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Published in:
IEEE Transactions on Magnetics

DOI:
[10.1109/TMAG.2017.2661381](https://doi.org/10.1109/TMAG.2017.2661381)

Published: 01/06/2017

Document Version
Peer reviewed version

Please cite the original version:
Nair, D. G., & Arkkio, A. (2017). Inverse Thermal Modeling to Determine Power Losses in Induction Motor. *IEEE Transactions on Magnetics*, 53(6), [8103204]. <https://doi.org/10.1109/TMAG.2017.2661381>

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Inverse Thermal Modelling to Determine Power Losses in Induction Motor

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An electrical motor's inverse thermal model formulates the precision with which its power losses can be predicted from noisy local temperature measurements. This paper proposes constrained linear least square optimisation followed by noise smoothing as a method to accurately predict a 37 kW induction motor's power loss components. The anisotropic heat transfer and complex geometry of the motor is represented well by the motor's lumped thermal network and 3D finite element models which characterise its intrinsic heat transfer processes. With the inverse solution method, satisfactory temperature to power inverse mapping was achieved for different sets of noisy temperature inputs simulated from analytical and numerical forward solutions. The paper demonstrates that even with measurement noise in input data, if reliable information about the expected response of the system is available, an accurate reconstruction of power losses can be achieved.

Index Terms—Heat transfer, induction motors, thermal inverse problems

I. INTRODUCTION

INVERSE modelling refers to the reconstruction of an unmeasurable source from its easily measurable, observable effects. Determining the heat sources in an electrical machine from its temperature distribution is thus a form of inverse thermal modelling which has its own unique advantages. An electrical motor's total power loss is usually obtained as a difference of its input and output powers measured by digital oscilloscopes or power analysers. High harmonics in the system can cause these devices to operate improperly at times. However, motor's temperature rises remain unaffected by such phenomenon, and serve as a direct indicator of its power losses. Hence there are benefits to measuring the machine temperatures instead of directly measuring its power losses. [1] investigated the local iron losses with temperatures measured on the machine's stator tooth. Moreover, through inverse source reconstruction, losses in some inaccessible machine parts can be determined from temperatures measured at others.

There exists a large body of work dealing with inverse heat problems; 2D conduction [2], source mapping in micro electromechanical systems [3], and also 3D spatial source reconstruction [4] with thermal camera input. Overall, the systems studied and solution methodologies adopted have been mostly restricted to structurally simple and homogeneous systems. This is partly due to the ill-posed nature of the inverse problems (high sensitivity to input data errors) which makes it challenging to solve. Usually this is overcome with stabilization techniques [5] that approximate the inverse problem to a well-posed function which is solved instead. [3] addresses the inverse heat conduction problem at microarchitecture level with constrained least squares optimisation quite effectively.

The complex geometry and large scope of an electrical motor along with the presence of different modes of heat

transfer pose additional challenges to inverse power mapping over its whole domain. In the present work, the machine of interest is a common 37 kW totally enclosed fan-cooled squirrel cage induction motor. Firstly, the direct forward relationship between its power losses and temperature rises is established with the motor's lumped thermal network. While the inverse of this relationship generates the losses accurately with noise-free input, with noisy temperature measurements the results are erratic. In the latter case, solution is obtained in a similar fashion as [3] by overdetermining the system and obtaining the loss vector which is the least square (LS) optimal solution satisfying the linear constraints imposed on the system. This approach is tested also with a different set of measurements, from the motor's numerical finite element (FE) thermal solution. This 3D numerical model of the motor was calibrated against experimentally measured motor temperatures so that the overall numerical results closely match real noisy measurements. Domain averaged temperatures from the FE results then replaced the simulated noisy temperatures as input to the lumped network's inverse formulation. The response with fewer measured data is also investigated. Later, the FE model of the motor itself is taken as the basis of inverse analysis. Compared to the lumped network this system is much larger and only outer frame's temperature measurements are considered available for inverse mapping. LS solution of the overdetermined system assisted by suitable noise smoothing is shown to yield good results here as well.

II. METHODOLOGY

A. Analytical Model

Formulation of the forward thermal problem in electrical motors is undertaken to estimate the nature of inverse approach required. The direct problem of ascertaining temperature rises from power losses in rotating electrical machines has been a well-researched and documented one [6]. The relationship between power loss P and temperature rise ΔT in steady state is established in the discretized form

$$[\Delta T] = [Y]^{-1} [P]. \quad (1)$$

Manuscript received November 20, 2016; revised January 20, 2017; accepted January 24, 2017. Date of publication xxxx xx, 20xx; date of current version xxxx xx, 20xx. Corresponding author: Devi Geetha Nair (email: devi.nair@aalto.fi).

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Digital Object Identifier (inserted by IEEE).

Here $[Y]^{-1}$ is the thermal admittance matrix, which is formulated on the basis of the lumped parameter thermal network of the 37 kW motor presented in Fig. 1 below. The physical

Fig. 1. Steady-state lumped thermal network of 37 kW induction motor. NDE: Non-drive end, DE: Drive end.

process of heat transfer is captured by the thermal network which encapsulates the heat flows due to conductive, convective and radiative processes in the whole machine including the shaft, frame and fluid regions. It is to be noted that the thermal resistances represent heat flow is only one direction, which is predominantly either radial or axial in the case of electrical motors. Out of the 31 thermal network nodes, 12 are source nodes representing the electrical and mechanical loss components (listed in Table I below).

TABLE I
HEAT SOURCES IN THE LPTN AT FULL-LOAD

Region	Power loss (W)
Stator iron	542
Rotor iron	171
Stator slot	582
Stator EW	317
Rotor slot	895
Rotor EW	13.5
Bearings	40
Windage	2
Ventilator	77.8

The motor's total loss was obtained from a temperature rise test following IEC 60034-1 standard. It was supplied from a 750 kVA synchronous generator and loaded by a DC machine. Upon reaching steady-state, the motor input power was measured by a power analyser and the shaft torque by a torque transducer. Immediately after the temperature rise test, the stator resistance was measured as a cooling down curve and extrapolated to the instant of power switch off. The average temperature of the stator winding was obtained from this resistance. J-type thermocouples were used to also measure temperatures of frame, stator endcoils and endspaces. Stator resistive loss was calculated from the measured currents and resistance, and friction loss was measured separately in deceleration tests. Bearing, windage and ventilator loss components were determined as per [7]. The agreement between

the measured and computed total electromagnetic loss was good. The rotor core and resistive losses were obtained from the FE analysis with the in-house code FCSMEK.

B. Steady state inverse model

The inverse model takes as input the machine temperature rises reported by the lumped network. Thus ideally the motor's power losses can be determined with the linear system:

$$[P] = [Y][\Delta T]. \quad (2)$$

However, while slight changes in power reflects the same way in temperatures, variations in temperature result in vastly different powers. Hence, this inverse formulation is fraught with issues, especially if the temperature measurements are noisy, which is usually the case. Out of all the network nodal powers, only 12 are non-zero. Hence the inverse solution subspace can be limited accordingly by reducing the fully defined system (1) to an overdetermined one with 12 unknowns:

$$[\Delta T]_{31 \times 1} = [Y]_{31 \times 12}^{-1} [P]_{12 \times 1}. \quad (3)$$

As the equations in this constrained system are no longer linearly dependent, there exists no exact solution. However, an approximate solution can be found with least squares.

Least Squares

The method of least squares solves the inverse problem by minimising the sum of square of deviations of the calculated data from the actual. The optimal solution of the overdetermined system in (3) that minimises this cost function is obtained with a MATLAB® least squares solver which uses the interior-point algorithm, with the method of Lagrange multipliers for determining the solution convergence. Additionally, linear constraints on the solution were imposed, which stipulated all power components to fall between 0 and 1 kW, and their sum to equal the motor's total power loss. Imposing these two constraints simultaneously improves the solution accuracy, as observed by [3].

To simulate the noisy temperature measurements, temperatures from the analytical model were corrupted with additive normally distributed random noise with zero mean and high standard deviation of 0.25. This data was used to determine the powers with the inverse formula in (2) and also with constrained linear least squares in the overdetermined system in (3). The result of this exercise is seen in Fig. 2 where the actual power components acting as sources in the thermal network are plotted alongside the power values reconstructed from noisy measurements by these two methods. As expected, the powers predicted with the ill-posed system in (2) is highly sensitive to the measurement error and differ widely from the actual values. On the other hand with constrained LS, the results match the actual power distribution very well.

III. MOTOR NUMERICAL MODEL

The lumped network is calibrated against the temperatures measured on the motor's frame, stator endcoils, and stator winding temperature at full-load. These are used to tune the thermal network [8], and the resulting calibrated analytical thermal coefficients are applied to the 3D FE model of

Fig. 2. Actual power loss components against the powers mapped from noisy temperature measurements with the ill-posed system and least squares.

the motor built in COMSOL[®] seen in Fig. 3. This explicit definition of the boundary heat fluxes makes the heat-transfer computation in coupled fluid-solid interfaces easier and faster, and results in a complete steady-state thermal profile of the motor. The idea is to use mean domain temperatures from these numerical results in place of the actual measurements to further assess the effectiveness of the constrained LS method in inverse mapping.

Fig. 3. 3D mesh of the 37 kW motor's axial section.

The new temperature vector now has 18 such average values corresponding to the unique machine parts depicted in the thermal network. The remaining subsidiary nodes retained the same values from the network's direct thermal solution. Inverse mapping with constrained LS using this erroneous data as input results in power components presented in Fig. 4. It can be seen that the LS optimised distribution does not match the actual one. The accuracy of optimisation is quantified in

Fig. 4. LS reconstruction from 18 COMSOL measured temperatures.

terms of root mean square error (RMSE), which can be the sole, yet reliable metric for comparing datasets as per [9]:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2}. \quad (4)$$

Here, the residual e is the deviation between the actual and projected power data. The RMSE in this case is 0.15 kW.

Noise smoothing

An explanation of this poor accuracy can be found in [3] which brings to attention that although power may change abruptly from one point to another, the change in temperature remains gradual. This however, is not visible in the lumped system's temperature response due to the coarse discretization of the machine. Also, the measurement data errors considered (from numerical model) are high and do not have a constant variance. Due to this nature of noise, which gives high weight to some nodes, and zero weight to others, the system solution is highly erratic, especially where elements in the admittance matrix are high. Thus at such nodes in particular, the resulting power map tends to be highly faulty. So it has to be ensured that noise affecting the nodal temperature distribution is gradual across adjacent nodes.

[3] addresses this by attenuating the high frequency variations in the noise with Gaussian smoothing which essentially convolutes the data with a Gaussian function of suitable standard deviation which in this case was determined to be 1.8 after trial and error. The improvement in performance of constrained LS inverse power mapping after error smoothing is seen in Fig. 5 below. For the same noise vector, the RMSE after smoothing is lower, around 0.52×10^{-2} kW, indicating a very good fit. However, in an actual running rotating electrical

Fig. 5. LS reconstruction from 18 COMSOL measured temperatures after noise smoothing.

machine, the number of different domain temperatures that can be measured without hindrance is limited; the frame surface temperatures being among them. The nodes 28-31 in the lumped network represent the outer frame sections over NDE endspace, stator core, DE endspace and the end cap at DE respectively. The outer frame geometry of the FE model is also made identically so that separate mean temperatures of each domain corresponding to these nodes can be ascertained from the numerical solution. Thus four mean surface temperatures of the motors outer frame from the numerical solution along with the lumped network nodal temperatures are used as

input in the inverse model. Compared to the previous set of COMSOL measurements, the error margin here is lower. Due to this, LS optimisation after noise smoothing returned a better fit with a lower RMSE of 7.7×10^{-4} kW. The reconstructed power map resembles that of Fig. 5.

IV. LARGER SYSTEMS

Since the LS constrained inverse solution method was seen to work well with the lumped network system, its performance was tested for a system of larger dimensions as well. For this purpose, the numerical model was considered the starting point for inverse modelling. Since the partial differential equations governing the forward thermal solution are the same for both numerical and analytical solutions, the stiffness matrix, load vector and solution vector extracted from FE solution correspond to $[Y]$, $[P]$ and $[\Delta T]$ respectively.

While the 3D FE model preserves the complete spatial information of the motor, the lumped thermal network had collapsed everything into single dimensioned nodes. Thus the challenge in working with the 3D model will be in ascertaining the spatial distribution of losses with accuracy. This is in fact a major application of inverse modelling wherein the field distribution within a body is estimated from available surface information. Here, this translates to ascertaining the motor's internal loss distribution from limited frame surface temperature measurements, as discussed previously.

Thus the numerical model's stiffness matrix and load vector become the inputs to the inverse model. In order to simulate measurement noise, firstly the surface nodes on the machine's frame which contribute to the degrees of freedom of FE model are isolated. There are 25 such nodes and the temperature solution herein is corrupted with normally distributed additive noise of the same nature described in previous section.

The overall system is then reduced to an overdetermined one, and 4558 unknown power components were solved for as before with the known temperature vector, 25 elements of which are noisy. The powers were normalised and the expected data range was set between 0 and 1. Fig. 6 below shows the inverse reconstruction achieved with constrained linear least square method on the FE model, after noise smoothing.

Fig. 6. LS reconstruction of powers for the FE mesh from 25 noisy frame temperatures, root mean square error 1.6×10^{-4} kW.

V. DISCUSSION

Compared to the lumped network, inverse modelling of the FE model is challenging in terms of the large number

of variables that need to be optimised simultaneously. The constraints used in the optimisation can be local or global in nature. Also, explicit constraints pertaining to sensitive nodes can be imposed to achieve desired convergence faster. The main idea is to initialise the inverse model with as much prior system information available as possible. This inverse method can be used to map the motor's loss distribution at different load conditions, and also transient operation. The power loss data thus obtained can further validate machine power models. Depending on the depth of information to be retrieved, the analysis can also make use of a finer mesh.

VI. CONCLUSION

Linear least square optimisation with additional constraints was found to be effective in reconstructing the strength of the heat source field from measured temperatures in the 37 kW motor. The measured data used included analytical results with simulated noise and also numerical results from the motor FE model that was calibrated against actual measurements. While the constrained least squares technique performed well with the former set of measured data, the latter required prior noise smoothing since noise deviated a lot from node to node. From the 1D steady-state power mapping of the machine with the lumped thermal network, the method is extended to the 3D FE model of the whole motor. The spatial mapping of the losses in the 3D motor structure was achieved with good accuracy since the basis of the analysis was the FE mesh, which is well representative of the motor's internal geometry.

VII. ACKNOWLEDGMENT

The research leading to these results has received funding from the European Research Council under the European Union's Seventh Framework Programme (FP7/2007-2013) / ERC grant agreement n°339380.

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