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OPTIMIZATION OF THE INDUCTOR OF AN INDUCTION COOKING SYSTEM USING PARTICLE SWARM OPTIMIZATION METHOD AND FUZZY LOGIC CONTROLLER

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Key words: Magneto- thermal, Finite element method, Self-adaptive particle swarm optimization (PSO), Fuzzy logic control.

To improve the performances of an induction cooking system we propose a method that yields a better homogeneity of the temperature on the pan's bottom and a good regulation of the temperature. Firstly we apply the optimization method based on Self-adaptiveparticle swarm optimization technique combined with the 2D FEM method in order to determine the inductor optimal slots distribution and their dimensions . Secondly, a temperature control technique based on the so-called Fuzzy logiccontrol is used in order to limit the excess temperature on the pan's bottom and to get the desired value suitable for cooking (150…200 °C).

1. INTRODUCTION

Induction cooking provides faster heating, improved thermal efficiency, and low pollution as compared to a gas burner [1]. The principle of induction heating is based on three rules (laws of Lentz, Lorentz and Joule) where the magnetic field created by the inductor induces eddy currents on the pan's bottom and these induced currents cause the heating of the pan by Joule effect.

The plan of this work is twofold: it aims at obtaining an inductor geometry which gives a uniform distribution of the temperature on the bottom of the pan. Secondly, we propose a technique of control of this temperature. The temperature distribution on the pan's bottom is determined by modelling the magneto thermal phenomena of the system by a 2D finite element method (FEM) and taking into consideration the nonlinearity of the system [2,3]. In order to have a homogeneous temperature on the pan's bottom, we propose an inductor structure in which the coils are optimally placed in slots (Fig. 1).

The optimal inductor geometry giving a uniform distribution of the temperature was obtained in previous researches by using intelligent methods of optimizations (Genetic Algorithms and Neural Networks) [3,4], but by varying distances (d_i**)** only (Fig. 1). The goal of this work is to find an optimal inductor geometry that gives a better uniformity of the temperature distribution than that obtained in [3,4], by varying both parameters (d_i and z_i) simultaneously (Fig. 1). However, to achieve such a goal, we model the magneto thermal phenomena of the system by a finite element method (FEM), combined with the self-adaptive particle swarm optimization method.

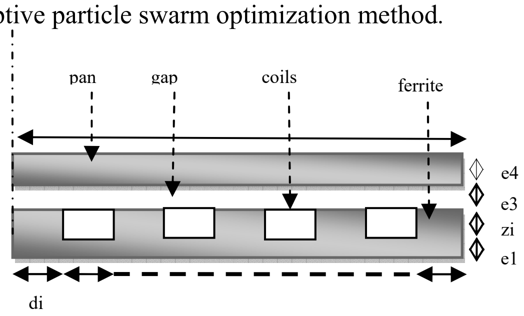

Fig. 1 – Inductor with four slots.

After obtaining the distribution of temperature (Fig. 8). The latter figure shows that the temperature increases up to 760 °C (Curie point of pan's material) which exceeds the value of cooking temperature (150…200 °C). To have the desired temperature of cooking, we used a regulation's technique of temperature based on Fuzzy Logic Controller (FLC) method [11,12]. This paper is organised as follows: in section 2, the mathematical modeling and finite element analysisare presented. The temperature distribution from the use of the uniform dimension of slots is determined in section 3. In order to have a uniform temperature distribution, the optimal dimensions of slots are calculated in section 4 using self-adaptive particle swarm optimization method. The utilisation of the Fuzzy logic (FL) method to control the temperature evolution is given in section 5. Finally, the conclusion is presented in section 6.

2. MATHEMATICAL MODELING AND FINITE ELEMENTANALYSIS

The aim is to search for a uniform distribution of the temperature on the pan's bottom of the cooking device.

To achieve this aim, it is important to establish the mathematical model of the system. The mathematical modeling of induction cooking devises uses both the magneto-dynamic and the thermal equations. The magneto-dynamic formulation is useful for the determination of the distribution of induced currents generated by the inductor which represents the image of the temperature distribution on the pan's bottom. The eddy current density and the heat source can be calculated by solving the coupled magneto-dynamic and heat equations. Since the system possesses an axial symmetry, a 2D solution is possible.

Using the magnetic vector potential $\mathbf{A} = r\mathbf{A}_\vartheta$, the electromagnetic phenomena are modeled by the well-known magneto-thermal equations [5,6]:

$$\mathrm{j}\,\omega\frac{\sigma\mathbf{A}}{r} - \frac{\partial}{\partial r}\left(\frac{\nu}{r}\frac{\partial\mathbf{A}}{\partial r}\right) - \frac{\partial}{\partial z}\left(\frac{\nu}{r}\frac{\partial\mathbf{A}}{\partial z}\right) = \mathbf{J}, \tag{1}$$

$$\lambda\nabla^2 T + q = \rho_m c_p\frac{\partial T}{\partial t}, \tag{2}$$

$$q = \frac{1}{r^2}\,\omega\sigma^2\,\mathbf{A}\cdot\mathbf{A}^*, \tag{3}$$

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where:

ν,σ,ω magnetic reluctivity, electric conductivity, angular frequency;

J, T electric current density, temperature;

λ,ρ_m,c_p thermal conductivity, masse density, specific heat.

It remains to achieve the magneto-thermal model to give boundary conditions. The finite element method 2D-FEM was used for the numerical modeling of both the governing eq. (1) and (2) using the following boundary conditions (4) and (5). The boundary conditions in the borders of the pan are of Neumann type conditions

$$-\lambda \frac{\partial T}{\partial n} = h(T - T_n). \tag{4}$$

The boundary conditions for the electromagnetic problem are of Dirichlet type

$$\mathbf{A} = 0, \tag{5}$$

where h is the convection coefficient, T_n is the ambient temperature and T is the calculated temperature.

The axisymmetric structure of the system makes h nonlinear due to the convection effect of the air nearby [7]. In our case we assume that h has a constant value along the radius of the pan. The pan is made of a material of stainless steel the properties of which are given in [3].

3. CALCULATION AND DETERMINATION OF THE TEMPERATURE DISTRIBUTION BEFORE OPTIMIZATION

The considered object is an induction heating pan. The inductor has four slots containing the exciting coils. For the first step we consider that the dimensions (widths d_i and thicknesses z_i) of the slots and distances between the slots have a uniform distribution as shown in (Fig. 1,2), where d_i = 15.55 mm and z_i = 2 mm. The other parameters are shown in Table 1.

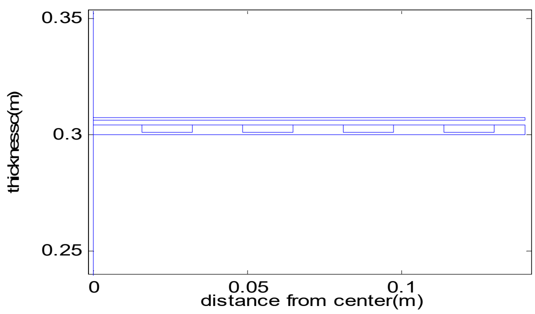

Fig. 2 – System model used in the Program

Table 1

Parameters of system.

Symbole	Magnitude	Quantity
R (mm)	Radius of pan	140
e_i (mm)	Inductor thickness	3.8
e_g (mm)	Gap thickness	4
e_c (mm)	Container thickness	3
$d_1,d_2,.d_i$ (mm)	widths	15.55
z_i (mm)	Throat thickness	2
μ_f	Ferrite relative permeability	2500
f (Hz)	Frequency	$20{*}10^3$
J (A/m^2)	Current density	$2.5{*}10^6$
λ (W/m*°K)	Thermal conductivity	26
h (W/m^2°C)	Convection coefficient	20
ρ_m (Kg/m^3)	Masse density	7700
C_p (J/Kg°C)	Specific heat	460

The magneto-thermal calculations are performed using the following steps:

- Step 1: initialization of the magnetic relutivity, the electric conductivity, and the temperature σ_0, μ_0, T_0;
- Step 2: calculation of the magnetic vector potential (**A**);
- Step 3: calculation of the heat source density $q = r^{-2}\mathbf{A}\cdot\mathbf{A}^*$;
- Step 4: calculation of the temperature T where we use a time step of 10 s. If $T \leq 650°\text{C}$ go back to step 2 or else go to step 5;
- Step 5: display of the results.

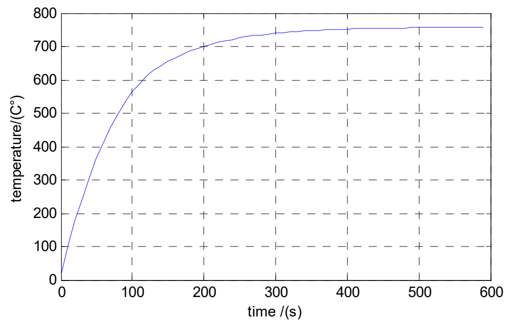

Fig. 3 – Temperature evolution versus time

The simulation results obtained are shown in (Fig. 3-4). It is clear from (Fig. 4) that the temperature distribution on the pan's bottom is not uniform. Figure 3 shows that the temperature evolution in the center of the pan’s bottom is limited at the value of 760 C°, the Curie point of pan's material [4–6].

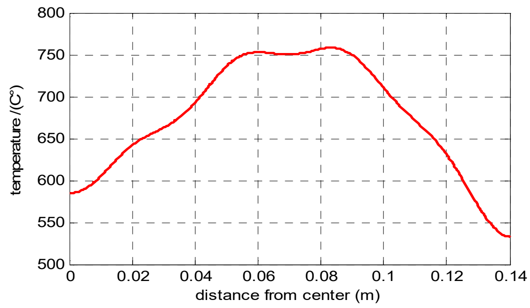

Fig. 4 – Temperature distribution on pan’s bottom.

4. TEMPERATURE DISTRIBUTION WITH OPTIMIZATION

The objective is to have a homogeneous temperature distribution on the pan's bottom. In this work we suggest the use of the PSO Algorithm to determine the best dimensions of slots (coils) in the inductor by modifying simultaneously the widths the slots, d_i, and their thicknesses, z_i. This type of optimization is widely used in nonlinear and complex systems [8].

4.1. PROBLEM PRESENTATION

The problem is to find an objective function, eq. (7), which gives the best results. For that, several iterations k of calculation tests must be done in order to determine the optimal geometry of the inductor. The diagram is summarized in Fig. 5.

The optimization problem consists of minimizing

$$f_{obj}(d_i, z_i) = f_{obj}(d_1, d_2, \ldots, d_4, z_1, z_2, \ldots, z_4), \tag{6}$$

$$f_{obj}(d_i, z_i) = \sum_{i=1}^{NT} \left(\frac{T_i - T_f}{T_i} \right), \tag{7}$$

where:

T_f is the desired temperature;

T_i is the calculated temperature at each point in the bottom of the pan;

NT is the number of elements in the bottom of the pan.

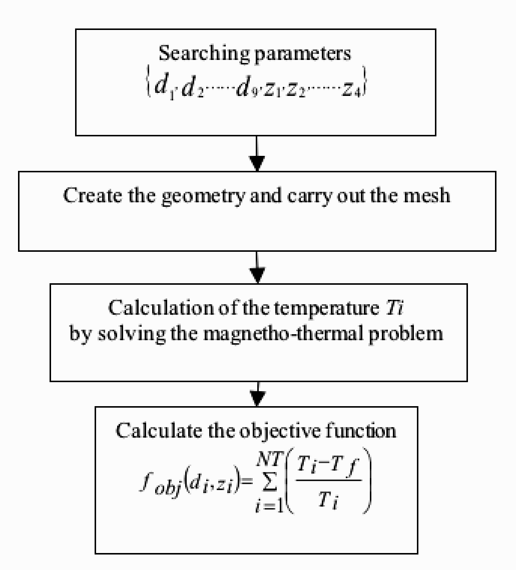

Fig. 5. – Diagram steps of evaluation the objective function.

4.2. SELF-ADAPTIVE PARTICLE SWARM OPTIMIZATION

PSO Algorithm has been developed by Kenedy and Eberharet in 1995, and it is based on the movement of a group of animals like a school of fish or a swarm of bees [8,9].

In this technique a particle swarm (population) comprises a number of particles (individuals) and each particle is represented by a number of parameters to be optimized. Each particle position represents a candidate solution of the optimization problem. In PSO, each particle in the swarm moves in a D-dimensional space searching for the best position which is defined by an objective function.

In this work, there are thirteen (13) parameters to be optimized, which are the dimensions of each particle: $\{d_1, d_2, \ldots d_9, z_1, z_2, \ldots z_4\}$.

The PSO Algorithm begins with a randomly generated position of the swarm and each particle moves in the search space with a randomly generated velocity [9].In this work, the i^{th} particle is defined as $\{d_{1i}, d_{2i}, \ldots d_{9i}, z_{1i}, z_{2i}, \ldots z_{4i}\}$.

The position x_{ij}^k and the velocity vector V_{ij}^k of the i^{th} particle at iteration k in the thirteen dimensional space are given by the eq. (8) and (9) respectively

$$x_{ij}^k = \left(d_{1i}^k, d_{2i}^k, \ldots d_{9i}^k, z_{1i}^k, z_{2i}^k, \ldots z_{4i}^k\right), \tag{8}$$

$$V_{ij}^k = \left(V_{d1i}^k, V_{d2i}^k, \ldots V_{d9i}^k, V_{z1i}^k, V_{z2i}^k, \ldots V_{z4i}^k\right), \tag{9}$$

- the position giving the best fitness value at k iteration of the i^{th} particle is saved and represented as

$$\left\{Pbestd_{1i}^k, Pbestd_{2i}^k, \ldots Pbestd_{9i}^k, Pbestz_{1i}^k, Pbestz_{2i}^k, \ldots, Pbestz_{4i}^k\right\}$$

- the best position giving the best values among all particles in the swarm at iteration (k) is represented by

$$\left\{Gbestd_1^k, Gbestd_2^k, \ldots, Gbestd_9^k, Gbestz_1^k, Gbestz_2^k, \ldots, Gbestz_4^k\right\}.$$

To improve the quality of the solution and the convergence characteristics, the standard PSO technique is modified by the use of the time varying inertia weight factor [10].

The updated position and velocity of i^{th} particle in self-adaptive PSO can be expressed as:

$$V_{ij}^{k+1} = \omega * V_{ij}^k + c_1 \times rand_1 \times \left(Pbest_j^k - X_{ij}^k\right) + c_2 \times rand_2 \times \left(Gbest_j^k - X_{ij}^k\right), \tag{10}$$

$$X_{ij}^{k+1} = X_{ij}^k + V_{ij}^{k+1}, \tag{11}$$

where:

V_{ij}^k is the velocity of particle i at iteration k;

ω is the inertia weight;

c_1, c_2 are the acceleration coefficients;

$rand_1, rand_2$ are random numbers between 0 and 1;

x_{ij}^k is the position of particle i at iteration k;

$Pbest_{ij}^k$ is the Best position of particle i at iteration k;

$Gbest_{ij}^k$ is the Best position of the swarm until iteration k.

At each time step, the position and the velocity of each particle (i) are updated by evaluating the objective function and comparing between the new solution (best position) with the old Pbest (the best position for the (i) particle at iteration (k-1)) and Gbest (the best position of the swarm at iteration (k-1)) [9-10].The weighting function is calculated as:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter, \tag{12}$$

where:

ω_{max}, ω_{min} are the maximal and the minimal weight values respectively;

$iter_{max}$, $iter$ are the maximum number of iterations and the current iteration number respectively.

4.3. PROPOSED IMPLEMENTATION WORK

To determine the optimal slots distribution and their dimensions, PSO algorithm has been used by the use of the following steps:

- **Step1.** Initialize the population size (m), set the maximum iteration, $iter_{max}$, inertia weight, ω, acceleration constants (c_1,c_2) and the number of parameter, n, to be optimized. Set the parameters of the simulated system as shown in Table 1.
- **Step 2.** Randomly generate the initial position and velocity of each i^{th} particle in swarm as shown in eq. (8) and (9).
- **Step 3.** For each particle parameter, solve the magneto-thermal problem and then evaluate the fitness function (the process of calculation of the fitness function for each particle parameter is shown in Fig. 6.
- **Step 4.** Assign (Pbest) as the best fitness values of particle position; assign Gbest as the best fitness values among all particles.
- **Step 5.** The steps 5-1 and 5-2 are repeated until the

termination criteria are achieved, or until the number of iterations reaches its maximum limit.

- **Step 5-1.** At each iteration k, the updated velocity and position of i^{th} particle are given by eq. (10), (11).
  Step 5-2. For each particle i^{th} evaluate a fitness function $f_{obj}(d_i, z_i)$ (similar to step3). Assign the new (Pbest) and (Gbest) (similar to step4).
- **Step 6.** Produce the Gbest of particles $\{Gbestd_1^k, Gbestd_2^k, \ldots, Gbestd_9^k, Gbestz_1^k, Gbestz_2^k, \ldots, Gbestz_4^k\}$ and then take them as optimal dimensions of the slots in the inductor which give a uniform temperature distribution on the pan's bottom.

4.4. SIMULATION AND RESULTS

The proposed method is developed using Matlab code, and the simulations were done on a computer with Intel (R) Pentium (R) CPU @2.16 GHz, 2 GB RAM The parameters of the self-adaptive PSO algorithms are shown in Table 2.

Table 2

parameters setting of self-adaptive PSO technique

Algorithm	Inertia weight ω	Acceleration coefficients c_1,c_2	Population size
Self-adaptive PSO	ω = 0.4 ω = 0.9	c_1 = 2 c_2 =2	30

The numerical results are achieved after 40 iterations corresponding to about 16 h, with an acceptable error of ε = 0.027. The temperature distribution is represented in Fig. 7. After convergence the Self-adaptive PSO method gives a homogeneous distribution of the temperature along a ray of the pan. The best dimensions of the slots are shown in Table 3, where the desired optimal geometry of the inductor is shown in Fig. 6. The evolution of the temperature as a function of time in the centre on the pan's bottom is shown in Fig. 8.

Table 3

Optimal dimensions of slots.

Parameters (mm)	WIPSO
d1	19.9
d2	15.6
d3	11.2
d4	19.3
d5	16.3
d6	15.6
d7	18.4
d8	17.3
d9	6.7
Z1	3.2
Z2	2.3
Z3	2.7
Z4	3.2

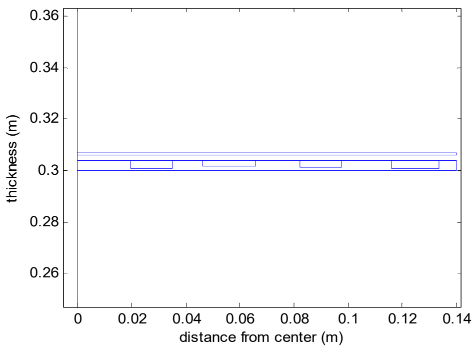

Fig. 6 – Geometry of the inductor obtained with Self-adaptive PSO.

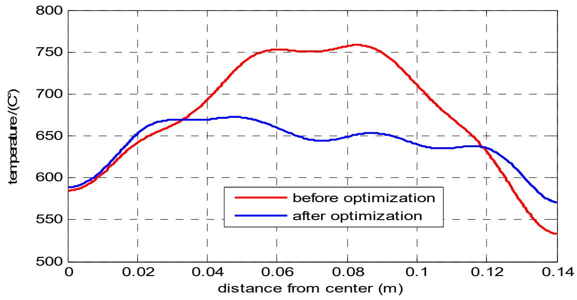

Fig. 7 – Temperature distribution on pan's bottom.

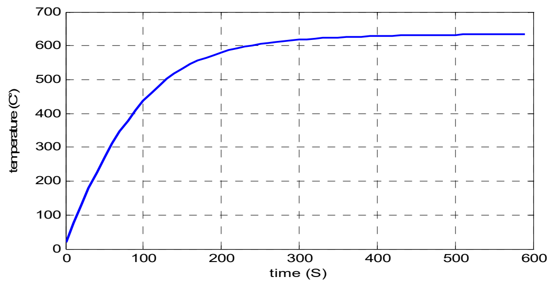

Fig.8 – Temperature evolution as a function of time in centre of pan.

Figure 8 shows that the temperature exceeds the desired temperature of cooking (150…250 °C) and increases up to 600 °C and more. For this reason, we suggest a control method of temperature based on fuzzy logic control.

5. FUZZY LOGIC

The purpose of using a controller is to regulate the temperature on the pan's bottom around the value of cooking temperature (150…250 °C). In this section, we will use the optimal geometry obtained with Self-adaptive PSO technique to control the temperature evolution versus time by the use of fuzzy logic control.

5.1. REGULATION

Fuzzy Logic Controller (FLC) was strongly requested these last years for nonlinear systems. In fuzzy logic, there are three main phases: fuzzification, inference and defuzzification [11,12].

Here the FEM is used to solve magneto-thermal formulation then to determining the evolution of the temperature, T_i, in the pan bottom, which can be adjusted by adjusting the current density, J, in the inductor.

In this part we use the characteristics of the fuzzy logic controller, FLC, to control the evolution of the temperatures in the pan bottom. The temperature, T_i, calculated in the pan's bottom at each time step was selected as the controller input, the current density, J, has been selected as the controller output and then injected into the bloc of induction cooking system.

For this, the FLC comprises an input parameter, T_i and an output parameter, J, as shown in Fig. 9.

5.1.1. FUZZIFICATION

In this step, the real variables are changed into linguistic ones. Here the values of the membership function are converted to the linguistic variables in three fuzzy subsets for input, which are: C (cold), M (medium), H (hot) into three fuzzy subsets for output: Low (L), (M) medium, upper (U).

The form of the membership functions and the repartition of fuzzy subsets for the input and output are shown in Fig. 10,11.

5.1.2. INFERENCE METHOD

In the fuzzy inference, the input is taken to generate the fuzzy outputs by the use of the fuzzy rules. In addition, the Min (minimum) operator is used to determine the output membership function of each rule. These rules are:

Rule1: If temperature T_i is C then current density J is U;

Rule2: If temperature T_i is M then current density J is M;

Rule3: If temperature T_i is H then current density J is L.

The determination of membership functions depends on the human expertise and the knowledge of the change in the temperature depending on the current density in the induction cooking system.

5.1.3. DEFUZZIFICAION

In the defuzzification phase, the FLC output is calculated using the Centroid method, which is the value of current density in this work.

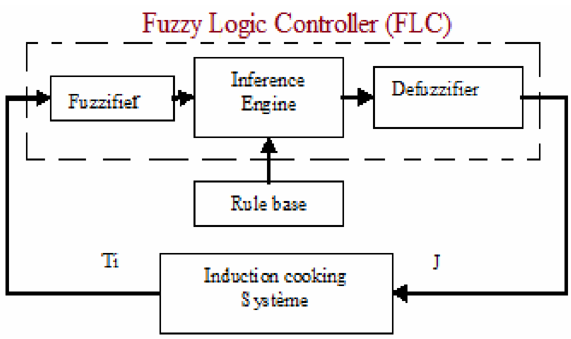

Fig. 9 – diagram of FLC.

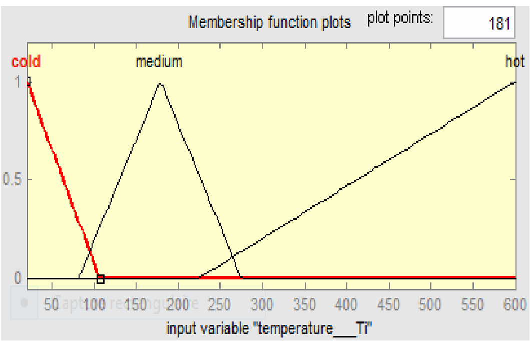

Fig. 10 – Fuzzy logic control membership function for input.

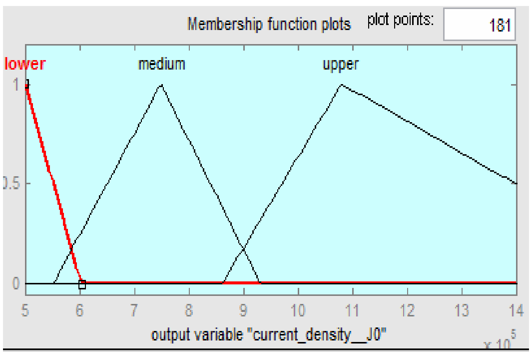

Fig. 11 – Fuzzy logic control membership function for output.

In this work, simulation is done with the help of the FLC designer toolbox in MATLAB. The results of the regulation are shown in (Fig. 12), where we see that the use of Fuzzy logic control assures a good regulation and limits the temperature variation within the band used for cooking which is fixed at 220 C°.

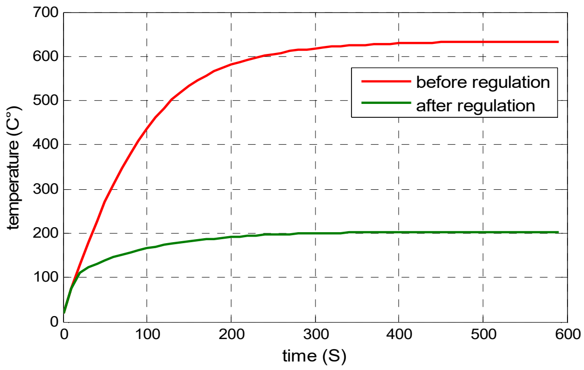

Fig. 12 – Temperature evolution as a function of time after regulation.

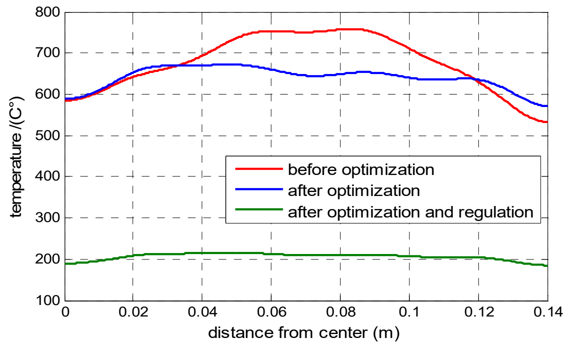

Fig. 13 – Temperature distribution after optimization and regulation.

Figure 13 show that after optimization and regulation of the temperature, we have the desired homogeneous temperature on the pan's bottom corresponding to the cooking temperature range.

6. CONCLUSION

In this paper we presented a way to achieve a uniform distribution of the temperature of induction cooking system. A finite element method is used to analyse the magneto-thermal problem and a Self-adaptive PSO technique is employed on the induction-heating cooking device to optimize the structure of the slots in the inductor.

A technique of regulation has been adopted for the work using the fuzzy logic control to find out the adapted temperature for the induction cooking system. The main feature of the fuzzy logic method is the simplicity of implementation and its robustness.

This study shows that the proposed fuzzy logic technique gives a good regulation of the temperature which is in the cooking range, *i.e.*, between 150 C° and 250 C°.

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