A Cascade Deep-Learning Approach for Design and Control Optimization of a Dual-Frequency Induction Heating Device

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A cascade deep-learning approach is proposed for optimizing the design and control of a dual-frequency induction heating system used in semiconductor manufacturing. The system is composed of two independent power inductors, fed at different frequencies, to achieve a homogeneous temperature profile along a graphite susceptor surface, crucial for enhancing layer quality and integrity. The optimization process considers both electrical (current magnitudes and frequencies) and geometrical parameters of the coils, which influence the power penetration and subsequent temperature distribution within the graphite disk. A two-step procedure based on Deep Neural Networks (DNNs) is employed. The first step, namely optimal design, identifies the optimal operating frequencies and geometrical parameters of the two coils. The second step, namely optimal control, determines the optimal current magnitudes. The DNNs are trained using a database generated through Finite Element (FE) analysis.

***Index Terms*—Multi-Physics Domain, Induction Heating, Finite Element Analysis, Deep Neural Networks.**

I. Introduction

Temperature control is one of the most important conditions for obtaining a high-quality epitaxial layer in semiconductor industries [1]. In this paper, a new optimization technique of a dual-frequency induction heating system for uniform temperature distribution on the graphite susceptor inside an epitaxial deposition reactor is applied. This work considers the electrical and geometrical parameters of the two power inductors, originates a wider range of freedom in reaching the desired uniformity of temperature. The proposed methodology has its core in two-step procedure based on DNNs. The first step is an optimal design procedure considering appropriate operating frequencies and geometrical parameters of both coils. In turn, the second step defines the optimal control and identifies the current magnitudes given to both coils aimed at achieving the target temperature.

II. The Field Model

A. The Device

The device contains a flat, circular graphite disk (Fig. 1) having electrical resistivity of 960 10^{-8} Ωm and thermal conductivity of 150 $Wm^{-1}K^{-1}$ at 1200 ºC.

The diameter of the graphite disk is 500 mm. The heating system consists of two copper coils: an internal 7-turn solenoid coil and an external 6-turn pancake coil. [1]. They are supplied separately from each other; the inner coil carries an electric current in the range 100-500 A and frequency range 20-100 kHz, while the outer coil is supplied with a current in the range 400-2000 A and frequency range 1-8 kHz.

B. The Finite Element model

To simulate the temperature distribution on the susceptor, three Finite Element (FE) analyses are developed [2]. Because the model has two coils fed by currents at different frequencies, the field analysis is challenging: specifically, two FE models for magnetic analysis (each one related to single frequency and one coil on), and one FE model for thermal analysis have been set.

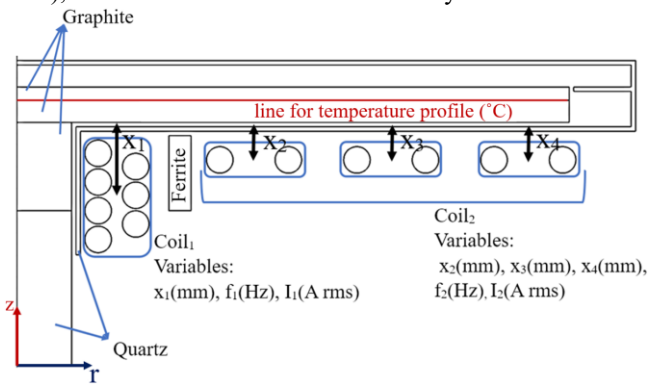


Fig. 1. Device geometry and design variables

The FE models are axisymmetric around the z axis; they were built in COMSOL 6.0 commercial software. For the sake of generality an A-V formulation has been used to enforce the uniqueness of field solution that would be mandatory in the case of a 3D analysis. Accordingly, both magnetic analyses are solved at time-harmonics condition with the A-V formulation, and thermal analysis is solved at steady state condition to handle both convective and radiative contributions for heat exchange. For thermal analysis, the convective exchange coefficient h is 10 $Wm^{-2}K^{-1}$, the emissivity coefficient ε is 0.8 and the external temperature is considered to be equal to 850 ºC [3]. The model mesh is composed of more than 19,000 second-order elements. Typical magnetic and temperature distribution maps are shown in Fig 2.

As the problem is a weakly coupled magneto-thermal problem, utilizing the superposition principle, two power densities calculated from single magnetic analyses, are added to each other in order to simulate the heat source term for

subsequent thermal analysis. The power density from each magnetic analysis is calculated while one coil on (single frequency) and the other one off. Equation (1) should be satisfied between two frequencies in order to superpose two power densities [3]:

$$m_1 f_1 = m_2 f_2 \quad (1)$$

where f_i is the frequency of each coil and m_i is positive integer number.

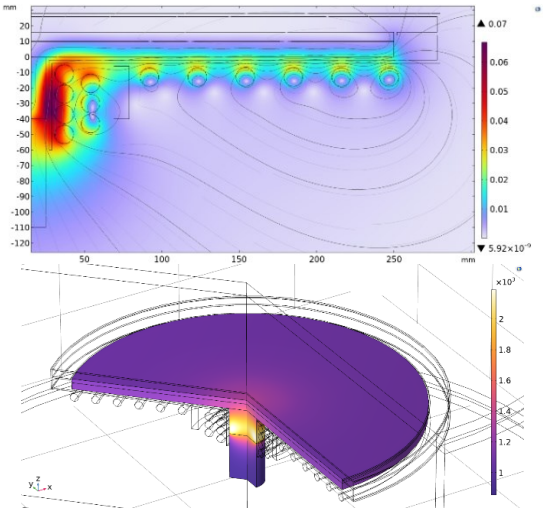


Fig. 2. Magnetic field (T) map (up), Temperature (C) field map (bottom).

III. Cascade Approach for Optimization

This approach is composed of the optimal design phase followed by the optimal control phase. The main database is created using the FE model: 2,500 simulations are run by changing the parameters x_1 to x_4, frequencies and current magnitude; the output is the temperature profile (250 points) along the line, highlighted in red in Fig. 1, in the upper surface of the susceptor. To cover the 8-dimensional input space, the Latin Hypercube method has been used [4]. The database is then filtered in a way that the first 25 mm of the disk in the inner part have a temperature in the range of ±5% around the target temperature (1,100 °C).

The filtered database, namely DB_1, ensures that the inner coil heats up the central part of the graphite; it contains 400 observations. For the optimal design (OD) phase, a feed forward neural network with 4 hidden layers and [30 15 10 5] neurons configuration has been trained with DB_1. The input is the temperature profile (250 points). The output is coil geometry (x_1 to x_4) and the frequency f_2 of the outer coil. This DNN is then used to predict the geometry and the frequency f_2, given a homogeneous temperature profile around 1,100 °C which approximates a uniform profile. For training the DNN of the second phase, the average of the frequency f_1 of the first coil in DB_1 is calculated. Hence, knowing the geometry of the coils and both frequencies (from both the solution of the OD problem and the average of f_1 in DB_1), a new database, namely DB_2, is generated with 300 observations of FE analyses by changing the current amplitudes in their range. For the optimal control (OC) phase, a neural network with 4 hidden layers and [30 15 10 5] neurons has been trained with DB_2 to determine the current amplitude of both coils, given the temperature profile as input. The accuracy of training is shown in Fig. 3.

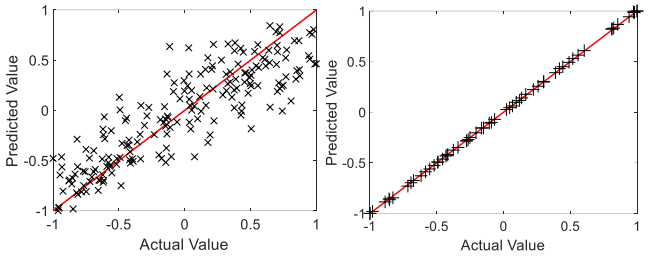


Fig. 3. The predicted vs. actual value, OD phase (left), OC phase (right)

In order to quantitatively assess the results, the Mean Absolute Percentage Error (MAPE) is calculated for the test set i.e. 10% of samples. The MAPE of OD is 24.8%, the MAPE of OC is 0.29%.

IV. Results

Using the proposed cascade approach, the geometry, frequencies and the current amplitudes have been determined (Table I) to achieve a more homogeneous temperature profile around 1,100 ºC, which is shown in Fig. 4.

TABLE I
Optimal Design and Optimal Control Results

	x_1(mm)	x_2(mm)	x_3(mm)	x_4(mm)	f_2(Hz)
OD	28.8	44.5	97.7	35.9	6111
f_1 is determined 61,129 Hz using the data in DB_1					
	I_1(A rms)	I_2(A rms)			
OC	388	1024			

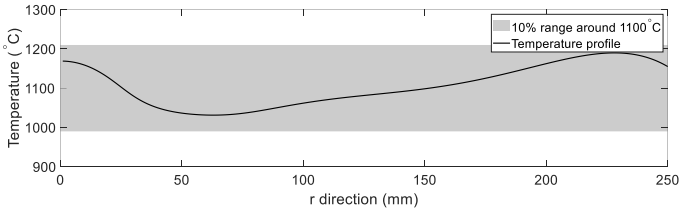


Fig. 4. Temperature profile using the result of cascade approach

V. Conclusion

The problem of geometry and current optimization has been successfully solved using a new cascade approach. While this approach shows its advantage in terms of optimal control phase, the optimal design phase is challenging. In the full-length paper, more investigations on the optimal design phase will be done to achieve more accurate results.

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