Neural Plug-In Motor Coil Thermal Modeling

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Abstract

With the latest advancement in technologies, many motor controls and protections now rely on the use of on-line motor data fed through embedded motor models (including thermal models) stored in microprocessors where the critical decisions are made. The accuracy of these embedded motor models has a direct effect on the performance and reliability of the motors. In this paper, we propose to use an Artificial Neural Network plug-in modeling concept to significantly increase the accuracy of the lumped-parameter motor thermal modeling approach. The neural plug-in approach could preserve the fast calculation response of the lumped-parameter model, preserve the physical meaning of thermal parameters, and increase the overall accuracy of the thermal model. This paper discusses and compares the motor thermal dynamics and its estimates by the three different models, lumped-parameter model, conventional neural network model, and neural plug-in model. The preliminary modeling results clearly indicate that the neural plug-in modeling approach is superior than either the lumped-parameter approach or the neural network approach.

Key Words: Motors, thermal models, neural networks.

1. Introduction

Winding heat losses are one of the major factors to be considered in the design of motors for performance, efficiency, safety, control, protection, fault detection and diagnosis concerns. Excessive winding heat losses due to incipient winding failures, overloads or shorted winding turns can overheat the motors, increasing the chances of burnt windings, burnt motors, and fire hazards [1-6].

The use of thermal relays and over-current relays are two popular ways to protect motors from potential winding thermal faults. However, overly conservative settings of these relays may result in too many false alarms, which may unnecessarily interrupt important processes. For example, let us consider a paper mill driven by many motors. If one of the motors is unnecessarily tripped by the over-current relays due to temporary current overloads, the paper company will need to discard all the paper being processed at that time and reinitiate the paper machines, a process that may take several hours. The downtime of the paper machines may cause the paper company to lose hundreds of thousands of dollars. On the other hand, if the relays are set too close to the thermal limit of the motor, the motor may catch fire before the relay is actually tripped. These fire hazards are also costly events for the company.

In general, engineers perform many scenario studies based on mathematical models of the motor thermal dynamics and performance in order to find the proper settings for the relays so that the motors can be operated to their full extent without sacrificing safety [2, 4, 5]. With the latest advancement in technologies, many motor controls and protections now rely on the use of on-line motor data fed through embedded motor models (including thermal models) stored in microprocessors where the critical decisions are made. The accuracy of these embedded motor models has a direct effect on the performance and reliability of the motors.

Due to the importance of correctly predicting motor coil thermal dynamics, many motor coil thermal models have been studied and developed [1, 3, 5]. The models can be classified into three categories or a combination of them:

- Component-based – Each component of the coil, such as the winding material and the length and area of the copper, are modeled separately by following physical laws. The component models are then aggregated to provide the overall model. This approach is generally tedious and requires much computing power and time and is more suitable for off-line usage, e.g., during the motor design stage.

- Distributed parameters – The motor thermal models are generally modeled by partial differential equations and the heat distributions are solved by finite element analysis [7]. This approach can provide two- and three-dimensional spatial heat distributions of the motor core and windings. However, finding the solution takes much computing power and time. So, again, this approach is more suitable for off-line usage.

- Lumped-parameters – The motor thermal models are parameterized by several parameters [3, 5]. This thermal modeling remains at the macroscopic level rather than at the microscopic level. This approach can provide fast calculations and can be used for on-
line applications, e.g., real-time for fault detection, diagnosis, and control.

Regardless of which modeling approach is taken, there are always trade-offs between accuracy and complexity. In this paper, we will focus on the lumped-parameter modeling approach because we are more interested in the on-line applications of the models.

In this paper, we propose to use an Artificial Neural Network plug-in modeling concept to significantly increase the accuracy of the lumped-parameter modeling approach [8]. The neural plug-in module will be used in conjunction with the conventional lumped-parameter model. Instead of learning the motor winding temperature prediction direction, the neural plug-in module will learn the differences between the actual temperature and the temperature prediction from the conventional lumped-parameter model. In this case, the neural plug-in is used to compensate for the local deficiencies that result from using the lumped-parameter approach alone. The neural plug-in approach could preserve the fast calculation response of the lumped-parameter model, preserve the physical meaning of thermal parameters, and increase the overall accuracy of the thermal model.

Section II of this paper will briefly describe the conventional lumped-parameter approach for winding thermal modeling and the feedforward artificial neural network technologies. Section III of this paper will describe the experimental setup of the thermal data gathering of a motor winding in our research lab. Section IV of this paper will technically describe 1) the conventional lumped-parameter motor winding thermal modeling, 2) the artificial neural network motor winding thermal modeling, and 3) the neural plug-in motor winding thermal modeling. Section V will compare and discuss the motor winding thermal modeling results from each approach.

II. Brief Description of Motor Winding Thermal Modeling and Feedforward Artificial Neural Networks

1. Conventional Lumped-Parameter Approach

The lumped-parameter thermal model of motor windings can be derived in the simple resistance-capacitance electrical circuit form. Since the thermal resistance to conduction in the core is small compared to the external resistance, we can assume a uniform temperature distribution in the motor windings and core [9]. In our model, only conduction and convection heat transfers are included because of the relatively low temperatures considered.

When a winding is energized, heat generated in the motor windings and core is equal to the electric power $P$ dissipated in the winding as $P = i^2 R$, where $i$ is the winding current and $R$ is the winding electrical resistance. This heat is transferred out from the winding by conduction to the stator core. Therefore, the heat transfer equation for the winding can be expressed as:

$$P = \frac{\Delta T_{w}}{R_{e, wc}} = C_{r, w} \frac{dT_{w}}{dt} \quad (1)$$

$$\Delta T_{w} = T_{w} - T_{e} \quad (2)$$

$$C_{r, w} = m_{w} c_{v} \quad (3)$$

where $C_{r, w}$ is thermal capacitance of winding (J/°C), $m_{w}$ is the mass of winding (kg), $c_{v}$ is the constant-volume specific heat of winding (J/kg °C), $\Delta T_{w}$ is the temperature difference between winding and stator core (°C), $T_{w}$ is the core temperature (°C), $T_{e}$ is the winding temperature (°C), and $R_{e, wc}$ is the thermal resistance between winding and stator core (°C/W).

At the stator core, the heat is transferred out to the environment by convection. Similarly, the heat transfer equation for the stator core can be derived as:

$$\frac{\Delta T_{e}}{R_{e, wc} - R_{e, ca}} = C_{r, e} \frac{dT_{e}}{dt} \quad (4)$$

$$\Delta T_{e} = T_{e} - T_{a} \quad (5)$$

$$C_{r, e} = m_{e} c_{v} \quad (6)$$

where $C_{r, e}$ is the thermal capacitance of stator core (J/°C), $m_{e}$ is the mass of stator core (kg), $c_{v}$ is the constant-volume specific heat of stator core (J/kg °C), $\Delta T_{e}$ is the temperature difference between stator core and environment (°C), $T_{e}$ is the ambient temperature (°C), and $R_{e, ca}$ is the thermal resistance between the stator core and the environment (°C/W).

Equations (1) and (4) can be considered as the thermal model equations of the motor winding and can be modeled in an electric circuit form as shown in Figure 1.

![Figure 1. The thermal model circuit used for lumped-parameter motor winding thermal modeling.](image)

2. Feedforward Artificial Neural Networks

The multi-layer feedforward net used in this paper contains three components: an input layer, one or more hidden layers, and an output layer, as shown in Figure 2.

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Each network layer contains a set of processing units called nodes or neurons. Each node in a network layer will send its output to all the nodes of the next layer unidirectionally. In the input layer, the nodes receive external signals from the outside world. The input layer of the neural network serves as an interface that takes information from the outside world and transmits it to the internal processing units of the network. Similarly, the output layer of the neural network serves as an interface that sends information from the neural network's internal processing units to the external world. The nodes in the hidden layers are the neural network's internal processing units. More detailed descriptions of feedforward net and their training can be found in [10, 11].

The schematic diagram of the training process is depicted in Figure 3. This will be used to train a feedforward net to learn the motor winding thermal dynamics in this paper.

III. Experimental Set-up and Data Gathering of Actual Motor Coil Thermal Data

A two-phase 10Ω permanent magnet stepping motor model CLA45-14601 manufactured by TEC was used in our motor winding thermal modeling experiment. For illustration purposes, we only consider the heat transfer between the motor winding and the core, hence the motor was taken apart and the rotor was removed, and the two phases were tied together such that each phase will have the same input voltage, as shown in Figure 4. Both phases were connected to a variable DC power supply model TS-280, manufactured by Tektronix.
The motor winding temperature and core temperature were continuously monitored and measured by two three-wire 100 Ω platinum resistance temperature detectors (RTDs), which were attached to the motor winding and core, respectively, and were connected to the National Instruments (NI) data acquisition system. The ambient temperature is monitored and measured by the IC sensor inside the NI system. The signals from the RTDs were conditioned by the NI SCXI-1121 module before logged by a Labview program running on a PC as shown in Figure 4(c).

Three different DC voltages, 6, 8, and 10 V were chosen as input voltage levels to the motor for 3600 seconds (1 hour) such that the motor winding thermal dynamics could reach its steady state. The sampling frequency for gathering the experimental data is 1 Hz, which is sufficiently fast compared to the thermal dynamics under investigation.

IV. Modeling Approaches

1. Conventional Lumped-Parameter Approach

The overall approach to model the motor winding thermal dynamics by conventional lumped-parameter approach is depicted in Figure 5. Based on the thermal circuit shown in Figure 1, the measurements of the motor are
\[ z(k) = [v(k), i(k), T_c(k), T_w(k)]^T, \quad k = 1, \ldots, K \]
where \( K \) is the time index when the motor thermal dynamics has reached its steady-state conditions (\( K = 3600 \) in our case). The input of the thermal model is
\[ P(k) = i(k)R(k) = i(k)v(k). \]
The thermal circuit parameters \( R_{i.e}, C_{i.e}, R_{c.w}, C_{c.w} \) are then calculated via a least square fitting [13] based on the measurements and the thermal circuit dynamic equations.

![Figure 5. Schematic diagram of the conventional lumped-parameter thermal circuit modeling.](image)

2. Conventional Neural Network Approach

The overall approach to model the motor winding thermal dynamics using a conventional feedforward neural network is depicted in Figure 6. The inputs to the neural network are
\[ x = [P(k), T_c(k), T_w(k) ]^T, \]
while the target outputs of the neural network are
\[ y = [\Delta T_c(k+1), \Delta T_w(k+1)]^T = [T_c(k+1) - T_c(k), T_w(k+1) - T_w(k)]^T, \]
the changes in the motor core and winding temperatures. The actual motor core and winding temperatures are then estimated as:
\[ \hat{T}_c(k+1) = \hat{T}_c(k) + \Delta T_c(k+1), \]
and
\[ \hat{T}_w(k+1) = \hat{T}_w(k) + \Delta T_w(k+1) \] [14]. A three-layer feedforward neural network structure with 10 hidden neurons has been used in this approach. The network structure has been selected with respect to the training time and performance after several educated trials on different network architectures such as the number of hidden nodes used. The activation function at the hidden layer and output layer in the network are the hyperbolic tangent and linear functions, respectively. The networks were trained by using the Levenberg-Marquardt algorithm with 1000 epochs, a point at which the training had already reached its steady-state.

![Figure 6. Schematic diagram of the training of a neural motor winding thermal model.](image)

3. Neural Plug-In Approach

The overall approach to model the motor winding thermal dynamics by neural plug-in approach is depicted in Figure 7. The targeted outputs of the neural network are modified from the conventional neural network approach. The network structure used in this approach is the same as the network in the conventional approach for performance comparison. Instead of learning to predict the changes in motor winding temperature with the given...
input data, the neural plug-in network is learning the difference between the actual winding temperature and the predicted value from the conventional lumped-parameter model. Thus, the inputs of the neural network are still \( x = [P(k), T_r(k), T_a(k), T_L(k)] \), while the target outputs of the neural plug-in module becomes \( y = [\delta T_r(k+1), \delta T_a(k+1)] \). The actual motor core and winding temperature is then reconstructed as: \( \hat{T}_r(k+1) = \hat{T}_r(k+1) + \delta \hat{T}_r(k+1) \) and \( \hat{T}_a(k+1) = \hat{T}_a(k+1) + \delta \hat{T}_a(k+1) \) where \( \delta \hat{T}_r(k+1) \) and \( \delta \hat{T}_a(k+1) \) are the estimates of \( \delta T_r(k+1) \) and \( \delta T_a(k+1) \) given by the neural network, respectively.

![Schematic diagram of the neural plug-in motor winding thermal modeling.](image)

Figure 7. Schematic diagram of the neural plug-in motor winding thermal modeling.

V. Results and Conclusion

Figure 8a shows the motor thermal dynamics and its estimates by the three different models, lumped-parameter model, conventional neural network model, and neural plug-in model, discussed in this paper. The respective modeling errors in time domain are shown in Figure 8b. In addition, we define three norm measures:

\[
E_1 = \frac{1}{2K} \left[ \| \hat{T}_r - T_r \|_1 + \| \hat{T}_a - T_a \|_1 \right],
\]

\[
E_2 = \frac{1}{2K} \left[ \| \hat{T}_r - T_r \|_2 + \| \hat{T}_a - T_a \|_2 \right],
\]

\[
E_\infty = \frac{1}{2} \left[ \| \hat{T}_r - T_r \|_\infty + \| \hat{T}_a - T_a \|_\infty \right],
\]

where \( T_r, \hat{T}_r, T_a, \hat{T}_a \) are all vectors, to compare the results obtained by the three different modeling techniques discussed in this paper. The metric results are listed in Table 1.

![Motor winding thermal dynamics modeling performance of the three different approaches.](image)

Figure 8. Motor winding thermal dynamics modeling performance of the three different approaches.
Table 1. Modeling errors of the three different motor winding thermal dynamics modeling approaches.

<table>
<thead>
<tr>
<th>Model type</th>
<th>$E_1$ (°C)</th>
<th>$E_2$ (°C)</th>
<th>$E_3$ (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lumped-parameter model</td>
<td>1.0172</td>
<td>0.0205</td>
<td>3.3422</td>
</tr>
<tr>
<td>ANN (10 hidden nodes) model</td>
<td>2.2185</td>
<td>0.0429</td>
<td>6.4546</td>
</tr>
<tr>
<td>Neural plug-in (10 hidden nodes) model</td>
<td>0.4085</td>
<td>0.0092</td>
<td>2.8606</td>
</tr>
</tbody>
</table>

These preliminary modeling results clearly indicate that the neural plug-in modeling approach is superior than either the lumped-parameter approach or the neural network approach. The lumped-parameter approach provides a reasonable good model, while the neural plug-in makes it even more accurate. The conventional neural network modeling approach is not as good as the others. This can be contributed to different factors such as the network size, training treatments, etc. Due to the page limit for this paper, the authors will report the detailed analyses of the modeling performance with respect to several key factors in another publication, while this article reports mainly the typical modeling results.

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