Generalized Material Models for Coupled Magnetic Analysis

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***Abstract*—The solution of coupled magnetic and thermal systems is important for the design of many electromagnetic devices. To achieve this, it is important to have an effective material model. This paper proposes a general material model based on a neural network which can take into account the temperature dependence of the magnetization curve.**

***Index Terms*—Adaptive learning, electromagnetics, finite elements, material models, neural networks.**

I. Introduction

AS PART of the design of an electromagnetic device, analysis is critical. This needs to take into account all the areas of physics relating to the device, not just those of electromagnetics. Thus, for example, an electric motor requires an electromagnetic analysis to determine the effectiveness of the conversion from electrical energy to mechanical. It also needs a thermal analysis to determine the effects of power losses in the device on the overall performance; and a structural analysis to ensure that the design can withstand the forces being generated. In general these analyzes are coupled through the material parameters. Thus the thermal analysis will result in temperature distributions throughout the material that can have the effect of altering the material properties locally. As the material temperature increases at certain points in the material, the permeability will decrease producing a result similar to that observed through magnetic saturation. In the reverse direction, the presence of changing magnetic fields leads to losses in the magnetic material (the iron losses) and these losses are the sources of heat in the problem leading to temperature changes. Thus a coupled problem exists between the magnetic and thermal solutions.

A similar set of effects may occur as a result of mechanical stresses. In general, these coupled effects have been ignored for many problems, and work to date in coupled problems has often been related to devices where the creation of heat is a major objective, e.g. induction heating. The justification for ignoring the temperature effects in many problems is the cost of performing the coupled analyzes and the fact that high temperatures will tend to occur near the high iron loss areas and these, in turn, will tend to be in the areas where the material is saturating. Thus temperature effects will compound the saturation effects but be largely limited to those areas. However, this may not be the case if thermal conduction is also included in the calculations and, in this situation, the effects of losses in one part of the device may seriously affect the magnetic performance in another.

In general, for many low frequency electromagnetic devices, where the primary goal is to develop forces and torques, the effects of losses and the consequent rise in temperature is an annoying side effect which may result in having to design an effective cooling system with a subsequent increase in cost. Thus a coupled electromagnetic-thermal solution has increased in importance as numerical tools have allowed designers to optimize the use of the magnetic materials in the system.

In many of the electro–magneto–mechanical devices where heat generation is a secondary effect, the thermal time constant is considerably longer than the magnetic one. This is not true, for example, in a fuse where the system is intended to have a relatively short thermal time constant. However, if the two time constants differ sufficiently, it is often possible to decouple the two analyzes and link the effects through the material properties alone. In this case, the process is to run an electromagnetic analysis and to follow this by a thermal analysis and then re-run the electromagnetic analysis, etc., until electromagnetic and thermal convergence is achieved.

Ideally, to make this work effectively, a material model is needed which can take into account the effects of temperature on the magnetic properties of the materials involved.

The intention of this paper is to describe developments to the neural network model, which has been published previously [1], [2], to include the effects of temperature and, eventually, stress, more effectively than current models. It is part of ongoing work to derive a single representational methodology for all material properties (magnetic, thermal, structural, ...)

II. Material Models

Just as materials are critical in a magnetic device, i.e. they affect the distributions and strengths of the magnetic fields, material models are critical in the performance of numerical simulations. The material model has two features that are of importance: it must be able to represent the physical material; and it must be designed to work effectively with the solution techniques employed.

Over the years many models have been proposed to represent the performance of ferromagnetic materials. These have included piecewise spline fits and exponential functions to try to provide the smooth gradient information a Newton–Raphson process requires; phenomenological models (such as Preisach)

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to represent the hysteretic performance; and many more. In general, the material models are constructed to be as efficient as possible for a particular class of problems. Thus a Preisach based model would not be used for solving a simple nonlinear magnetostatic problem—there are much simpler models. This diversity of models, each tuned to a particular class of application can result in great complexity in storing models and accessing them based on the problem type.

However, many of the existing models appear to give good results when the material behavior is compared with measured results, but at some price. Some of the phenomenological models may be expensive in terms of memory and time when used in a finite element based analysis system, especially when each element is operating with the material in a different state.

In an effort to try to create a unified model of the magnetic performance of a material, models based on neural networks have been proposed recently [1]–[4] and appear to be able to match the performance of spline and function fits while having the property of providing one model that can handle material performance from isotropic anhysteretic through to anisotropic and hysteretic.

When coupled problems are considered (e.g. magnetics plus temperature and/or stress) the magnetic material models have to be enhanced to include these effects. Conventionally, for temperature, the approach is to store the curves for several temperatures and to interpolate between them for the needed temperature. Kvasnica and Kundracik [5] have proposed a modification to the Jiles–Atherton [6] anyhsteretic model that allows temperature and stress to be taken into account by making some of the model parameters functions of temperature and stress. An alternate approach is to extend the neural network model to include the effects of temperature—thus expanding the capabilities of the generalized model.

III. The Neural Network Model

A neural network implements an adaptive learning process. It consists of layers of fully interconnected simple (usually summing) processors. Each interconnection has a weight associated with it and it is these weights that control the performance of the network. By adjusting the weights the value of the output for a particular input vector can be controlled. In effect, a neural network provides an implicit high order polynomial fit to the desired surface. The more neurons there are in the hidden layer(s), the higher the degree of the polynomial. The goal of constructing and training a neural network is to adjust the numbers of neurons used plus the interconnection weights. Too many neurons, and the representation will introduce high frequency ripples in the surface limiting the ability to generalize (i.e. generate an accurate result for an input vector not previously seen), too few neurons and the network will not be able to approximate the function. In operation, data flows through the network (hence the name—"feedforward"). In training, errors are propagated backward. Training is a form of optimization—i.e. derive the weight values to minimize the error in the system. The network in this work used a Levenberg–Marquardt approach to training and consisted of simple summing processors with a sigmoidal activation function to limit the range of the output.

In previous work [1], [2], the design of a network to handle anisotropic and hysteretic materials has been discussed with a particular emphasis on two issues—the network architecture and the performance of the final system in comparison with existing and proposed models. The goals of the work are to create a material model that requires minimum memory for storage and can be evaluated in minimum time. When considered in the context of a present day, three dimensional analysis system, these two issues are critical. In a large three-dimensional finite element model, there may well be of the order of 10^5 elements of which more than 10% may involve a magnetic material. In an iterative solution approach (such as Newton–Raphson) this can involve hundreds of thousands of material property evaluations.

In modeling hysteresis, a network consisting of an input layer of 5 neurons, a hidden layer of 6 neurons and a single output has been found to be effective [2]. The five inputs represented the previous two magnetization states in terms of the magnetization and the corresponding magnetic field and the current magnetic field. It has been shown that this model can also work for single valued magnetization curves.

The introduction of temperature and/or tensile stress to the model result in a need to add extra inputs for these quantities, i.e. expanding the input vector. Also, to be able to store the extra information, more neurons will be needed in the hidden layer. In the work reported below, the network was expanded to 12 neurons and only the current H value was used as input along with a new input representing the temperature.

However, if a coupled analysis is to be performed, it is not sufficient to store only the magnetic properties of the material. In addition, the thermal and electric conductivities must also be considered as well as the iron losses in the material. In other words, the material model has to be much more complete than that needed solely for magnetics analysis. To avoid massive complexity in the system and minimize the training time for the neural network, it is proposed that each constitutive relation be modeled by a separate neural network, Fig. 1. Then, as the coupled analysis is performed, the information from one analysis, employing one particular constitutive relationship will be fed back to the other via the inputs of the appropriate networks.

Thus, in the coupled electromagnetic–thermal situation, the electromagnetic problem is solved using the neural network trained on the M–H–T (magnetization, magnetic field and temperature) hypersurface to represent the material behavior. The temperature at each point in the model is determined from a thermal analysis. The thermal problem also has a constitutive equation relating heat flow and temperature gradient and the resulting output is a set of temperatures, while the input is a set of losses derived from the electromagnetic analysis.

IV. The Training Sets

While many electrical machines problems require a coupled electromagnetic–thermal analysis, the practicality of this depends on having appropriate material data. This is not easy to obtain. So, to verify the concepts outlined, a circuitous

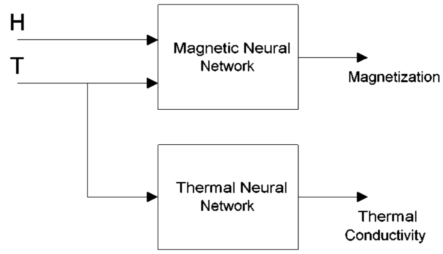

Fig. 1. Neural nets for magnetic and thermal properties.

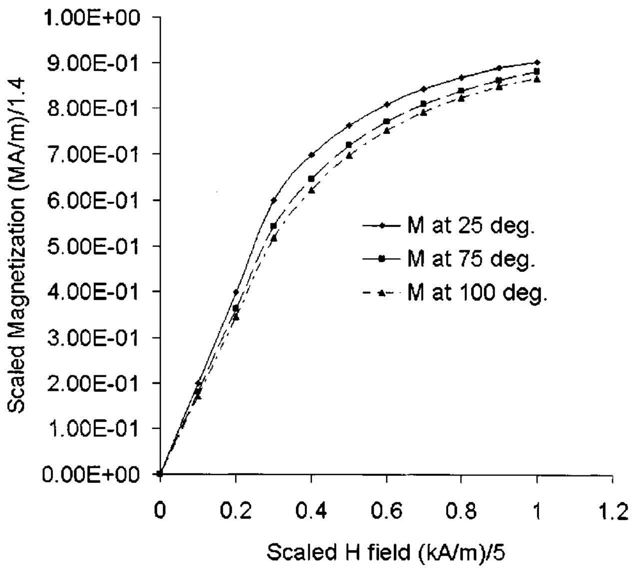

Fig. 2. Basic temperature dependent M–H curves from J–A model.

route was used by implementing a temperature dependent anhysteretic Jiles–Atherton model as described in [5]. This allowed the generation of a set of training curves for the system. In practice, this data would be replaced by measured results. The magnetization curves for three temperatures, predicted by this model, are shown in Fig. 2.

The data from these curves is then used to train a neural network having inputs of the current values of magnetic field and temperature (the previous states relating to a hysteresis model are not needed here). A state is defined as a triple (M, H, T). Thus the neural network uses 2 inputs and generates one output, i.e. the new state of the magnetization. The network was trained once with a large data set derived from the curves at 25, 75 and 100 degrees.

The trained network is finally tested using a fourth curve generated for a different temperature.

V. The Numerical System

The final trained network is used within a finite element based system but, since it cannot generate derivative information in its current form, a Newton–Raphson approach cannot be used for solving the nonlinear magnetic problem. Instead successive substitution is used. This leads to slower convergence. However, there are speed gains to be had since the network operates as a look-up function for the material properties. The entire system then iterates between the magnetic and thermal systems until convergence is reached. The systems used were MagNet 6 [7] and LUSAS [8].

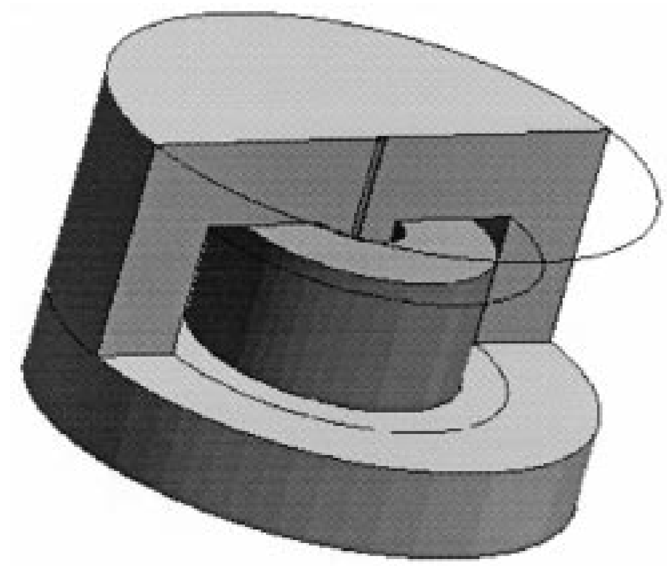

Fig. 3. Potcore structure used for analysis—half the top is transparent to show the coil.

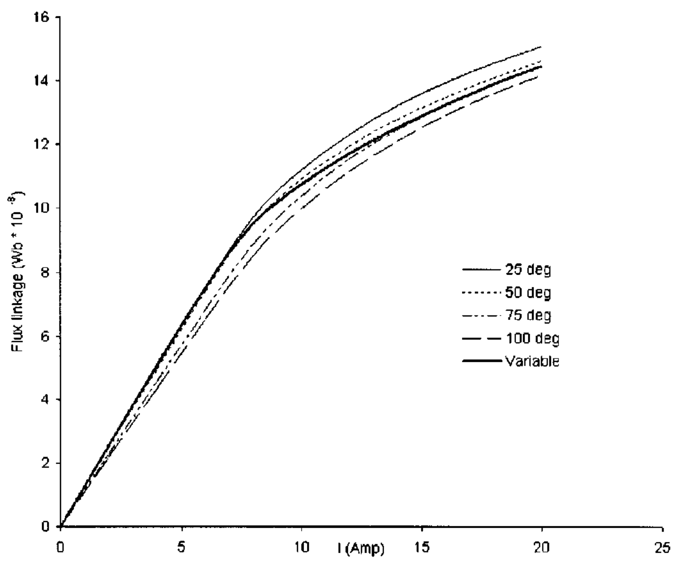

Fig. 4. Flux linkage for fixed and variable temperatures for increasing current.

VI. Results on a Potcore

The material network was trained using the data in Fig. 2 and tested on a curve at a different temperature. It was shown to generalize extremely well. The material model was then used in the analysis of the potcore device shown in Fig. 3.

The device was analyzed at a series of fixed temperatures (25, 50, 75 and 100 degrees Centigrade) and the flux linkage calculated at each temperature. The magnetics analysis was then coupled to a thermal calculation to generate the temperature distributions within the core. This analysis took into account both diffusion and conduction and used a room temperature of 25 degrees. The resulting flux linkages as the current is increased

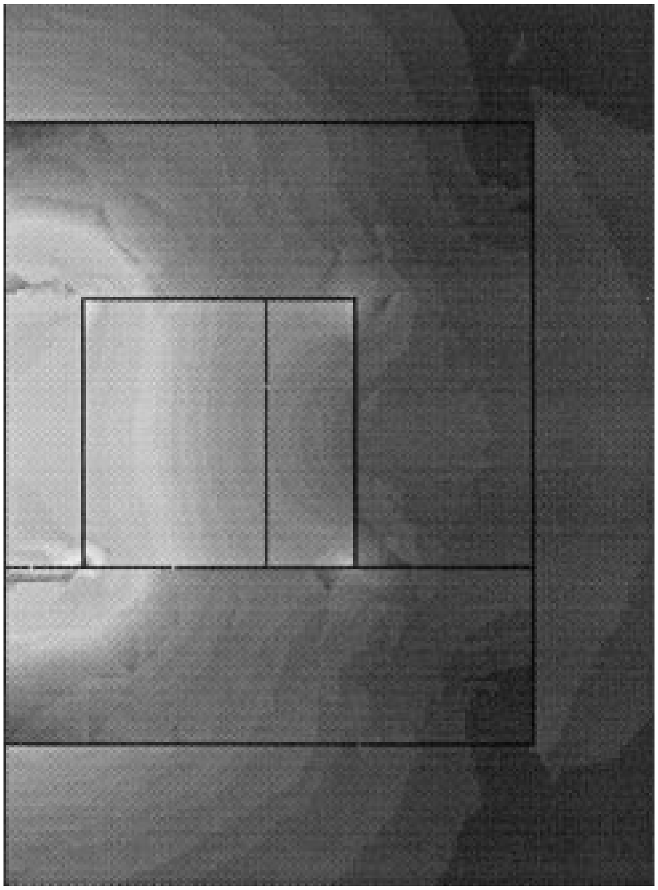

Fig. 5. Difference in H values between 25 deg fixed temperature and variable temperature from the thermal solution.

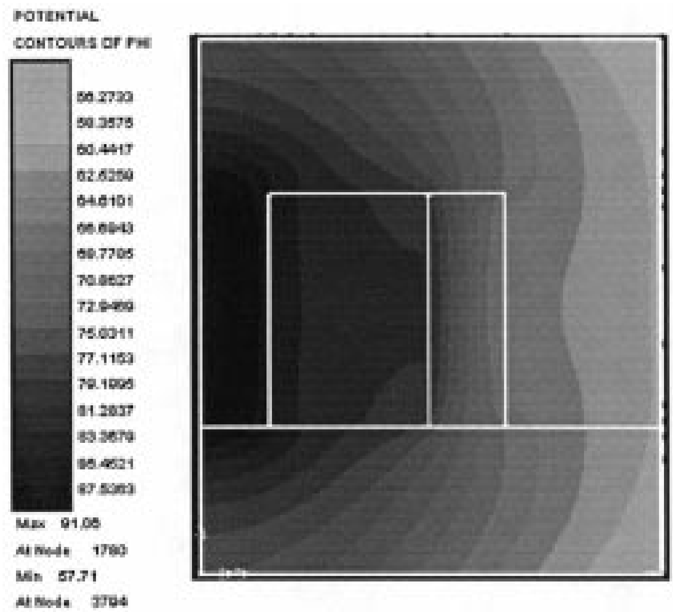

Fig. 6. Temperature plot for potcore at 20 Amps.

are shown in Fig. 4. The effects of temperature, and the operation of the neural network in changing the properties can be seen clearly. It is important to note that the convergence of the nonlinear iterations maintained the same pattern whether the operating temperature was the one used for training the network or some other temperature. This feature is key in a generalized material model since during the nonlinear iterations, the system may request the material properties with random values for the input parameters until the operating point is found.

Fig. 5 shows the difference in the magnetic field values between the solution for a constant 25 degrees and the variable temperature (thermal) solution. As expected the largest variation occurs within the center limb. Fig. 6 shows the temperature distribution in the core.

VII. Conclusions

The paper has described a generalized form of a material model which takes into account thermal as well as magnetic properties. It can be applied in a numerical coupled analysis which uses an iterative approach to link the thermal and magnetic problems. The extensions to the network to include thermal effects have been discussed and results shown for a coupled thermal analysis of a simple device. The overhead in terms of speed and memory usage is minimal and the training is extremely quick. The memory required to store the network is less than a hundred floating point numbers. The model could be easily extended to include the effects of stress allowing a linkage to a structural system. However, at this point in time, very little measured data for magnetic materials in terms of temperature and stress has been published. To use the proposed system effectively requires that measured data is obtained.

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