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A neural network combined with a three-dimensional finite element method applied to optimize eddy current and temperature distributions of traveling wave induction heating system

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In this paper, neural networks with a finite element method (FEM) were introduced to predict eddy current distributions on the continuously moving thin conducting strips in traveling wave induction heating (TWIH) equipments. A method that combines a neural network with a finite element method (FEM) is proposed to optimize eddy current distributions of TWIH heater. The trained network used for tested examples shows quite good accuracy of the prediction. The results have then been used with reference to a double-side TWIH in order to analyze the distributions of the magnetic field and eddy current intensity, which accelerates the iterative solution process for the nonlinear coupled electromagnetic matters. The FEM computation of temperature converged conspicuously faster using the prediction results as initial values than using the zero values, and the number of iterations is reduced dramatically. Simulation results demonstrate the effectiveness and characteristics of the proposed method. © *2011 American Institute of Physics*. [doi:10.1063/1.3560902]

With recent advances in artificial intelligence, genetic algorithms, and the neural network, searching procedures based on the mechanisms of natural selection and genetics have been regarded as effective and efficient tools in design optimization.[1] The method has been used in optimal design of electrical machines with various degree of success.[2] Effective use of optimization techniques to solve practical engineering problems is therefore still an area of research.

The finite element method (FEM) is nowadays routinely used for analyzing and evaluating the performance of electromagnetic devices, accounting for the effects of nonlinearity and geometric complexity of the physical problems. Some methods have been proposed to decrease the FEM computation time in transverse flux induction heating design.[1,2] But there has been no viable approaches applying the classical optimization methods to 2D or 3D simulation of the traveling wave induction heating (TWIH) system.

In this paper, a method that combined a neural network with a FEM is applied to the design of a TWIH system to offset the resulting inhomogeneous eddy current or power density, which dominates the temperature distributions on the surface of the work strip. Figure 1 shows the cross-sectional view schematic of a typical axisymmetric configuration. Two linear inductors with six coils are equipped on opposite sides of the strip and slots perpendicular to the direction of the movement. Due to the thickness of the interposing refractory materials, there is a relatively large air gap between the inductor and the strip.[3] Symbols for the parametric model of the heater are also indicated. Nonlinearity in the material properties of the yoke and coils are taken into account in the FEM simulation. The design problem is subject to three constraints, the total height of the heater, the air gaps and the speed of the strip movement.

Figure 2 shows the structure of the mesh generation of the TWIH device. Alternating current through every two in-phase sets of coils induces a magnetic field, which is perpendicular to the surface of the sheet, and alternating magnetic flux induces the eddy current on the work strip. The coil is placed in close proximity to the strip surface and is excited by

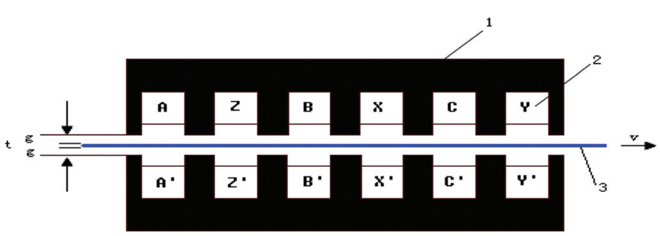

FIG. 1. (Color online) Schematic of a double-side TWIH (1—magnetic yoke; 2—exciting windings; 3—load metal sheet; *t*—strip thickness; *g*—air gap between inductor and load; ans *v*—strip movement directions).

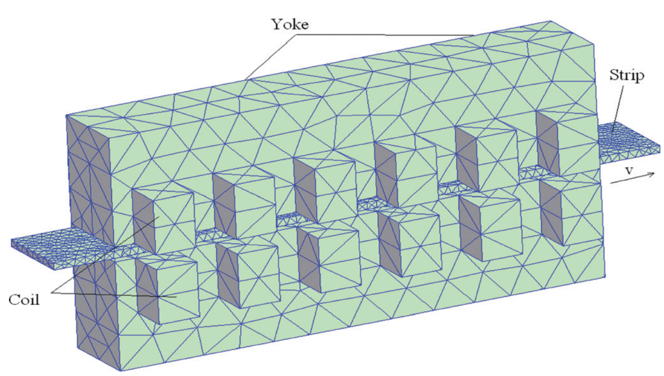

FIG. 2. (Color online) Mesh generation of TWIH device structure.

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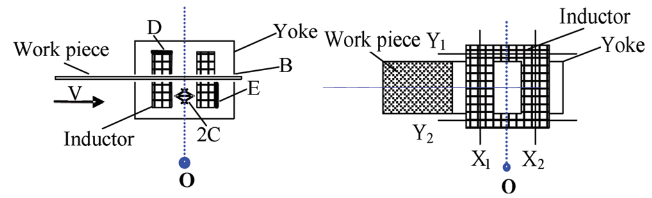

FIG. 3. (Color online) The 1/3 structure of the TWIH device and the parameters corresponding to the units of input layer.

a large alternating current at medium frequency about 500 Hz. The eddy current induces heat in the strip, most notably at the surface, which quickly raises the surface temperature.

Prediction for eddy current field and temperature field distributions on the work strip are based on the multilayer neural network *B–P* algorithm. A learning process is composed of forward spread and reverse spread. In order to decrease the error signals and make the network become convergent, error signals would adjust the near layers' connection weights and each neuron layer's offset, when transmitting from output layers to input ones.

The neural network's input layers contain a number of neurons, but the output layer has only one neuron variable, which represents the predicted point's eddy current in the eddy current field analysis.[4] In order to combine with a FEM solution, predicted points are chosen to be the objected region's nodes, and results of FEM analysis would be used as the expected neural network training outputs. For TWIH neural network prediction of eddy current on the surface of the work strip, the key factor is to determine the right input variables.

Based on the relationship between eddy current distributions and the shape of the induction coil and the structure of the heater, it is not difficult to determine the variables in the neural network input layer. Figure 3 shows a 1/3 structure of a typical diagram of the induction heater, which has four coil center lines X_1, X_2, Y_1, and Y_2. Distances from a predicted point to these four lines are denoted as d_1, d_2, d_3, and d_4, which serve as the neural network's four input variables. Other input variable is the end effects, which depend on the distance between the coil and the width of the trip (expressed as A). Through training, the neural network has built the model that the eddy current density is more intensive from the center along the radius direction inside the projection coil. The parameters B, C, D, and E also partially influence the eddy current distributions.[2,5] Because C is determined by X_1, X_2, and D, the C value cannot be the input variables. So, the neural network prediction about the eddy current field has totally eight input layer variables which are d_1, d_2, d_3, d_4, A, B, D, and E.

In order to let the network learn that the eddy current distributions vary with changes of A, B, D, and E parameters,

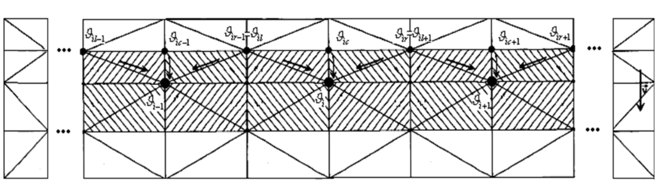

FIG. 4. Input data used for the temperature estimation shown in a partial view of a triangle mesh.

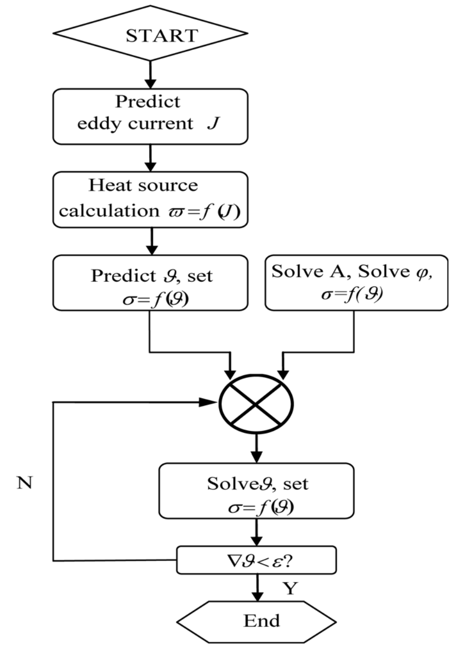

FIG. 5. The combined calculation flow of the proposed neural networks with FEM.

it is better to select a large number of combinations of these parameters for the network training. The parameters selection uses the orthogonal L_9 program to improve the training efficiency. As a result, the FEM computation of the eddy current field has been carried out, and finally attains a learning network sample collection.

The whole coupled problem can be solved with the FEM, using the trained networks to improve the convergence. The electric conductivity of the work-piece, which depends on the temperature, is applied to the electromagnetic part. The electromagnetic problem is solved with the $A-\varphi$ method and calculating the coil current $\vec{J}$:

$$P_V = \left|\vec{J}\right|^2/\sigma, \tag{1}$$

$$\frac{\partial(c\rho\vartheta)}{\partial t} = \nabla\cdot(\lambda\nabla\vartheta) + P_V + \vec{v}\cdot(c\rho\vartheta), \tag{2}$$

where P_V stands for the heat source (power loss), v is the reluctivity, and c is the heat capacity. Then the temperature dependency of the conductivity σ is considered and this is solved iteratively until the changes of the temperature field $\nabla\vartheta$ fall below a certain tolerance value ς.

The prediction of the temperature field distributions are based on a second feed-forward neural network. The output layer is only one neuron representing the temperature value at a specific point on the work-piece, marked as ϑ_{i-1}, ϑ_i, and

TABLE I. Results of neural network prediction.

Sample group	Average relative error (%)	Maximum relative error (%)
1	3.3	7.2
2	3.0	10.1
3	2.9	12.7
4	4.2	15.3

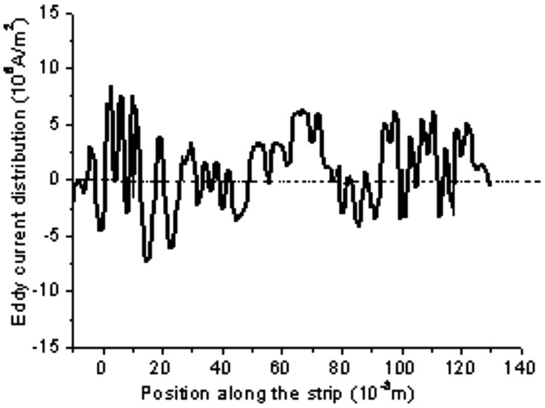

FIG. 6. The predicted result of eddy current distributions along the surface of the work strip with neural networks.

ϑ_{i+1} in Fig. 4. These values depend 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_{il}, ϑ_c, and ϑ_{ir}, in Fig. 4 influence the values ϑ_{i-1}, ϑ_i, and ϑ_{i+1}, by heat flow, which are three units of the input layer of the neural network. And the objective function is $\nabla\vartheta = |\vartheta_i - \vartheta_{\mathrm{FEM}}|$, where ϑ_{FEM} is the FEM calculation results.

The calculation flow of the proposed neural networks combined with FEM is shown in Fig. 5. The dependency of the loss density is taken into account by calculating the total losses in the four quadrants given by the neighboring elements. 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_{il}, ϑ_c, and ϑ_{ir}) and the quadrants.

As 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, the solution of the neural networks, i.e., the eddy current distributions, speeds up the entire process.

Select four structure parameter groups that are not used in the training process to carry out the neural network prediction for eddy current field. Neural network predicted results are shown in Table I.

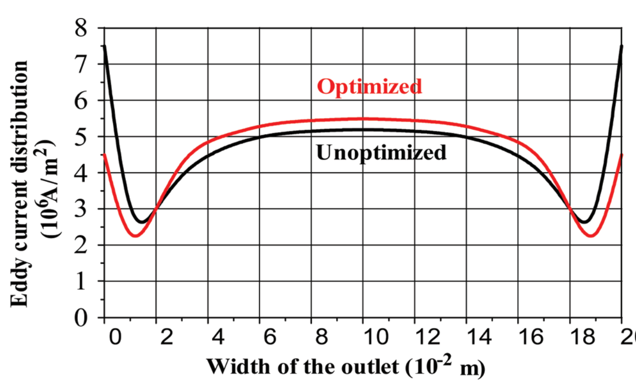

FIG. 7. (Color online) Comparison between optimized and unoptimized eddy current distributions along a line near the outlet of the work strip.

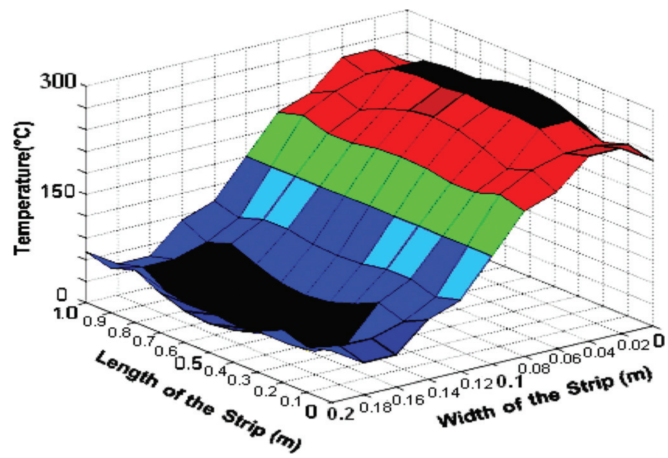

FIG. 8. (Color online) The predicted result of temperature field distributions on the surface of the one half work strip with neural networks.

From Table I, we can see that the average relative errors of the predicted values are only 2.9%– 4.2% for 600 predicted nodes on the work strip, and the biggest relative error is 7.2%–15.3%, which are much less than the FEM computed results.

Predicted eddy current distribution results are shown in Fig. 6, and its origin of coordinate corresponds to the ***O*** point in Fig. 3. The neural network 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.

Comparison between optimized and unoptimized eddy current distributions with value offsets is shown in Fig. 7. It is found that the eddy current distributions are improved after the proposed optimization method. Network prediction results speed up the iterative solution process for the nonlinear coupled electromagnetic thermal problems. Figure 8 shows the predicted result of temperature field distributions on the surface with neural networks.

The results presented in this paper show quite a good accuracy of the estimated solutions. This allows the use of the proposed method in order to get the distributions, 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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