Prediction of the Eddy-Current and Temperature Distribution in a TFIH Device using Neural Networks in order to improve the Convergence of the Finite Element Calculations

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***Abstract*—This paper presents a method of predicting the eddy-current distribution in transverse flux inductive heating devices (TFIH) with the help of one neural network. A second neural network is used to obtain the temperature distribution in the thin moving conducting sheet caused by the eddy-current losses. Both solutions are initial solutions for the finite element calculations of this non-linear coupled electromagneto-thermal problem.**

***Index terms*—Induction heating, Finite element methods, Neural networks, Nonlinear estimation**

I. Introduction

The transverse flux inductive heating device contains symmetrically placed coils on both sides of the non-ferromagnetic moving sheet as shown in Fig. 1. The currents in two opposite coils are in phase and produce a magnetic field perpendicular to the surface of the workpiece. This field induces eddy-currents in the thin conducting sheet. The caused losses warm the material up continously.

Compared to longitudinal induction heaters a much lower frequency can be used resulting in a higher electrical efficiency, which is why transverse flux heaters are given priority heating thin strips.

The main disadvantage of the TFIH is the resulting inhomogeneous temperature distribution. To improve the device, the coil geometry can be changed by parameter variations or optimization procedures, e.g. genetic algorithms. Every optimization step requires the calculation of both the eddy-current and the temperature distribution for the proposed geometry, usually with the finite element method (FEM) [1], [2]. Creating the three dimensional meshes and solving the coupled problems are very time consuming tasks. Adaptive remeshing based on the solution causes additional computational effort.

At the beginning of optimization processes the search space is scanned with thousands of parameter trials to get a rough idea of the problem. In this phase the solutions don't need to be exact, but they should be evaluated rapidly.

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This paper proposes methods in order to reduce the time of optimization by the use of neural networks. They predict both the magnetic field and temperature distribution taking geometrical data as input.

In this paper the proposed methods of both the eddy-current and temperature calculation by the neural networks are presented, and the combination with the finite element modelling along with results of this non-linear coupled electro-thermal problem.

II. The Neural Network Implementation

For this paper feedforward nets trained by backpropagation are chosen. The signals flow from the input layer to the output layer, in a forward direction using several hidden layers [3], [4].

The considered coupled problem consists of two main numerical problems, i.e. an electromagnetic and a thermal one. For each problem an appropriate neural network is used with different input variables, which are explained in the following subsections.

A. Prediction of the eddy-currents

The electromagnetic problem is defined by the geometry, the enforced currents in the coils and the material parameters. The solution is the eddy-current distribution in the moving sheet. The frequency used causes a penetration depth smaller than the thickness of the sheet, what leads to a two-dimensional current distribution valid for the depth of the sheet. In rough approximation, the

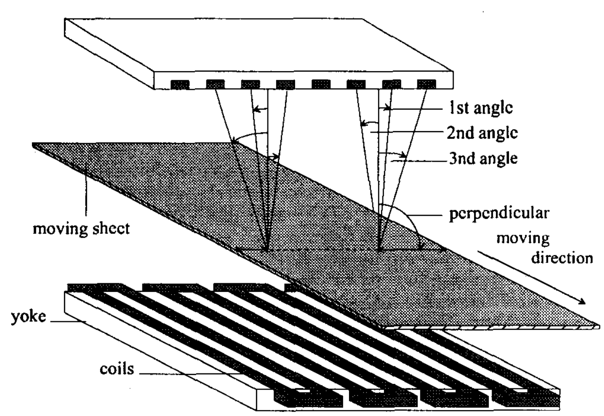

Fig. 1. The principle of the transverse flux inductive heating device

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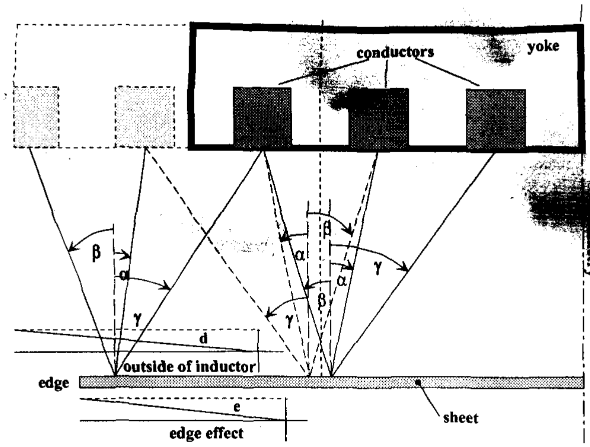

Fig. 2. The angles defining the local position on the sheet relative to the conductors

currents induced in the strip are a projection of the coil geometry onto the strip surface [5]. This paper takes advantage of that effect and trains the dependencies to a neural network with the aim to guess a good solution.

In order to take the geometrical dependencies into account *each* training set of the neural network represents *one* point on the surface of the strip, defined by different angles, measures and other geometrical parameters partly shown in Fig. 1 and 2. The angles α, β and γ describe the position relative to the conductors, which helps the artificial network to learn that the absolute value of the eddy-currents in the sheet reaches its maximum under the conductors while it vanishes between them. Each angle is represented by one unit of the input layer.

Close to the corner of the inductor the induced currents don't follow the periodical distribution of the middle part because of the end effects while they vanish far outside. Another input unit of the neural network takes care of this end effect. The activation depends on the distance of the location to the last conductor (marked d in Fig. 2). An additional unit (e) represents the distance to the edge of the workpiece where the induced currents are constrained to a smaller space and the current density rises. The same applies to the coil head windings leading to two more input neurons. In total the input layer contains 7 neurons.

The output layer consists of one single unit which activation stands for the absolute value of the eddy-currents at the considered location.

The learning points are the nodes of the finite element representation of the sheet leading to about 30 000 training sets. While one data set is connected to the input layer the output is compared to the value of the eddy-currents at this point and the weights are updated with the backpropagation algorithm.

B. Prediction of the temperature distribution

The region of interest for the thermal problem is the body of the moving sheet. The problem is stated by the distribution of the losses of the induced currents, the velocity, the width and the material parameters of the sheet. The result is the temperature field. The following discussion assumes constant material properties of brass and the velocity to be fixed leading to a steady state solution. Thermal conductivity is considered. Because of the very thin material the temperature is constant across the depth leading again to a two-dimensional solution. The sheet enters the device with a constant initial temperature.

The prediction of the temperature distribution is based on a second feedforward neural network. The output layer is again only one neuron representing the temperature value at a specific point on the workpiece, marked ϑ_n in Fig. 3. This value depends on the temperature values and the loss density around that point. The value of velocity chosen prevents a heat flow against the moving direction. Therefore only the temperature values ϑ_{left}, ϑ_{center} and ϑ_{right} in Fig. 3 influence the value ϑ_n by heat flow, which are three units of the input layer of the neural network.

The dependency of the loss density is taken into account by calculating the total losses in the 4 quadrants given by the neighboring elements. Four more neurons represent the total losses w_1, w_2, w_3 and w_4.

The heights and widths of the quadrants influence the heat flow. Therefore, four more neurons are added to the input layer leading to a total of 11 units.

Special attention is given to the boundaries of the squared region of the sheet, i.e. the entrance and exit of the device and the two remaining edges. Concerning the neural network the points on these corners lack one or more of both the temperature value points (ϑ_{left}, ϑ_{center}, ϑ_{right}) and the quadrants (w_1, w_2, w_3, w_4). Because on these boundaries no heat transfer to the outside is assumed, i.e. the gradient vanishes, the value of losses in the outside quadrant is set equal to the appropriate value in the inside quadrant. For the points on the entrance edge the preceding outside values of the temperature are set to the initial temperature.

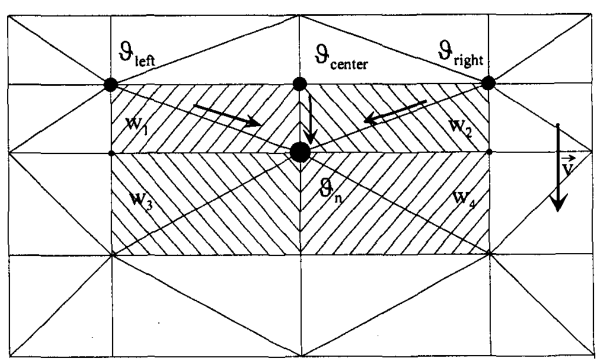

Fig. 3. Input data used for the temperature extimation shown in a partial view of a triangle mesh

III. The Flow of Calculation

Two main applications arise for the proposed neural network implementation.

On the one side the proposed networks are used purely to get a rough solution for both the eddy-current and the temperature distribution. This is of interest in the field of optimization, where especially at the beginning fast but not neccessarily exact solutions are demanded.

On the other hand the entire coupled problem can be solved with the finite element method using the trained networks to improve the convergence. The electromagnetic part uses the conductivity of the workpiece, which depends on the temperature. The algorithm of solving this weak coupled problem with the finite element method is shown in Fig. 4 on the right hand side and given by

$$\nabla \times \vec{T} = \vec{J}_e \quad (1)$$

$$\nabla \cdot (\mu \nabla \Omega) = \nabla \cdot (\mu \vec{T}) \quad (2)$$

$$\nabla \times (\underline{Z}_s \nabla \times (\Omega \cdot \vec{n})) = j\omega\mu_0 ((\nabla \Omega) \cdot \vec{n}) \cdot \vec{n} \quad (3)$$

$$-\nabla \cdot (\lambda \nabla \vartheta) + \varrho c \vec{v} \nabla \vartheta + \frac{\alpha}{a}(\vartheta - \vartheta_a) = w. \quad (4)$$

After solving the electromagnetic problem with the $T - \Omega$ method using the boundary impedance $\underline{Z}_s = f(\sigma)$ and the enforced currents J_e (1)-(3) and calculating the losses w as function of the eddy-currents, the temperature distribution ϑ is evaluated (4) [6], [7]. ω stands for the angular frequency, λ for the thermal conductivity coefficient, c for the heat capacity, ϱ for the mass density, α and $2a$ represent the coefficients of heat transmission and the thickness of the workpiece respectively.

Then the temperature dependency of the conductivity σ is considered. This is solved iteratively until the changes of the temperature field $\Delta\vartheta$ fall below a tolerance value ϵ. The solution of the neural networks, i.e. the temperature distribution speeds up the entire process, because a rather good value for the conductivity for each finite element is known in advance and an initial solution for the thermal part of the problem is provided as well.

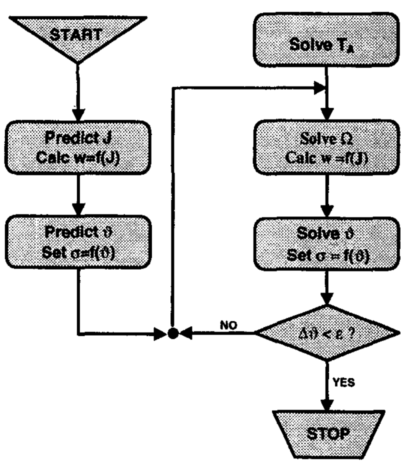

Fig. 4. The flow of calculation combining FEM and the proposed neural networks

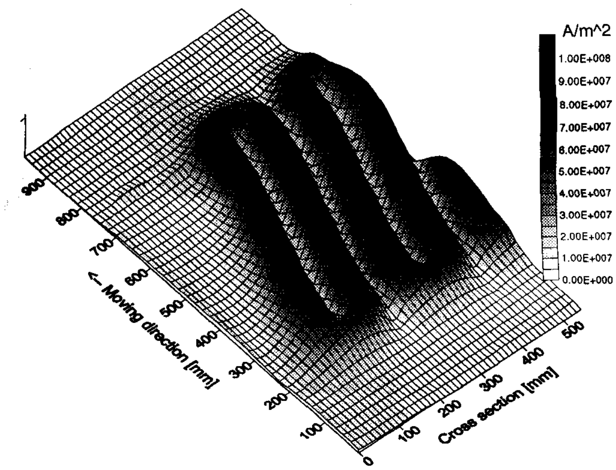

Fig. 5. The propagated current distribution in the sheet (half width)

IV. Results

The neural networks are fed with training data obtained by finite element calculations. Two different devices are used, one with coils parallel to the moving direction shown in Fig. 1, and a second device with the coils turned by 15 degrees. A set of solutions is obtained by varying the sheet width.

The next two subsections discuss the learning ability of the proposed implementation of the neural networks. Then a top-down algorithm of temperature propagation is introduced. Finally the combination of the FEM and the neural networks is presented.

A. Eddy-currents

Fig. 5 shows the propagated eddy-current distribution. The neural net was given a problem with a sheet width not used during the training. The ability of propagating a good result is measured as the residual difference between the proposed and the finite element result. This leads to a deviation of 9 % [8].

B. Temperature

Fig. 6 displays both the estimated temperature value for each node of the FE mesh and the accompanying relative error compared to the *reality*, i.e. a FEM solution. Each temperature value is obtained by giving the neural network the losses and the previous temperature values taken from the FEM solution. This allows verification of the ability to give reasonable responses to the input. The relative error is mostly below 0.4 %, but show peaks up to 2.8 %. The distribution of these peaks is remarkable. They fall geometrically on regions where the mesh is coarse, and hence less training data is available. The overall residual error is 0.8 %.

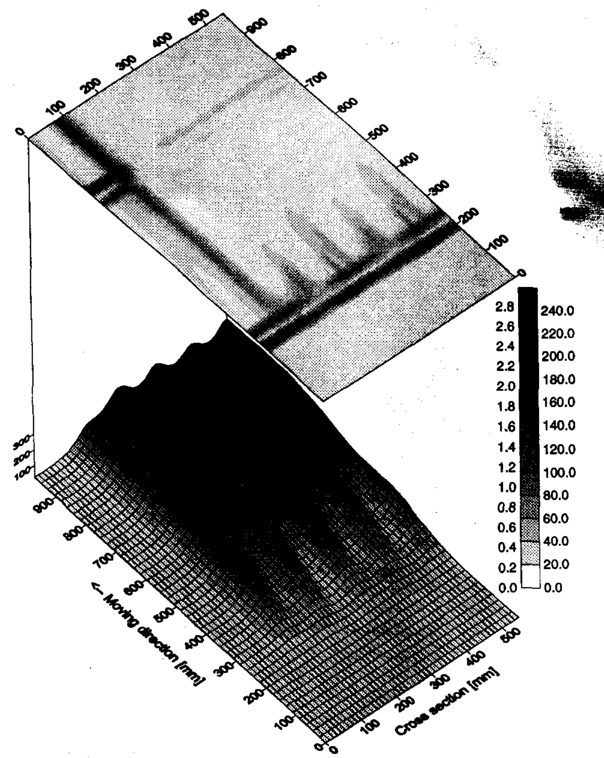

Fig. 6. The temperature field propagated by the neural network and the relative error on top [%]

C. Top-down

Note that the temperature distribution of Fig. 6 is not the answer to the question of whether a neural network can estimate the temperature field of an TFIH device. The reason is that every value in Fig. 6 is obtained with input values ϑ_{left}, ϑ_{top} and ϑ_{right} taken from a FEM solution, which is actually the desired result.

To acquire a solution from scratch, the temperature field is calculated top-down, i.e. in moving direction. The nodes at the entrance of the device are initialized to the ambient temperature, the others are propagated row by row.

The relative error for both geometries is plotted in Fig. 7, which reveal the error propagation in direction of motion. The right graphic belongs to Fig. 6. The relative error lies mostly below 4 % but reaches values up to 40 %.

D. Improving the Convergence of the FE Calculations

Now, both neural networks are used in sequence to obtain the temperature field from scratch given only the geometry and the enforced currents. According to Fig. 4 this is used as the initial solution for the FE calculations.

Applied to this device the number of iteration was reduced from 6 to 3. Also the first FE temperature computation converged noticeably faster than the one using the usual initial solution, where the entire temperature field is set to the ambient temperature.

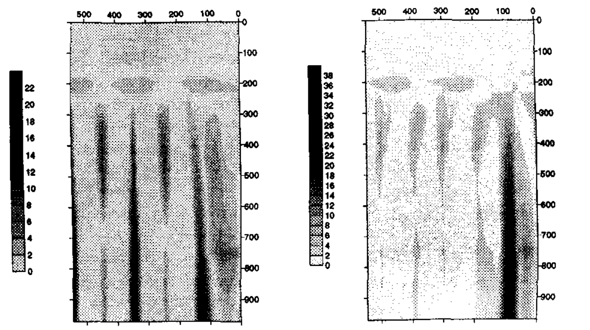

Fig. 7. Relative error [%] of the temperature distribution between a finite element solution and the neural network estimation using the top-down method. Left: straight coils, right: turned coils

V. Conclusions

This paper presents the implementation of two neural networks to estimate the eddy-current and temperature distribution in a transverse flux inductive heating device. The first neural network is trained to respond to geometric information to give the eddy-current distribution from scratch. Then the second one provides the temperature depending on neighboring temperature values and induced losses.

The results presented show a quite good accuracy of the estimated solutions. This allows the use of the proposed method in order to get the distribution, which is not of the accuracy of finite element calculations but obtained very fast. The solution time of the finite element method is reduced in this application by initializing with the estimated distributions, which speeds up the optimization processes. Further investigation could reduce the overall error by implementing more input neurons.

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