

Estimation of Heat Transfer Coefficient Using an Improved LPTN with Particle Swarm Optimization

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This paper addresses the lumped parameter thermal network(LPTN) analysis method for temperature prediction of an interior permanent magnet synchronous motor (IPMSM). As the systems incorporating motors demand higher output power and torque, the need for motor downsizing continues to grow. However, the reduction in surface area for dissipating the losses generated within the motor has led to persistent thermal issues. Consequently, the importance of accurate temperature analysis for motors has become increasingly significant. In the proposed LPTN analysis, the accurate prediction of motor temperature heavily depends on the estimation of the convective heat transfer coefficient and thermal contact resistance coefficient. To address this, the paper presents a method that employs particle swarm optimization, a global optimization algorithm, to minimize the error between experimental results and analytical predictions.

Index Terms—Convective heat transfer coefficient, interior permanent magnet synchronous motor, lumped parameter thermal network (LPTN), particle swarm optimization (PSO), thermal contact resistance coefficient

I. INTRODUCTION

THE DEVELOPMENT direction of automotive technology is shifting towards improving the efficiency and weight reduction of onboard components to extend the driving range. Particularly, as motor systems are increasingly integrated into vehicles, the demand for high power density and downsizing has risen significantly. Consequently, thermal management systems are becoming more diverse and complex. While early systems relied on indirect cooling methods such as water jackets, direct cooling methods like oil-sprayed cooling are now being adopted. This transition has introduced challenges in deriving various parameters for thermal analysis[1].

Various cooling methods and structures have been studied to achieve effective cooling performance. In [2], to account for variations in the convective heat transfer coefficient across different operating regions of the motor, a surrogate model was employed to estimate the coefficients based on speed variations. In order to study the thermal behavior of the SPMSM used as the driving motor of electric vehicle under the real driving duty cycle, a lumped parameter thermal model is presented in [3].

In this study, particle swarm optimization (PSO) was applied to minimize the error between test results and analytical predictions, facilitating the derivation of parameters required for conventional lumped parameter thermal network (LPTN) analysis [4, 5]. Through this approach, key parameters such as convective heat transfer coefficients and contact thermal resistance coefficients were indirectly determined. The proposed method can be used in the design of motors with similar capacities and cooling systems.

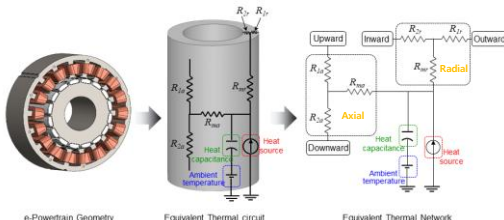


Fig. 1. Concept of LPTN

II. IMPROVED LPTN WITH PARTICLE SWARM OPTIMIZATION

A. Lumped Parameter Thermal Network for optimization

For the thermal analysis of the motor, an LPTN considering the geometry of the Interior Permanent Magnet Synchronous Motor (IPMSM) was utilized. The concept of the thermal equivalent circuit is shown in Figure 1. Each part of the motor was modeled considering three-dimensional heat transfer in both axial and radial directions. The thermal parameters in the model consist of thermal resistance, heat sources, and thermal capacitance. The LPTN is a function of speed and torque, and under various operating conditions, losses such as copper loss, iron loss, mechanical loss, and eddy current loss act as heat sources. The target model of this study is an air-cooled IPMSM, where heat dissipation to the exterior occurs through convective heat transfer via the housing. Additionally, heat is transferred through forced convection in the air gap. The convection heat transfer coefficient and the thermal contact resistance coefficient, which are critical factors in thermal analysis, were used as optimization variables.

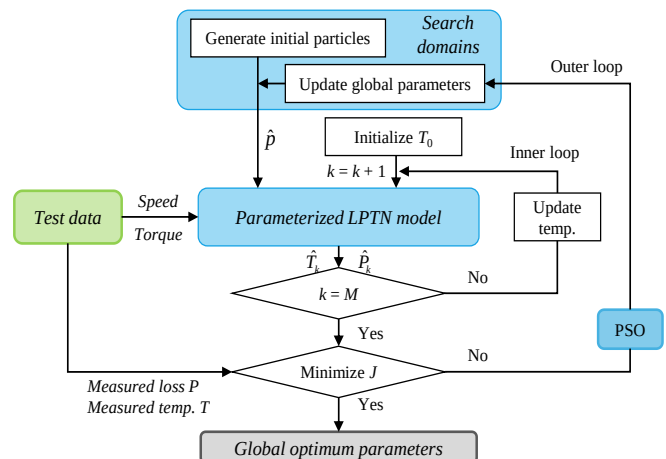


Fig. 2. Procedure of LPTN using particle swarm optimization for minimizing the temperature error between the test and analysis

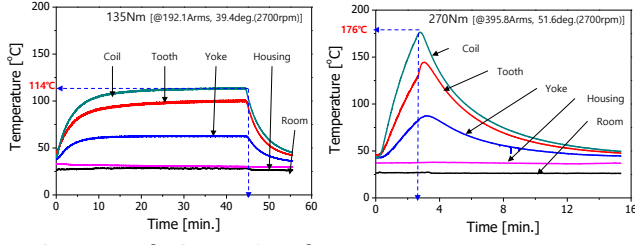


Fig. 3. Test result @ max. / rated power

B. Particle Swarm Optimization using thermal parameters

The temperatures of each part derived from the conventional LPTN may significantly deviate from the test results. As heat dissipation conditions become more diverse and complex, parameters such as the convective heat transfer coefficient and the thermal contact resistance coefficient are increasingly difficult to predict. Therefore, to address these challenges, the global optimization algorithm, PSO, was employed to minimize the errors between the analytical predictions and the test results. Fig. 2 shows procedure of LPTN using particle swarm optimization for minimizing the temperature error between the test and analysis. The proposed algorithm consists of two loops. The inner loop calculates the temperature at measurement points over time using the LPTN configuration parameters provided as initial values. These initial values include the convective heat transfer coefficients, contact thermal resistance coefficients, and thermal capacitance, which are difficult to compute directly. The parameters optimized in this study consist of 5 convective heat transfer coefficients, 3 contact thermal resistance coefficients, and 10 thermal capacitance values. The calculated temperatures at each location are then used to evaluate the error compared to the test results.

The errors of temperatures between prediction and measurement are taken as optimization objectives, and they are, respectively, defined as follows:

$$e_i(k, \hat{p}) = T_i(k) - \hat{T}_i(k, \hat{p}), (i = 1, 2, \dots, N) \quad (1)$$

where k is the sampling sequence number, i is the LPTN node sequence number, N is the number of the LPTN nodes, $\hat{p}$ is the parameter estimation vector, $\hat{T}$ is the predicted temperatures vector.

Therefore, the objective function can be given by

$$\min J(\hat{p}) = \frac{1}{M} \sum_{k=1}^M w_i e_i(k, \hat{p})^2 \quad (2)$$

with the constraints

$$\begin{cases} g(\hat{p}) = 0 \\ h(\hat{p}) \leq 0 \end{cases} \quad (3)$$

where M is the number of the sampling points, w_i are the weighting coefficients.

The outer loop is a step where various combinations of parameters for applying PSO are generated. This process involves composing the combinations of the convective heat transfer coefficient, contact thermal resistance coefficient, and thermal capacitance within their respective upper and lower boundaries, and passing these combinations to the inner loop. Ultimately, the PSO algorithm identifies the parameters that

TABLE I
SPECIFICATION

	Unit	Value
Pole / Slot	-	8 / 48
Max. / base speed	rpm	10,000 / 2,700
Max. Torque	Nm	270
Max. / rated output power	kW	80 / 40
Cooling	-	Water jacket cooling

minimize the error. The derived convective heat transfer coefficient and contact thermal resistance coefficient can then be utilized in the design as the values that minimize the discrepancy between test results and analytical predictions.

III. TARGET MOTOR AND TEST RESULT

The target motor is an 80 kW-class traction motor, with detailed specifications listed in Table 1. It is a water-cooled motor equipped with a water jacket. To derive the convective heat transfer coefficients and contact thermal resistance coefficients using PSO, temperature test results measured under various speed and torque conditions would yield the most optimal results. However, due to time and cost constraints, the test results shown in Figure 3 were applied. As seen in the test results, although there are only two combinations of speed and torque, comparing the transient and steady state results between the tests and analysis provided sufficient and reliable data.

IV. CONCLUSION

As motor design technology advances and higher power outputs are required, solving thermal management issues has become an essential challenge. Although numerous methods for analyzing complex cooling systems have been developed, this study successfully applied PSO based on test results to derive the convective heat transfer coefficients and contact thermal resistance coefficients. While the target motor does not have a particularly complex cooling structure, the proposed method could be beneficial for designing higher power density motors, such as those utilizing advanced cooling techniques like oil-sprayed cooling, by determining their heat transfer coefficients. In the 4-page manuscript, we will provide a detailed discussion on the proposed method compared to conventional methods, including numerical results, comparisons with experimental data, and the advantages of the PSO-based approach.

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