A Fast Hybrid Algorithm for Solving Materials Properties Determination Inverse Problem

Naamane Mohdeb and Mohammed Rachide Mekideche

***Abstract*—The aim of hybrid algorithm is to distinguish the best solution of optimization problem with a low cost function and CPU time. In this work we shall consider an effective method for solving inverse electromagnetic problem by applying a new hybrid algorithm. The new approach combines the adaptive simulated annealing and generalized pattern search method. The GPS algorithm is used for accurate local exploration to complement the global exploration provided by the ASA. To have the quality of this hybrid algorithm the performances of HASAGPS are compared with other algorithms such as hybrid genetic algorithm pattern search (HGAPS) and simplex genetic algorithm (SGA) in term of accuracy of the solution and computation time. The improved method ASAGPS is applied for solving inverse electromagnetic problem. The coupled electromagnetic circuits method (CECM) and the hybrid approach (HSAGPS) are used to characterize the electric conductivity and magnetic permeability of a circular material under test. The reached results suggest that the proposed algorithm has an excellent effectiveness in finding best solution.**

***Index Terms*—Coupled Electromagnetic Circuits Method, Generalized Pattern Search, Adaptive Simulated Annealing, Genetic Algorithm, Simplex method, Parameters Identification.**

I. INTRODUCTION

Optimization of devices is one of the main problems in electromagnetic area that is associated to a general set of inverse problems including synthesis, defect detection, identification [1][2][3]. Optimization is the hunt of the best solution of a function that is commonly referred to as cost function. This function is dependent on the propose variables, which are the unknown system parameters. The objective of the optimization process is to determine the values of these variables that minimize the cost function. In addition to optimizing the objective function, the design has to meet certain specifications which may be represented mathematically by constraint equations.

Several heuristic tools have evolved in the past decades that facilitate solving inverse electromagnetic problem or optimization problem that were previously difficult or impossible to solve. These tools include evolutionary computation, simulated annealing, tabu search, particle swarm, and so forth [2]. It is required to make use several well-known methods for decrease the time when we solve the inverse electromagnetic problem. The goal of this paper is to propose a new hybrid approach, for solving inverse electromagnetic problem in electrical engineering, for reduce the time CPU and reach the best solution.

The inverse electromagnetic problem (IEP) needs a forceful technique to distinguish its optimal solution when it is multimodal. Sometimes, finding the global solution of an inverse electromagnetic problem is a principally difficult. To overcome this difficulty, robust methods were found to calculate the optimal solution. However, Methods used for finding of the global minimum or global solution demand much more time than methods for finding of a local minimum [3]. Indeed, at the worst it is necessary to find all local minima, and then by their comparison allocate the global minimum. To reduce the search time for the global minimum, methods of meta-heuristics [2] can be applied. A meta-heuristic, such as adaptive simulated annealing method [4][5][6] may provide a good solution to this problem. The ASA algorithm present some great advantage over classical gradient methods: they are able to find the global solution and they do not require the use of derivatives.

Recently, the methods using adaptive simulated annealing are widely used because they are simple to use and are well-organized. But the convergence theory for ASA is reviewed, as well as recent advances in the analysis of finite time performance [5]. Especially, in the optimal electromagnetic field where the functions are frequently nonlinear and multimodal, the adaptive simulated annealing cannot afford the adequate fidelity of the electromagnetic inverse problem because the convergence to an optimal solution cannot theoretically be guaranteed after a number of iterations. To overcome the slow convergence of adaptive simulated annealing, we will integrate it with the generalized pattern search technique [7]. The pattern search, which does not require derivative information and indeed is one of the "derivative-free" direct search methods [8], can render the procedure efficient and robust and provided a very simple and effective means of searching the minima of objective function directly with several local solutions.

For the improved HASAGPS algorithm, the adaptive simulated annealing and generalized pattern search algorithm are integrated to obtain a robust and an efficient process. Interestingly, when a combination of adaptive simulated annealing and the generalized pattern search method was applied, an even better result was achieved. This can be explained with the fact that the two methods have different strengths. The adaptive simulated annealing is very good at finding the correct area of the solution, tolerant of local maxima and minima, and the generalized pattern search

Manuscript received June 28, 2009.

Naamane Mohdeb is with the Department of Electrical Engineering, Jijel University, Electrical Engineering Study and Modeling Laboratory, Algeria (phone: +213-34 50 11 89; fax: +213-34 50 26; e-mail: noa_men@yahoo.fr).

Mohammed Rachide Mekideche is with the Department of Electrical Engineering, Jijel University, Electrical Engineering Study and Modeling Laboratory, Algeria (e-mail: mek_moh@mail.univ-jijel.dz).

method is excellent at refining a solution systematically to the nearest maximum or minimum. The new algorithm is better equipped for global optimization because it is more aggressive in the exploration of the search space. This improved hybrid algorithm can be worked adequately when the cost function is multimodal.

In this paper deals with the identification of material parameters using an inverse approach. The method based on the use of coupled electromagnetic circuits method (CECM-code) and hybrid adaptive simulated annealing generalized pattern search algorithm (HASAGPS). The identified material parameters are the relative permeability and electric conductivity. In order to quantify the quality of the agreement between the measured and calculated responses, an objective or cost function has to be defined.

II. New Hybrid Method

A. Adaptive Simulated Annealing

Simulation optimization by simulated annealing was first described by Kirkpatrick et al [9], and is based on work by Metropolis et al [2][5] in the area of statistical mechanics. Metropolis devised a method of simulating the behavior of a collection of atoms at various temperatures. For this, at higher temperatures atoms are more likely to move to new locations in a collection than they are at lower temperatures. SA is inspired from the heating process of a crystalline structure. That metal is slowly lowered until it achieves its regular crystal pattern.

Simulated annealing (SA) is a random-search technique which exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the search for a minimum in a more general system; it forms the basis of an optimization technique for combinatorial and other problems [10]. Annealing is the physical process of heating up a solid metal above its melting point and then cooling it down so slowly that the highly excited atoms can settle into a (global) minimum energy state, yielding a single crystal with a regular structure.

A simulated annealing optimization starts with a metropolis Monte Carlo simulation at a high temperature [1]. This means that a relatively large percentage of the random steps that result in an increase in energy will be accepted. After a sufficient number of Monte Carlo steps, or attempts, the temperature is decreased. The metropolis Monte Carlo simulation is then continued. This process makes a sequence of state for reach the final temperature with regular crystal pattern. If the new state is better than the previous, it becomes the current solution for the next steps. The acceptance of the novel solution is according to the Metropolis's condition based on the Boltzman's probability [2][9][10]. The acceptance probability of accepting solution point *j'*, is defined by:

$$P = \exp(Cj^{'} - Cj / kT) \tag{1}$$

Where k is a physical constant known as the Boltzman's constant and T is the temperature of the heat bath, $C\,j'$ is the current energy state for the system and Cj is a subsequent energy state. If $Cj^{'} - Cj \leq 0$, j' is accepted as a starting point for the next iteration; otherwise, solution j' is accepted with probability (1). The above procedure is repeated n time until temperature T is reduced. The aim of the Metropolis's succession is to authorize the system to attain thermal equilibrium [10].

In practice, a geometric cooling schedule is generally utilized to have SA settle down at some solution in a finite amount of time. It has been proved by some authors that by carefully controlling the rate of cooling of the temperature, SA can find the global optimum. However, this requires infinite time. Fast annealing and very fast simulated reannealing (VFSR) or adaptive simulated annealing (ASA) are each in turn exponentially faster and overcome this problem [5].

The first simulated annealing employed Gaussian distribution as a generator and was proposed by Kirkpatrick [9]. In 1987, Szu and Dartly [1] proposed a fast simulated annealing by using Cauchy/Lorentzian distribution. Another modification of the SA, the so-called adaptive simulated annealing was proposed by Ingber [6][5] and was designed for optimization problem in a constrained search space. For a parameter x^k in dimension i at annealing time k with rang $x^k \in$ [$x_i^{\max}$, $x_i^{\min}$], the new value is generated by:

$$x_i^{k+1} = x_i^k + \lambda(x_i^{\max} - x_i^{\min}) \tag{2}$$

Where $\lambda_i \in$ [-1, 1], $x_i^{\max}$ and $x_i^{\min}$ are the maximum and minimum of the i^{th} domain. This is repeated until a legal x_i between $x_i^{\max}$ and $x_i^{\min}$ is generated. The generating function for λ_i is [6]:

$$g\left(\lambda_i, T_I\right) = \frac{1}{2} + \frac{sign\left(\lambda_i\right)}{2} \frac{\ln\left(1 + \frac{\left|\lambda_i\right|}{T_I}\right)}{\ln\left(1 + \frac{1}{T_i}\right)} \tag{3}$$

To simplify this generating function for λ_i a uniform distribution is preferred. Each parameter is generated using a cumulative function. By the procedure of Ingber it can be seen to choose $g\left(\lambda_i, T\right) = u_i$; where u_i is the uniform distribution function. To calculate λ_i according to the preceding distribution, we can apply this formulation [5]:

$$\lambda_i = sign(u_i - 0.5) T_i \left[(1 + \frac{1}{T_i})^{\left|2u_i - 1\right|} - 1 \right] \tag{4}$$

Where u_i is a distributed random variable between 0 and 1. A rule for decreasing the temperature T is a main element in cooling down the system in the ASA algorithm. According to the idea of Ingber a global optimum can be obtained statistically if the annealing schedule is:

$$T_i(k) = T_i(0)\exp(-c_i k^{1/n}) \qquad (5)$$

Where c_i is a user-defined parameter whose value should be selected according to the guidelines in reference [5][6] [10], but n is the dimension of the space under exploration. In calculation, the temperature may reduce after pre-determined increments of iterations.

A significant component of an ASA code is the random number generator, which is used both for generating random changes in the control variables and for the (temperature dependent) increase-acceptance test.

B. Generalized Pattern Search

Pattern search, though less commonly used today than simulated annealing, has been used in many contexts since it was first described by Hooke and Jeeves in 1961. Pegden and Gately [11] used pattern search as the basis for a simulation optimization module they designed to work with a simulation programming language. More recently, Torczon [12] introduced and analyzed the PS for derivative-free unconstrained optimization. This technique has been exploited by some authors to take account of non linear constrained.

Generalized Pattern search method is a class of direct search method for solving non linear optimization problems. Compared to the direct search, the Generalized Pattern search is a relatively new heuristic approach to minimizing nonlinear and non differential functions in a real and continues space [7][8]. The advantage of this procedure is their aptitude to locate most favorable solution without the make necessary derivatives. The pattern search algorithms find a sequence of points that approaches the optimal point.

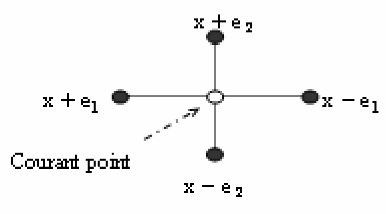


Fig. 1 The sample used in pattern search

The generalized pattern search is based on two ways, in each iteration, an optional search and local poll. The first is a user specified method, that is allowed to complete an exploration moves (mesh) around the current point. In the second, the complete poll computes the objective function values at all mesh points. The local poll computes the objective function at the mesh points to see if there is one whose function value is less than the function value at the current point. If the pattern search finds a mesh point that improves the value of the objective function, it stops the poll and sets that point as the current point for the next iteration. When this occurs, some mesh points might not get polled. Some of these unpolled points might have an objective function value that is even lower than the first one the pattern search finds.

To construct the defining mesh it is more important to find a set of positive spanning direction D in $\Re^n$ [7][12]. At each iteration, a set of positive directions is used to create trial points. The positive spanning sets are constructed by the vectors as $\{e_1,.., e_n, -e_1,.., -e_n\}$[12]. Where e_i is the i^{th} unite cartesian vector. The Fig. 1 illustrates the formation of the model used in pattern search. The mesh at the current iterates is given by:

$$M = \{x_k + \alpha_k d : d_k \in D_K\} \qquad (6)$$

Where D is a positive spanning domain of direction d, α the mesh size parameter for control the cost fitness.

The essential of this intelligent method is as follows; at the first iteration, the poll step is accepted by computing the objective functions around the current point x_k if the difference $f(x_k + \alpha_k \mathrm{d}_k) - f(x_k) < 0$ is verified, in this case the poll is successful. After a successful poll, the algorithm multiplies the current mesh size by 2. In the contrary case, if all the values on the pattern be unsuccessful to generate a reduced, the mesh dimension is decreased or the algorithm multiplies the current mesh size by 0.5. In this case, the poll is unsuccessful and the algorithm does not change the current point at the next iteration. The GPS algorithm will reiterate the poll and search phases until it finds the best solution of the cost function.

C. Combining ASA and GPS

The development of the hybrid adaptive simulated annealing was conducted through the combination of global and local search. The designed method has both the advantages of adaptive simulated annealing, the ability to find global result and evade premature convergence, and that of GPS algorithm, the capacity to perform a local search.

The new hybrid ASAGPS algorithm is explained in the following section. First, the adaptive simulated annealing searches the global optimum in the total solution region to obtain an optimal solution. Second, the GPS then operates on the solution using poll search, and an optional search to produce optimistically better solution. The best solution obtained from GPS is the initial solution of ASA for the next iteration. The ASA and GPS exchange continues until the required number iterations and the final temperature are completed.

III. Inverse Electromagnetic Problem Resolution

A. Description of the System

The test configuration chosen for the evaluation of the new hybrid optimization is shown in Fig. 2.

The simplified 2D configuration is a circular conductive plate placed underneath a flat spiral coil where the optimization target is to identify the electric conductivity and magnetic permeability from the coil impedance measurement. The flat spiral coil is constituted of a bobbin with Nw wires (in our problem two wires). The bobbin is supplied by a sinusoidal voltage source with constant amplitude $\boldsymbol{U}$ and pulsation w.

The forward problem (CECM-code) predicts the coil impedance calculation with more excitation frequencies using the coupled electromagnetic circuits method [13][14].

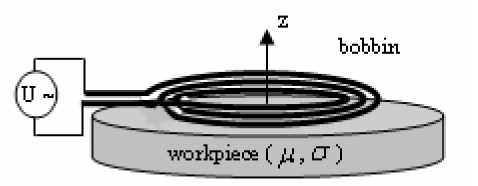
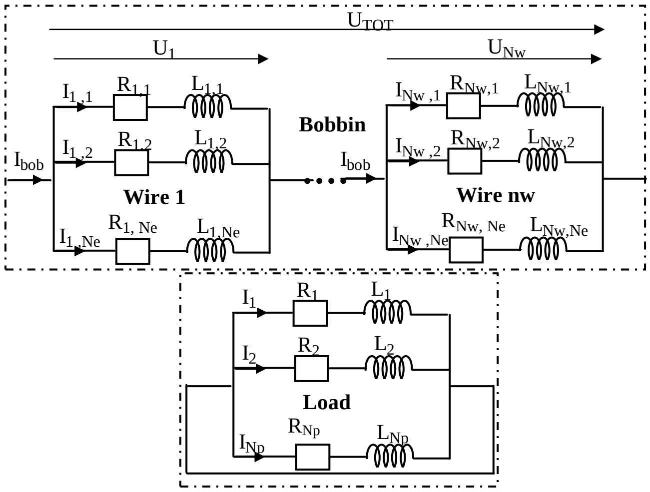


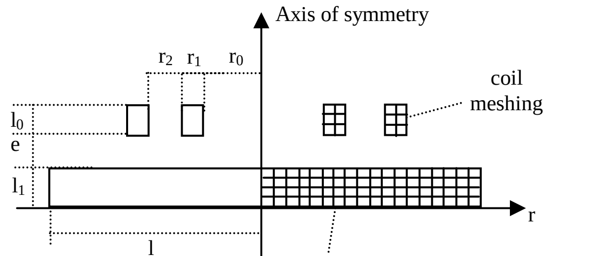
Fig. 2 Example of typical joining application

B. Electromagnetic Field Computation

Our 2D-axisymmetrical case is based on the coupled electromagnetic circuits method [13] which permits to calculate the coil impedance sensor. The CECM analysis is used to calculate the coil impedance and the current densities from the magnetic potential vector A. Generally, this method is suitable for some hypothesis: 1) the geometry of system is axisymmetric. 2) the materials are linear and homogeneous.3) the regime is quasi-static harmonic. In this work, we can exploit it for solving materials properties determination inverse problem because this model is fast-running.



a. Equivalent electric circuits



b. CECM discritization

Fig.3 Model of Coupled Electromagnetic Circuits Method

The CECM consists in associating the integral type of the solution to a portion in elementary loops. In CECM only the conductive regions are meshed. The current densities are the unknown vector in the inductive coil and the load. To, the materials are discretized in elementary loops for determine these unknowns. The bobbin and load are represented by *Nb* and *Np* elementary coaxial loops respectively (*Nb*; Bobbin and *Np*; Plate). Each elementary loop is in magnetic interaction with itself and with the other ones. Each loop is discretized in several elements (*Ne* discretizations). So, the total number of unknowns is *Nb+Np*. The CECM mesh generated for the regions conductive is shown in Fig. 3.b for two wires. The relations between two loops can be explicated with the electric transformer model (Fig.3.a). Our discretization scheme is an extension of this electric transformer model [13].

Maxwell's equations are a set of equations stating the relationship between the fundamental electromagnetic quantities. We are going to search from Maxwell's equations and the Ohm's law an equation that describes the electromagnetic phenomena in an elementary circular loop (Fig.4). This equation is the basis formulation of the coupled electromagnetic circuits method (CECM).

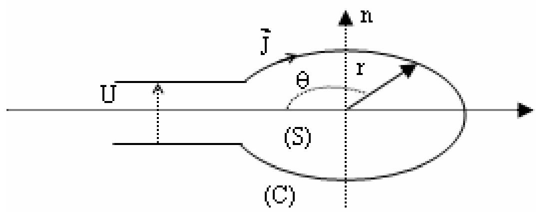


Fig. 4 Representation of an elementary circular loop

The magnetic and induction effects between the different domains in axisymmetric devices are represented by the Maxwell's equations. Then, the mathematical model with 2D axisymmetrical case, for quasi-static problem can be written from Maxwell's equations as follow:

$$Rot\,(\frac{1}{\mu}\,Rot\,(A)) = -\sigma\,\frac{\partial A}{\partial t} - Gr\vec{a}d\,(V\,)\vec{e}_{\theta} \quad (7)$$

Where *V* is the scalar potential due to the voltage *U* applied to one circle of the inductive loop (see Fig.4) and μ is the magnetic permeability, σ is the conductivity of the investigated material (in this case is subdivided in σ_s and σ_c for the source coil and the load respectively).

The gradient of the potential in the circular reference is given by $Gr\vec{a}d(V\,)\vec{e}_{\theta} = -U\,/\,2\pi r$ .In our problem the excitation varies sinusoidally with time then $\partial\,/\,\partial t$ can be written as $j\omega$.

From both the Maxwell's equations and the Ohm's law and considering the simplified notation of the gradient of the potential in the circular reference, the combination of electromagnetic system and the voltage supply, in elementary loop p, is given by:

$$U\,(\,p) = 2\pi r\,(\,p)(\frac{J\,(\,p)}{\sigma} + \,j\omega A(\,p)) \quad (8)$$

To calculate the potential vector magnetic *A* at point *p* generated by the current densities *J (q)* at *q* point, we use Biot Savart's law. This law is:

$$A = \frac{\mu}{2\pi}\iint_{\upsilon} G(\,p,q)J\,(\,p)d\,\upsilon \quad (9)$$

By simplification of this equation, the sum magnetic vector potential A in a known point p with the current densities, is expressed as:

$$A(p) = \frac{\mu}{2\pi}\sum_{q=1}^{Np+Nb} J(q)S(q)\sqrt{\frac{r(q)}{r(p)}}G(p,q) \quad (10)$$

Note that:

$$G(p,q) = \frac{(2-k^2)E_1(k) - 2E_2(k)}{k} \quad (11)$$

Where S is the gross section of the elementary loop p, r and z are cylindrical coordinates. The functions E_1 and E_2 are the Legendre function of the first and second kinds. When applying circuit's laws, the equation (10) is simplified (after elimination magnetic potential in our system) in a linear system as [14]:

$$[Z][J] = [B] \quad (12)$$

Where *[J]* is the vector of current densities in the coil and the plate, *[B]* is the vector of the elementary voltage at wire. But, the dimension of the square matrix *[Z]* is the total number of the elementary loops in the source and the load and represents physically the impedance of the system (sensor).

Once the magnetic vector potential has been determined, all electromagnetic field quantities can be calculated. The current densities in the conducting plate are expressed as:

$$J(p) = -j\omega\sigma A(p) \quad (13)$$

The total impedance of the exciting coil can be calculated from the voltage supply and the current densities in the loops. In that case, the expression is:

$$Z_{coil} = \frac{\sum_{p=1}^{Np} 2\pi r(p)(\frac{J}{\sigma_s} + j\omega A(p))}{\sum_{p=1}^{Ne} J(p)S(p)} \quad (14)$$

Where Z_{coil} is the coil impedance of the eddy current sensor.

C. Eddy Current Calculation

The geometry of the problems considered is illustrated schematically in Fig.3.b. Considering the symmetry, the model is only designed for the half. The aim of the simulation study is to calculate the coil impedance from the current densities in the all system (bobbin). The parameters used in the computation for harmonic excitation are inner radius of the coil (r_0 =2.5 mm), outer radius of coil (r_1= 3.5 mm), coil width (l_0 =1mm), the distance between coils is 1 mm ($r2$), relative permeability (μ_r =1 for coil and air, 100 for load), conductivity of half space (σ_s = 5.7e7 S/m for coil (copper) and σ_c =7.6e6 S/m for load (steel)), lift off (e =1 mm). Frequencies used for excitation of the bobbin are 0.1 kHz to 30 kHz. The piece to test is a cylinder of 0.80 mm thickness (l_1) and the dimension of it is 14 mm length (l). The coil with two wires has been energized by voltage supply with U=30 V at several frequencies cited above. The model of the probe coil is showed in Fig.3.b.

Table I shows the variation of the coil impedance with several frequencies using our CECM-code. The Fig.5 and Fig.6 show the distribution of the current densities in the load. It is important to choose an enough mesh to represent correctly the electromagnetic phenomena and then, to reduce the numerical errors that can influence the convergence of the identification process. In this case, every coil of this sensor contains 64 elementary loops distributed in 8 following the axial direction and 8 following the radial direction and we have considered 320 loops in the load (40 along the radial direction and 8 in the axial direction).

Table I The results from the CECM-code

Calculations terms	Results from CCM				
f (Hz)	100	400	1500	9000	30000
Impedance Z(mΩ)	1.612	1.898	3.997	21.037	69.042

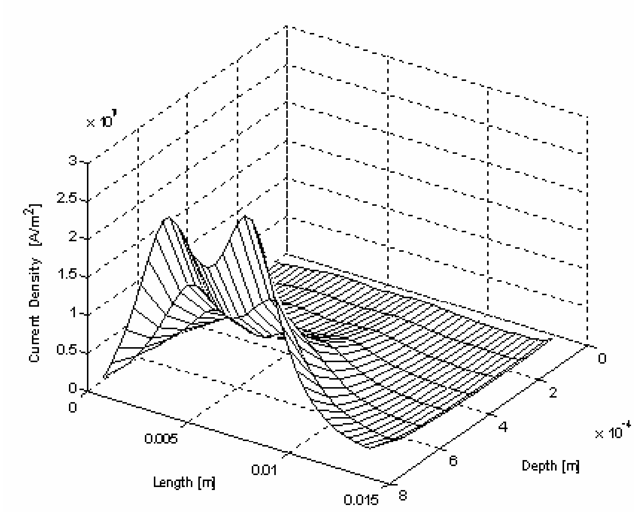


Fig. 5 Distribution of eddy current in load at frequency 3 kHz

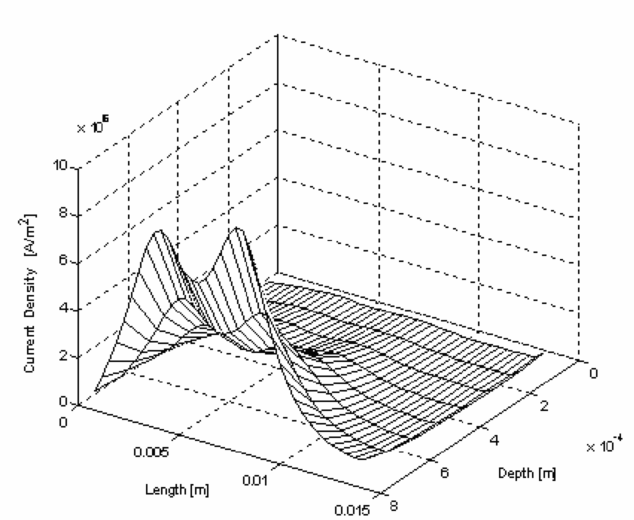


Fig. 6 Distribution of eddy current in load at frequency 10 kHz

In this test, when a voltage supply is used to excite a coil, a magnetic field is produced and magnetic lines of flux are concentrated at the center of the coil. Then, as the coil is brought near an electrically conductive material, the magnetic field penetrates the material and generates continuous, circular eddy currents. Larger eddy currents are produced near the test surface. As the penetration of the induced field increases, the eddy currents become weaker. The induced eddy currents produce an opposing (secondary) magnetic field. This opposing magnetic field, coming from the material, has a weakening effect on the primary magnetic field and the test coil can sense this change. In effect, the impedance of the test coil is reduced proportionally as eddy currents are increased in the test piece.

The model in voltage source driven, gives the possibility to compute the inductive current and therefore the impedance of the system that is interesting for solving material properties determination inverse problem while using as "observables" the coil impedance of the eddy current sensor.

D. Methodology of Parameters Materials

For estimation parameters of the real parameters, a lot reiterate are required for predicting the permeability magnetic and the electric conductivity. In this step, we will explain the implementation of the hybrid algorithm in parameters identification approach. Fig.7 shows the scheme of electromagnetic inverse problem. Our proposed methodology can be summarized as follows: Step 1: Choose a true experimental test and used it for the identification procedure and saving the measured Z^{mes}. Step 2: Generate randomly the input parameters. Step 3: The forward problem or the model program is applied to simulate the output vectors Z^{cal}. Step 4: Identification analysis by hybrid algorithm HASAGPS simulation. This step is performed by the calculation of the error function for new materials parameters X^{sim}. Step 5: Verification of the HASAGPS results with original measured parameters X^{mes}. Step 6: The CECM-code is calculated for obtained the new results Z^{cal} and compared it with original measured results Z^{mes}.

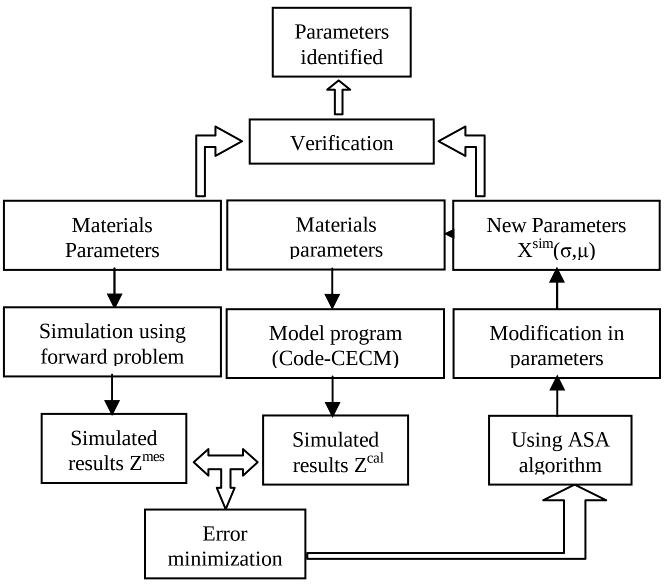


Fig.7 Methodology of inverse problem procedure

This figure (see Fig. 7) shows the identification procedure in the case of non destructive testing of material parameters (σ_c and μ_r) from the measured (or true) impedance Z_{mes} and the calculated impedance Z_{cal}. If the calculated values are generally different from than that of measured values the HASAGPS algorithm is used for minimized this difference margin. We perform the estimation approach of the electric conductivity and the relative permeability of the material under test while solving an inverse problem. Here, the inverse problem to analysis is expressed as follow:

$$\text{To find } (\mu_r, \sigma_c) \text{ giving } Z_{cal}(\mu_r, \sigma_c) = Z_{mes} \tag{15}$$

Where Z_{cal} is the impedance calculate and Z_{mes} is the impedance measured. In this paper, the measured values are replaced by those gotten while using the direct model (CECM-code).

We define the error function as the difference between the properties measured and calculated values by the coupled electromagnetic circuits method. Then, the identification is considered as nonlinear problem to find a solution *x* that minimizes the function *f*. This is written as follow:

$$f = \frac{1}{2}\sum_{1}^{M}\{(X_{cal,m}(\mu_r,\sigma_c) - X_{mes,m})^2 + (R_{cal,m}(\mu_r,\sigma_c) - R_{mes,m})^2\} \tag{16}$$

Where R_{cal} and X_{cal} denote the resistance and reactance calculated by the CECM-code, R_{mes} and X_{mes} are the resistance and reactance measured at the m^{th} point due to a frequency. This function is minimized by using the new hybrid CECM-HASAGPS. The values of σ_c and μ_r are predicted through minimization of this cost function.

Table II The parameters for the hybrid approach

Problem	Two tests
Termination tolerance tol	1e-20
Maximum number of iterations	500*length(x)
Epoch length	4
Cooling rate	0.9
Reduction factor of mesh size	0.7
Step size for descent directions	1e-3

E. Identification of Relative Permeability and Electric Conductivity in Presence Noise

The first experiment involved the use of additive noisy data to examine the proposed method. Two cases are investigated; the same parameters geometric and physic are used. The material properties of cases are respectively set as:

1. Case 1: σ_c = 7.6e6 and μ_r =100.
2. Case 2: σ_c = 1.0e6 and μ_r =112.

It should be mentioned that these material properties are used only to provide the simulated measurements of impedance responses using CECM-code and to check the accuracy of the material properties determined by the inverse analysis (CECM-HASAGPS) using these simulated measurements. The settings of parameters used in this method are shown, for the two tests, in Table II. Minimal and maximal initial values of the materials were respectively for σ_c (1e6 to 15e6) and μ_r (50 to 120). The bounds on the materials parameters are required to define a finite search space for the HASA. In engineering practice, a narrower range is always preferred for accuracy in inverse solution and for computational efficiency.

the determination of converges toward the real values of the materials.

The cost function during the iterations process is shown in Fig. 8.a obtained by the HASAGPS algorithm. If we consider the number of necessary iterations to obtain a correct solution, we can remark the superiority of the HASAGPS method compared to the other algorithms.

The experiment was run on a Dell, witch contain an Intel Pentium 4, 3.6 GHz CPU and 256 Mb RAM. The program was implemented in MATLAB 7.1.

Table III HASAGPS results with different noise levels

	Test N° 1					
	Noise Free		Noise 4 %		Noise 9 %	
expected	obtained	Error %	obtained	Error %	obtained	Error %
μ_r =100	99.999	0.01	97.251	1.41	105.872	12.24
σ =7.6e6	7.600e6	0.02	7.43e6	2.57	7.71e6	48.50
	Test N° 2					
μ_r =112	112.01	0.05	110.41	1.35	115.23	23.25
σ = 1e6	9.99e5	0.06	9.91e5	6.25	10.84 e5	14.65

Noise is inevitably involved in the measured data in practice. A few test cases were also run considering noisy data. The results are shown in Table III. In order to simulate the measured impedance, a Gaussian noise defined by traditional equation ($\tau\ \delta$ where τ is a random number in the range [-1, 1], and δ represents the standard deviation of the measurement errors) is directly added to the coil impedance responses and then the noise-contaminated responses are used as inputs for the identification. To investigate the sensitivity and stability of the present inverse procedure to the noise level, two noise levels of 4 and 9% are considered.

The presence of noise can make the identification much more complicated compared to the noise-free case. If the noise is too large, a local optimum could be found as the true results rather than the global optimum. It has been found that when the noise is larger than 9%, the true results were not identified. If the noise is less than 4%, the true results can still be found, as shown in Table III, and the characterized result remains stable regardless of the presence of the noise.

F. Compared with Other Methods

The performances of adaptive simulated annealing generalized pattern search algorithm are compared with the similar approaches such as hybrid genetic algorithm pattern search [15] and simplex genetic algorithm [16]. Table IV shows the values of parameters of the material under test, and the results of optimal computations, using the HASAGPS and SGA, HGAPS for the noise-free case.

The suitable choice of starting values of parameter electric conductivity and magnetic permeability are necessary to assure the stability of the identification parameters.

In Fig.8.a is shown the process parameters evolution of the relative permeability and electric conductivity with respect to identification iterations for the Test n°2. We note from that

For this problem, all methods were successful in finding the ferromagnetic materials properties in the proposed tests. It can be seen from Table IV and Fig.8 that the combined optimization technique using the hybrid HASAGPS is quite effective for solving inverse problem using noise-free cases. It is noticeable that the low cost value obtained using HASAGPS is less than the minimum cost function and that the CPU time is little than those of other algorithms.

From the comparison between obtained and expected parameters of the material under control, one can see the good agreements between these ferromagnetic parameters, demonstrating that the association of the CECM-code and HASAGPS in very powerful in the solution of inverse problems like materials properties determination inverse problem of a material under tests.

Table IV Simulation results for various search algorithms

		obtained		
		HASA	SGA	HGAPS
		Test N° 1		
Expected	μ_r =100	99.99	99.89	99.91
	σ =7.6e6	7.60e6	7.58e6	7.59e6
Cost function		2.20e-10	7.35e-7	6.37e-9
CPU time (s)		880	1440	1260
Iterations		52	120	70
		Test N° 2		
Expected	μ_r =112	112.01	111.98	111.99
	σ = 1e6	9.99e5	9.92e5	9.96e5
Cost function		7.96e-12	3.51e-7	4.64e-10
CPU time (s)		936	1800	1332
Iterations		60	220	80

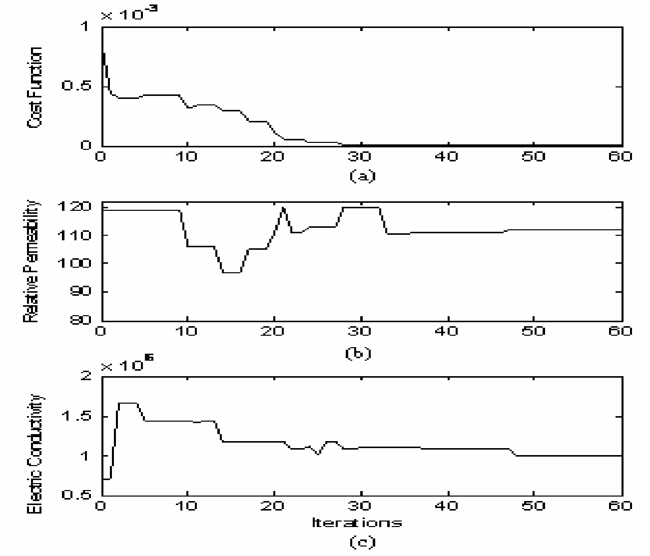


Fig.8 Results of the identification using new hybrid algorithm (Test N°2)

IV. Conclusion

A new methodology, combining the hybrid optimization with a semi-analytical method called coupled electromagnetic circuits method (CECM), is applied to inverse electromagnetic problem. The CECM-code is used in the optimization procedure to calculate the impedance response corresponding to the identified ferromagnetic parameters for all iterations. This approach is an efficient model to characterize the electric conductivity and relative permeability because it has a considerable potential for solving computing time problems related to the inverse identification without losing accuracy. It is experienced on the parameters identification problem of material under test as reported in this document.

The paper has presented the application of new optimization and illustrated their applicability to solve inverse problem. The new method combines the adaptive simulated annealing and generalized pattern search algorithm. In order to improve the routine or the performance of adaptive simulated annealing algorithm, we have integrated it with local procedure as generalized pattern search method for solve inverse electromagnetic. It is expected to combine adaptive simulated annealing and a fast optimization method so as to provide an ideal performance for the optimization procedure, which is often vital in nonlinear identification problems. As such, not only can the global optima be ensured but results can also be obtained at a reasonably fast speed.

When compared the HASAGPS with the genetic algorithm pattern search method (HGAPS) and simplex genetic algorithm (SGA), the numerical results show that the hybrid adaptive simulated annealing outperforms the other methods an excellent forcefulness and convergence. The other advantages of HASA are the capability to escape from the local optima in presence noise (see Table III).

Finally, the new hybrid algorithm can be extensively used in any other situation to solve different optimization problems of electromagnetic devises.

Overall, this work makes the following contributions:1) a semi-analytical model of eddy current sensor, 2) an approach to identify the ferromagnetic materials from the coil impedance of eddy current sensor.

References

[1] T. Hacib, M. R. Mekideche, F. Moussouni, N. Ferkha and S. Bressit, “Generalized RBF Neural Network and FEM for Material Characterization through Inverse Analysis,” in *Proc. 12th International Symposium on Electromagnetic fields in Electrical Engineering, ISEF’07, Prague, Czech Republic, 13-15 Sep 2007. pp. 44-46.*

[2] F. Glover. *Handbook of Metaheuristic,* Kluver Academic publishers, 2003.

[3] R Fletcher. Practical Methods of Optimization, John Willy et Sons 1987.

[4] L. Ingber.(2003). ASA-User Manual. Available: www.ingber.com

[5] H. Brauer, M. Ziolkowski, “Shape Optimization with Adaptive Simulated Annealing and Genetic Algorithm,” in *Proc. 11th International Symposium on Electromagnetic fields in Electrical Engineering, ISEF’03, Maribor, Slovenia, 18-20 Sep 2003. pp. 25-30.*

[6] S. Ziaei-Rad, M. D. Emami, “Design optimization of supersonic diffusers using adaptive simulated annealing,” *Proc. of the 10th Asian Congress of Fluid Mechanics, Peradeniya, pp. 1-10, May.2004.*

[7] C. Audet, J. E. Dennis “Analysis of generalized pattern searches,” *SIAM Journal on Optimization, Vol. 13, pp. 889-903, 2003.*

[8] N. Mohdeb, M. R. Mekideche, T. Hacib, Z.Belli and H. Bouchekhou, “Generalized Pattern Search for Solving Materials Properties Determination Inverse Problem,” in *Proc. 13th International Symposium on Electromagnetic fields in Electrical Engineering, ISEF’09, Arras, French Republic, 10-12 Sep 2009. pp. 157-159.*

[9] S. Kirckpatrick, S. D. Gellat, M. P. Vecchi, “Optimization by Simulated Annealing,” *Science, Vol. 220, No. 4598, pp. 671-680, Jun. 1983.*

[10] O. Hajji, “Contribution au développement de méthodes d’optimisation stochastiques. Application a la conception des dispositifs électrotechniques,” *PHD Thesis, Lille University, French, Dec. 2003.*

[11] C. L. Chen, N. Chen, “Direct Search Method for Solving Economic Dispatch Problem Considering Transmission Capacity Constraints,” *IEEE Transaction on Power System, Vol. 16, pp. 764-769, 2001.*

[12] V. Torczon, “On the convergence of pattern search,” *SIAM Journal on Optimization, Vol. 7, pp. 1-25, 1997.*

[13] N. Mohdeb, M. R. Mekideche, H. Bouchekhou and M. Chebout “Identification of Ferroamgnetic Materials Properties Using Generalized Pattern Search ,” in *Proc. 1th International Conference on Systems and Processing Information, ICSIP’09, Guelma, Algeria Republic, 02-04 May 2009. pp. 42-46.*

[14] Y. Cheriguen, M. R. Mekideche, “A 2D model with voltage source for Electromagnetic forming of Metallic Cylinder Taken into Account non Uniform Electromagnetic loading of the Cylinder,” in *Proc. 6th International Symposium on electric and magnetic fields, Aachan, Germany, 2003, pp.31-35.*

[15] M. Wetter, J. Wright J. L. Payne, “Comparison of a generalized pattern search and genetic algorithm optimization,” *Proc. of the 8th IBPSA Conference, Eindhoven, Vol. 1, pp. 1401-1408, Aug. 2003.*

[16] J. Yen, J. C. Liao, B. Lee, D. Randolph,“A hybrid approach to modelling metabolic system using a genetic algorithm and simplex method,” *IEEE Transaction On System Cybernetics, Vol. 28, pp.197-201, 1998.*

Naamane MOHDEB was born in Jijel, Algeria in 1980. He received the engineer degree in Electrical Engineering in 2004, and the Magister in Electrical Engineering in 2007 from the Electrical Engineering Institute of Jijel University, Algeria, where he had now an P. h. D student. Here current research interests include inverse problems, computations of electromagnetic field and hybrid methods in shape optimization of electromagnetic systems. He is member of LAMEL laboratory.

Mohammed Rachid MEKIDECHE was born in Jijel, Algeria in 1957. After his first diploma as electrical engineer at the USTO University at Oran, he joined, in 1981, the National Polytechnicas School at Algiers as an assistant and post-graduate student preparing a Magister. He got the "Maître assistant" degree in 1986. After his PhD degree from the University of Nantes (France) he became "Maître de Conferences" and then Professor. He is now at the University of Jijel, as a teacher and Dean of the engineering faculty. Prof. MEKIDECHE is now heading the LAMEL laboratory of the University of Jijel and is the author or co-author of about 50 works published or presented at international conferences.