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Imperialist Competitive Algorithm and Particle Swarm Optimization Comparison for Eddy Current Non-destructive Evaluation

***Abstract**. Imperialist competitive algorithm (ICA) and particle swarm optimization (PSO) are two approaches for determining the solution of any objective function, but they use different strategies. Therefore, a comparison of their performance is required. The comparison is made on the basis of test functions, and then both techniques are applied to an eddy current non-destructive evaluation system to reconstruct from an impedance measurement. An axisymmetric groove shape of a conductive tube is inspected by a differential probe.*

***Streszczenie.** W artykule przedstawiono wykorzystanie algorytmów ICA i PSO w systemie defektoskopii prądów wirowych. Jako model badań zastosowano rurę z materiału przewodzącego o rowkowym kształcie. (**Wykorzystanie algorytmów ICA i PSO w defektoskopii prądów wirowych**)*

Keywords: Imperialist competitive algorithm, particle swarm optimization, eddy current non-destructive evaluation, inverse problems.
Słowa kluczowe: algorytm ICA – imperialist competitive algorithm, algorytm PSO – particle swarm optimization..

Introduction

Eddy current non-destructive evaluation (NDE) is a method based on the fact that when a coil powered by a variable energy source is brought near a conductive part, a change in impedance at the terminals of the coil is driven by the changing of magnetic field lines due to the existence and the distribution of induced currents in the conductive part. The signal information representing the change in impedance of the coil is used for the evaluation of physical and geometrical characteristics of the latter. The geometric profile evaluation remains a major challenge because of complex shapes it takes in reality.

The evaluation in eddy current non-destructive method is considered as an inverse problem that has been intensively studied in recent years [1-5]. Thus, the problem of forms reconstruction is formulated as an optimization problem to search for all geometrical parameters, and iteratively minimizing an objective function that represents the difference between the calculated signal and the measured one [6, 7]. Therefore, increasing interest is granted in recent years, with the use of stochastic optimization methods that guarantee convergence to the global optimum of the function to be optimized [8-10]. These methods are adaptable and applicable to a wide class of problems and can provide solutions to optimization for larger classic problems and for many applications that it was impossible to deal with formerly [11-13]. Among these strategies, we find the particle swarm optimization algorithm (PSO) which was developed in 1995 by Russell Eberhart and James Kennedy [14, 15]. The latter soon began to compete with genetic algorithms which remain an essential reference whose impact on the area of optimization is undeniable. Indeed, the use of this algorithm (PSO) in a lot of applications often gave results comparable to those of genetic algorithms [16]. However, while this powerful algorithm (PSO) continues to attract many researchers from different backgrounds, a new algorithm called Imperialist Competition Algorithm (ICA) is developed in 2007 by Esmaeil Atashpaz-Gargari and Caros-Lucas [17]. This algorithm, very efficient, interested more and more scientists and it has been applied for the first time in eddy current non-destructive evaluation in [18].

This paper presents a comparative study of imperialist competitive algorithm and particle swarm optimization algorithm to deal with the inverse problem in eddy current non-destructive evaluation. Initially, the comparison is done using test functions whose optimization difficulties are different, and then both algorithms are compared by applying them to an eddy current non-destructive evaluation system. The aim is to reconstruct, from an impedance measurement, the dimensions of an axisymmetric groove practiced inside an aluminium tube examined by a differential probe. The solution is obtained using a direct model based on the finite element method and both algorithms to solve the optimization problem.

Problem description

The geometry of the problem is described in fig.1. A differential probe is used to scan an aluminium tube. The supposed groove, having the shape of an internal throat, is characterized by its height and its depth. The impedance change of the probe reflects the material in-homogeneities of the inspected tube. The cost function is defined as:

(1) $$J = \frac{1}{2}\left(Z_c - Z_m\right)^2$$

where: Zc – the model predicted coil impedance at scanning position, Zm – the corresponding probe impedance from actual measurement.

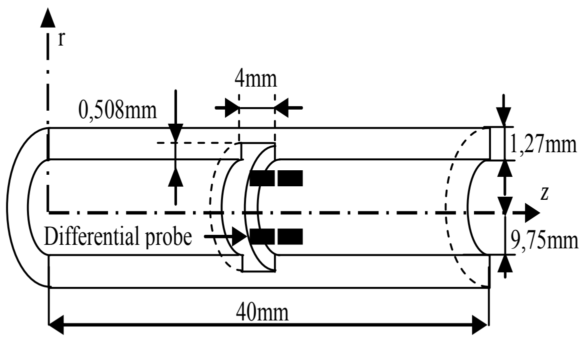


Fig.1. Geometry of the problem

The total impedance of the circular coil whose cross section is subdivided into N triangular elements is given by [19]:

(2) $$Z = \frac{j\omega.2\pi.J_s}{I_s^2}\sum_{i=1}^{N}(r_{ci}.\Delta_i).A_{ci}$$

Δ_i – area of the i-th element, r_{ci}, A_{ci} – central values of r, A in the i-th element.

So the total impedance of a differential probe can be obtained by summing the impedance of each coil of the differential probe.

The inversion is based on an iterative approach. The inversion algorithm starts with an initial estimate of the groove profile and then determines the signal by solving the finite elements direct problem. The squared error between the measured and the calculated signals is minimized iteratively by updating the groove parameters by keeping the best profile of the previous iteration. When the error is below a threshold, the profile determined is the desired solution.

Particle swarm optimization

Particle swarm optimization (PSO) is a population based on stochastic optimization technique, inspired by social behaviour of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem space in the direction of the current optimum particles. Each particle adjusts its position being the best position produced by itself (pbest) and by its neighbours (gbest), according to the following equations [14,15]:

(3) $$v_{i+1} = wv_i + c_1r_1(pbest_i - x_i) + c_2r_2(gbest_i - x_i)$$

(4) $$x_{i+1} = x_i + \Delta t v_{i+1}$$

where: v – the particles speed, r_1 and r_2 – two random numbers generated in the interval [0, 1], c_1 and c_2 – intensities of attraction towards pbest and gbest respectively, Δt – a time parameter which symbolizes the advance step of the particles, w – a factor of inertia which controls the velocity influence.

At iteration $i+1$, the velocity of a particle is changed from its current value, assigned a coefficient of weight inertia, and two forces that attract the particle to its own past best position and best position of the whole swarm.

Imperialist competitive algorithm

Like PSO, ICA starts with an initial population. Population individuals called countries are divided into two types: colonies and imperialists that all together form some empires. Imperialistic competition among these empires forms the basis of ICA. During this competition, weak empires collapse and powerful ones take possession of their colonies. Imperialistic competition hopefully converges to a state in which there is only one empire and its colonies are in the same position and have the same cost as the imperialist. The pseudo code of imperialist competitive algorithm is as follows [17]:

- Select some random points from the function and initialize the empires;
- Move the colonies towards their relevant imperialist (Assimilation);
- Randomly change the position of some colonies (Revolution);
- If there is a colony in an empire which has lower cost than the imperialist, exchange the positions of that colony and the imperialist;
- Unite the similar empires;
- Compute the total cost of all empires;
- Pick the weakest colony (colonies) from the weakest empires and give it (them) to one of the empires (Imperialistic competition);
- Eliminate the powerless empires;
- If stop conditions are satisfied, then stop, if not go to the second point.

The colony moves toward the imperialist by x units. In this movement, θ and x are random numbers with uniform distribution as illustrated in formula (5) and d is the distance between the colony and the imperialist.

(5) $$x \sim U(0, \beta \times d), \theta \sim U(-\gamma, \gamma)$$

where: β and γ – parameters that modify the area where colonies randomly search around the imperialist.

In our implementation β and γ are fixed to 1.5 and 0.5 (Radian) respectively.

Validation with test functions

PSO and ICA were implemented and then tested with some benchmark functions. The selected functions have different characteristics to test algorithms on various aspects namely the ability to avoid local minima, the ability to optimize functions with a relatively high number of parameters, the quickness convergence, finally accuracy and repeatability of the results.

De Jong's function is one of the simplest test benchmark. It is continuous, convex and unimodal. It is used to test the performance of algorithms in terms of exploration and refinement around the optimum value. It is defined as:

(6) $$f_1(x_i) = \sum_{i=1}^{n} x_i^2$$

Test area is usually restricted to $-5 \le x_i \le 5$, $i = 1,..,n$. Global minimum $f(x_i) = 0$ is obtained for $x_i = 0$, $i = 1,..,n$.

Rastrigin's function has multiple local minima and one global minimum. This is very interesting to evaluate the performance of the algorithms in terms of global exploration of the search area. This function has the following definition:

(7) $$f_2(x_i) = \sum_{i=1}^{n}\left(x_i^2 - 10 \cdot cos(2 \cdot \pi \cdot x_i) + 10\right)$$

Test area is usually restricted to $-5 \le x_i \le 5$, $i = 1,..,n$. Global minimum $f(x) = 0$ is obtained for $x_i = 0$, $i = 1,..,n$.

The Hartmann's function has five local minima and one global minimum. With six variables, it is used to test algorithms on their capacity to avoid local minimums and to optimize functions with several parameters. Besides, in the same view, we will use De Jong's function a second time but with ten variables. Hartmann's function is defined as:

(8) $$f_3(x) = -\sum_{i=1}^{m} c_i \cdot exp\left(-\sum_{j=1}^{n} a_{i,j} \cdot (x_j - p_{i,j})^2\right)$$

where c_i, $a_{i,j}$ and $p_{i,j}$ – coefficients given for $n = 6$ in table1.

Test area is usually restricted to $0 \le x_i \le 1$, $i = 1,..,n$.

Global minimum $f(x) = -3.32237$ is obtained for: $x_i = (0.2017, 0.15001, 0.47687, 0.27533, 0.31165, 0.6573)$

Table 1.a. Coefficients of Hartmann's function ($a_{i,j}$, c_i)

i	$a_{i,j}$						c_i
1	10.0	3.00	17.0	3.50	1.70	8.00	1.0
2	0.05	10.0	17 .0	0.10	8.00	14.0	1.2
3	03.0	3.50	1.70	10.0	17.0	8.00	3.0
4	17.0	8.00	0.05	10.0	0.01	14.0	3.2

Table 1.b. Coefficients of Hartmann's function ($p_{i,j}$)

i	$p_{i,j}$					
1	0.1312	0.1696	0.5569	0.0124	0.8283	0.5886
2	0.2329	0.4135	0.8307	0.3736	0.1004	0.9991
3	0.2348	0.1451	0.3522	0.2883	0.3047	0.6650
4	0.4047	0.8828	0.8732	0.5743	0.1091	0.0381

For ICA, the initial population is of 30 countries. We choose 8 of the best countries to form the imperialists. For PSO, the initial population is of 30 particles. To make a comparison, other parameters about both algorithms are chosen among the best given by the literature summarized in table 2 [14, 15, 17].

Table 2. Algorithms parameters

PSO coefficient	Value	ICA coefficient	Value
c_1, c_2	1.4	β	1.5
w_{max}	0.9	γ	0.5
w_{min}	0.4	Revolution rate	0.2

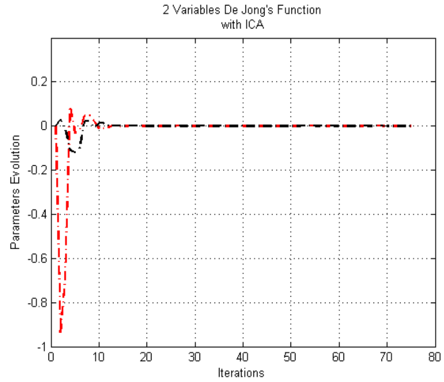
Results given in table 3 show that with ICA, convergence is reached more quickly than with PSO. In addition, minimums of functions are achieved with good accuracy and repeatability equal to 100%. With PSO, convergence is obtained with good accuracy and relative speed to the first and second function, while for the third and the fourth function, the performance deteriorated markedly particularly in terms of execution time and repeatability of the results. This degradation is due to the relatively high number of function parameters. Indeed, the fourth function, which is exactly the same as the first, was used a second time with ten variables for the sole purpose to put the algorithms to the test with functions having a high number of parameters. The table shows, in this case, that the performance of ICA remains practically unchanged while those of PSO significantly regressed.

Table 3. Algorithms performances with test functions

Functions	Convergence iteration		Execution time (second)		Success rate for 100 executions	
	PSO	ICA	PSO	ICA	PSO	ICA
f_1 (2 variables)	100	75	0.26	0.32	100	100
f_2 (3 variables)	217	168	0.71	0.45	97	100
f_3 (6 variables)	1322	90	20.34	0.57	50	100
f_1 (10 variables)	1016	189	88.32	1.22	30	100

Figure 2 (a-h) illustrate the variation of each parameter according to the iterations. It shows starting from which iteration convergence is obtained. We note that the results obtained with ICA are significantly better than those obtained with PSO; this reasserts the values given in table 3.

a)



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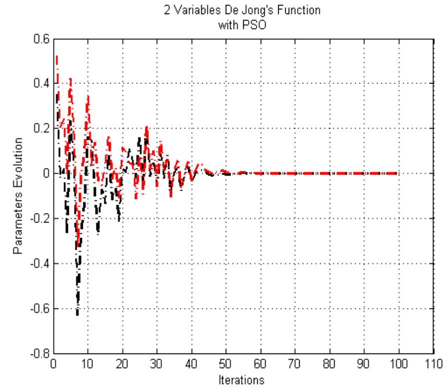

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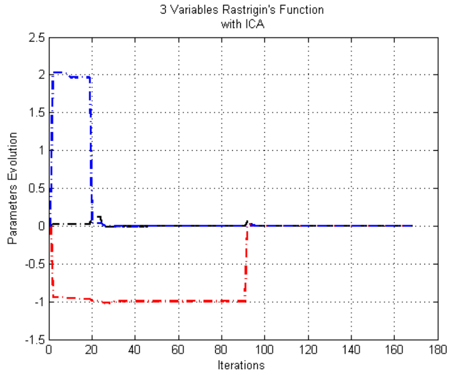

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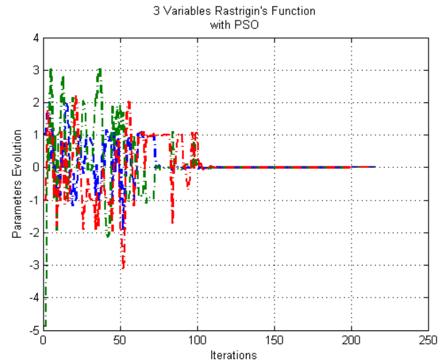

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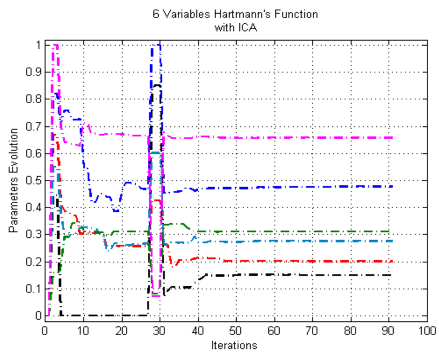

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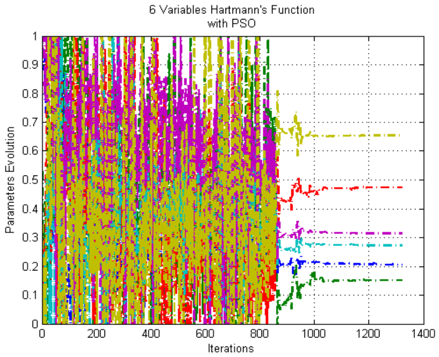

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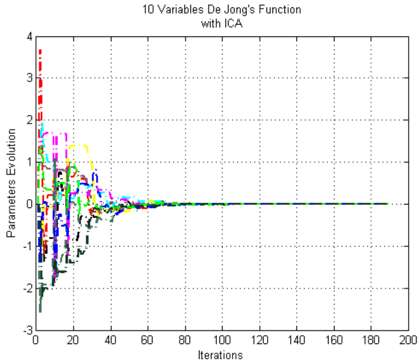

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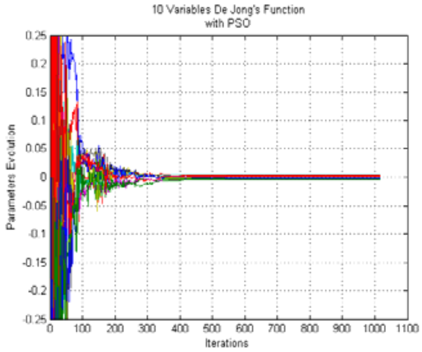


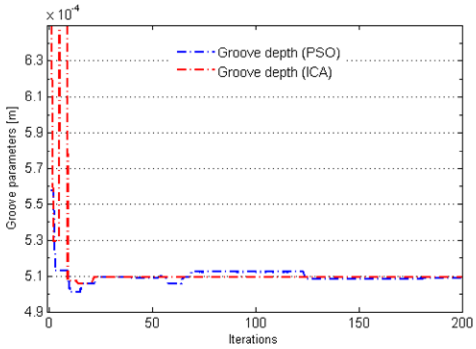
Fig.2. Functions parameters evolution

Application to the groove shape evaluation

The geometry of the problem is that described previously. A differential probe is used to scan an aluminium tube having an electrical conductivity $\sigma_c = 1M[S/m]$. The geometrical and electrical data of the eddy current differential probe is as follows: height of a coil according to z is 0.75e-3 m, inner radius of a coil is 7.75e-3 m, outer radius of a coil is 8.5e-3 m, vertical distance between the coils is 0.5e-3 m, and number of turns of a coil is 70. The probe is supplied by a current with intensity $5mA$ and a frequency of $100kHz$. The impedance measured when the medium of the coil is opposite to the lower edge of the groove is $Z_m = (0.55 - j1.45)\Omega$.

Figure 3 (a, b) illustrate a groove depth and height comparison obtained by ICA and PSO respectively. By PSO, convergence is obtained after 124 iterations. The value of the height and the depth of the groove are $h = 3.98mm$ and $p = 0.508mm$ respectively. By ICA, convergence is practically obtained with 22 iterations and then the value of the height and the depth of the groove are $h = 3{,}96mm$ and $p = 0{,}509mm$ respectively. In order to make comparison we used the same number of particles in PSO as of countries in ICA i.e. 30. We noted that the execution time of iteration is practically the same one for both algorithms. Consequently, this enables us to conclude that ICA converges more quickly than PSO algorithm.

a)



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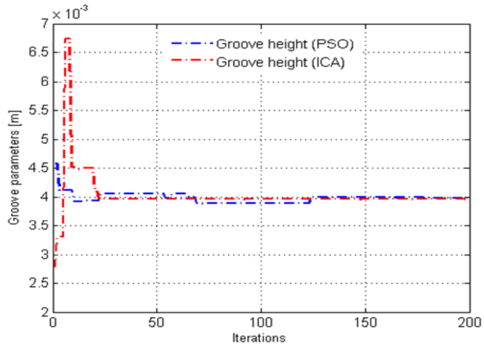

Fig.3. Groove parameters comparison

Figure 4 shows the cost-function evolution. It reaches the value 6e-7 at iteration 22 with ICA and 6e-8 at iteration 124 with PSO. The absolute difference between these two values is of 5.4e-7. Obviously, it is a negligible difference in the context of our application.

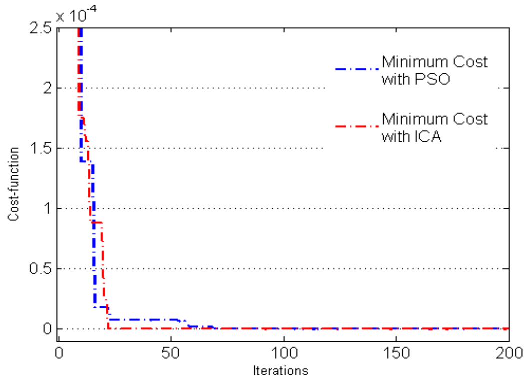

Fig.4. Cost-function evolution

Conclusion

Methods proposed in this paper, Imperialist Competitive Algorithm (ICA) and Particle Swarm Optimization (PSO), were compared and applied to the eddy current non-destructive evaluation. Initially, the comparison was made on the basis of test functions. We have shown that both algorithms always converge to the global optimum even if the function has multiple local optima. When the function to be optimized has a reduced number of parameters (< 6), the two algorithms have almost similar performance although ICA is slightly faster than PSO. On the other hand, when the number of function parameters increases (≥ 6), the performance of PSO in terms of convergence speed, optimum accuracy and repeatability of results regress significantly while the performance of ICA remain unchanged. Subsequently, we used both techniques to reconstruct the axisymmetric groove shape of a conductive tube. Again, we found that ICA reaches the solution faster than the PSO and with sufficient accuracy. ICA strategy has shown great performance in both convergence rate and global optima achievement. Indeed, it can be seen that the ICA method outperforms the PSO one which remains a method that gives results with a good precision but for functions with a small number of parameters. Under these last conditions, ICA works best, thus it is recommended.

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