + (u \cdot \nabla)T\right] = k\nabla^2 T + \varphi \quad (2)$$

Where ρ denotes the material density, C_p the specific heat and u the fluid's velocity. Boundary conditions were properly defined i.e. inlet speed, pressure outlet, symmetry boundary condition at the axis line and standard heat flux of 350 Watts from the copper solid. Oil and copper thermal properties are presented in table I. Various end winding designs were implemented with a Matlab script to produce random shapes based on the number of turns and conductor's dimensions which represent different surfaces and aid the neural network's generalization ability. A random end-winding formulation with 6 turns is depicted in figure 3.

Table 1. Material Properties

	Density (kg/m$^{3)}$	Thermal Conductivity (W/m/K)	Specific Heat (J/kg/K)	Viscosity (mPa·s)
Copper	8920	360	401	-
Oil	806	0.1398	2191	15.86

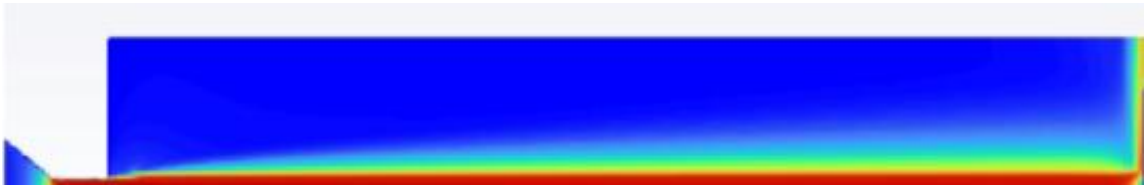

Figure 2. Axisymmetric CFD – velocity field.

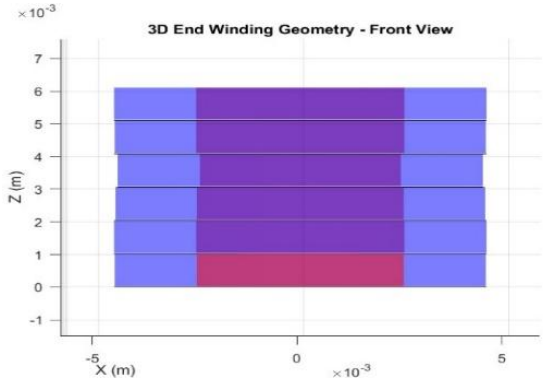

Figure 3. Front view of random end winding configuration.

These simulations provided detailed data under different configurations. The results were post-processed to extract the transient spray cooling HTC, and they were fed into a 3D FEA transient thermal model as convective boundary conditions, to calculate the temperature distribution on a linear stator. The final computed temperature profile can be seen in figure 4.

2.2 RNN model with LSTM

The neural network employed is a regression model with Recurrent Neural Network (RNN) architecture and Long Short-Term Memory (LSTM), chosen for its ability to capture temporal dependencies specifically on sequential data representing dynamic spray and heat transfer behaviours. LSTM is a special kind of RNN that has memory units to get around being dependent on data for a long time. LSTM control the information flow with three gates from a time-series data, where $X_t, C_t, H_t, i_t, f_t, o_t$ are the input quantity from a time-series data, cell state, hidden state, input gate, forget gate, and output gate, respectively, shown in figure 5.

It consists of an input layer with 7 input nodes representing the parameters reported in table 2:

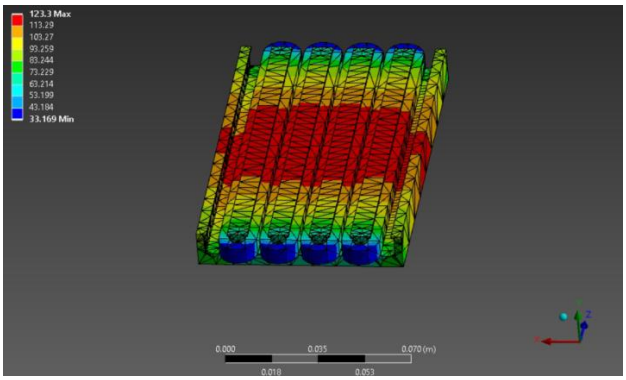

Figure 4. Temperature distribution on a linear motor configuration.

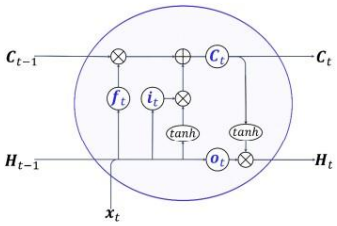

Figure 5. LSTM unit.

Table 2. Input parameters

EM	Fluid	Geometry
Initial Temperature	Viscosity	Number of turns
Copper Losses	Inlet Speed	Nozzle Distance
	Oil Temperature	

The selected input parameters capture both the electromagnetic aspects regarding the copper losses and the fluid flow properties, thus allowing the model to extract dependencies. In total, the train dataset is comprised of 50 different simulations, with various values of inlet speeds, nozzle distances and oil temperatures. The remaining parameters were kept constant. Additionally, the neural network contains one hidden layer, with 32 neurons, employing hyperbolic tangent function as activation (described in equation (2)) for non-linearity and dropout for regularization.

$$g(z) = \frac{2}{(1+e^{-2z})} - 1 \tag{2}$$

The number of hidden layers was selected to avoid over-fitting on the training data. The output layer generates a single predicted HTC of oil convection on copper. Hyperparameter tuning, including learning rate adjustment and batch size, was performed with Bayesian Optimization to enhance model

convergence. This multi-physics simulation methodology ensures scalable and efficient estimation of the HTC for integration into LPTN models.

3. Results and Discussion

The proposed neural network demonstrates very good predictive performance, as evidenced by an R^2 score (coefficient of determination) of 0.96 on the test set, as stated in equation (3):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{3}$$

where SS_{res} denotes the residual sum of squares and SS_{tot} the total sum of squares. This indicates a high degree of correlation between the predicted and actual values of the normalized HTC. Furthermore, the Root Mean Square Error (RMSE) on the test set was calculated at 0.035, showcasing the model's ability to predict h with minimal error. This trained model is then incorporated into the LPTN model to produce transient convective resistances simulating oil cooling.

The predicted values of HTC vs the values acquired from CFD can be seen in figure 6 where it is apparent that their relation is almost linear.

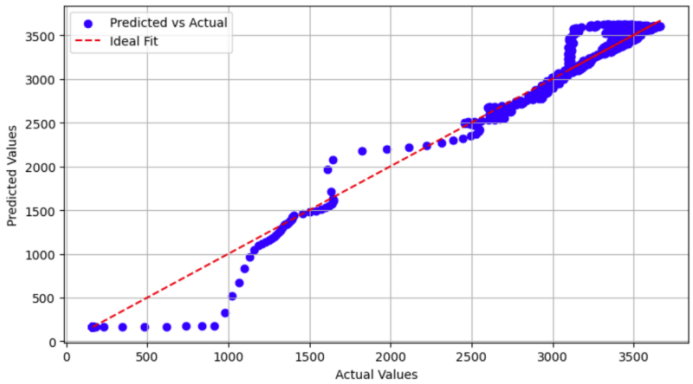

Figure 6. HTC_{CFD} vs HTC_{RNN}.

The CFD method required an average of ~1 hour of computation time per configuration (with 4 parallel CPU cores), leveraging a Eulerian multiphase model as presented previously. On the other hand, trained RNN completed predictions almost instantly per configuration. This represents a big improvement in computation time, enabling real-time analysis. In figure 7, we can see the accuracy advantage provided from the proposed methodology, where we have monitored the hot spot temperature on the winding predicted from a combined 3D-FEA/CFD model, a transient LPTN with RNN predicted HTC values and an LPTN with empirical correlations for spray cooling, respectively.

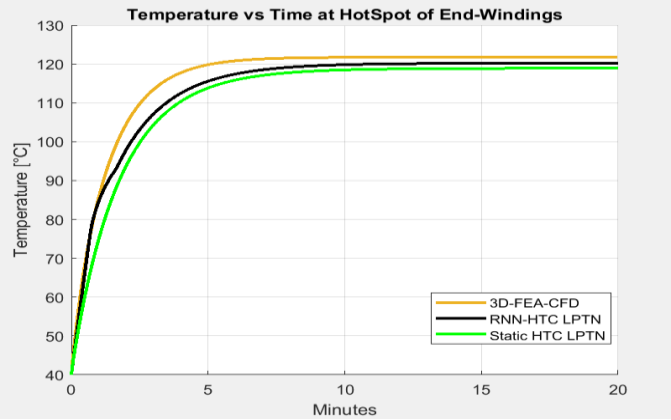

Figure 7. Winding Temperature calculated using 3 methods

The accuracy of LPTN calculations improved not only on the steady state values but also on the transient part of temperature curve, which is mainly because the model captures transient thermal phenomena. The enhanced model predicted temperatures within 2°C of 3D thermal FEA calculation, an improvement over the baseline model's error range of ~4°C in steady state. This can be attributed to the RNN's ability to anticipate the delay in heat propagation due to the thermal mass of the windings.

4. Conclusion

This paper presented a novel methodology for temperature prediction in directly oil sprayed copper windings of electric motors. Three methods for HTC estimation in oil spray cooling on copper end-windings have been compared: empirical formulas, 3D FEA/CFD and RNN with LSTM approach. The proposed model demonstrated remarkable performance, with an R^2 score of 0.96. Empirical formulas fail to capture important transient phenomena of conjugate heat flux, thus by incorporating the RNN with LSTM, which is trained on sequential CFD-generated data, this work bridges the gap between accuracy and efficiency. The RNN effectively captures the nonlinear behaviors of HTC, providing results that align with CFD combined with calculation time speedup.

Although the proposed approach demonstrates promising accuracy, it has been currently trained on a limited dataset derived from CFD simulations under specific boundary conditions. To that respect, generalization across different motor geometries or oil formulations is intended to be validated. Future extensions are scheduled involving a more diverse dataset including experimental data from tests conducted on a linear motor configuration. Nevertheless, the paper denoted the potential of machine learning in providing more efficient, accurate, and scalable solutions for thermal management in modern electric machines.

5. Acknowledgment

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