Can Tournament Selection Improve Performances of the Classical Particle Swarm Optimization Algorithm?

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Abstract— Particle Swarm Optimization (PSO) algorithm is known to be a very efficient solution for electromagnetic (EM) optimization problems. In this paper we show that binary tournament selection applied to PSO algorithm further speeds-up its convergence. Having in mind that EM simulation is the most time-consuming part of the optimization, reducing the overall number of iterations (EM solver calls) is of a paramount relevance.

I. INTRODUCTION

The Particle Swarm Optimization (PSO) algorithm is known to be a very good optimization algorithm for various multidimensional problems with medium number of optimization variables [1]. Because of its implementation simplicity and relatively fast convergence, it has been continuously gaining popularity since it was introduced by Kennedy and Eberhart in 1995 [2]. The method was first used by the antenna community in 2004 and it was shown to be very efficient for electromagnetic problems [3]. In this paper, we apply a binary tournament selection strategy to the classical PSO algorithm [4] to see if it can further improve performances of the classical PSO. After the whole swarm has moved, binary tournament selection is applied to form a new swarm. We randomly choose a pair of particles. The one with the lower cost-function wins the tournament and becomes the particle of the new swarm. Both particles are then placed back to the pool of particles, and the process is repeated for p times, where p is the number of particles in the swarm. The new swarm, built in this manner, can have several particles with the same starting position.

Both the Classical PSO and this hybrid version of PSO, called Tournament Selection PSO algorithm, have been applied to several layered media problems, in order to compare convergence performances of these algorithms. The geometry of the EM structure is optimized by PSO, and a cost-function is evaluated using in-house solvers based on mixed potential integral equations specially tailored to model planar multilayered structures [5], [6].

As suggested in [3] and [4], for both variants of PSO algorithms the maximal velocity \( v_{\text{max}} \) is set to be equal to the dynamic range for each dimension of the optimization space, while cognitive and social rate coefficients are \((c_1, c_2) = (1.5, 1.5)\). As the boundary condition, an invisible wall strategy [3] is used. For the Classical PSO, the intertial weight \( w \) is linearly decreased from 0.9 to 0.4 over the course of the run, while for Tournament Selection PSO it is constant and set to \( w=0.73 \). A variable total number of particles is considered.

II. 1ST OPTIMIZATION PROBLEM

The first optimization problem is a classical microstrip antenna [7]. It consists of a feeding line, a quarter-wavelength transformer, and a radiating patch as illustrated in Fig.1.

![Geometry of the problem](image)

Fig. 1 Geometry of the problem

The optimization parameters are the length \( L \) and the width \( W \) of the patch (that determine the operating frequency of the antenna) and the length \( L_m \) and the width \( W_m \) of the quarter-wavelength transformer (a matching transmission line that ensures the impedance of the patch is matched to the 50Ω feeding line). The length and the width of the 50Ω feeding line are \( L_f = 20 \text{ mm} \), \( W_f = 2.403 \text{ mm} \). The dielectric layer on which the metallization is printed is Duroid \( e_r = 2.2, \tan\delta = 0.0009 \) of thickness \( h = 0.7874 \text{ mm} \) and backed by a ground plane. Microstrip antennas are narrowband radiators and by optimizing the specified geometry its bandwidth is not
affected, but we will be able to target its operating frequency (in our case set to be $f = 3 \text{ GHz}$). The optimization space is:

- $20 \text{ mm} \leq (L, W) \leq 50 \text{ mm}$
- $10 \text{ mm} \leq L_m \leq 30 \text{ mm}$
- $0.1 \text{ mm} \leq W_m \leq 1 \text{ mm}$

The optimization goal is to minimize $s_{11}$ at the operation frequency. The cost-function is defined:

$$f = 200 \text{ dB} - |s_{11}|$$

Both algorithms are run for 10 times to estimate the average outcome of the optimization. The averaged-best found solutions versus the number of iterations are shown in Fig.2. We see that the tournament selection significantly speeds up the convergence of the PSO algorithm.

### III. 2ND OPTIMIZATION PROBLEM

The second optimization problem is an SSFIP (Strip-Slot-Foam-Inverted-Patch) antenna, shown in Figs. 3-4. It is well-known that microstrip patch antennas have significant advantages in terms of size, ease of fabrication and compatibility with the printed circuits. However, their main drawback is their relative narrow bandwidth. In order to overcome this problem, SSFIP antenna concept was developed [8]. The coupling from the line to the patch is provided by a slot etched in the ground plane. The slot must not resonate over the operating frequency band of the antenna in order to avoid radiation toward the back of antenna, which would interfere with the radiation from the patch.

The optimization parameters are: the length $L$ and the width $W$ of the patch antenna, the length $L_s$ and the width $W_s$ of the slot, offset $\Delta$ between the centres of the patch antenna and the slot, and the length of the feeding line $L_f$ (see Fig.4). The optimization space is:

- $10 \text{ mm} \leq (L, W) \leq 100 \text{ mm}$
- $0.5 \text{ mm} \leq L_s \leq 4 \text{ mm}$
- $10 \text{ mm} \leq W_s \leq 90 \text{ mm}$
- $0 \text{ mm} \leq L_f \leq 50 \text{ mm}$
- $-30 \text{ mm} \leq \Delta \leq 30 \text{ mm}$

The optimization goal is to minimize $s_{11}$ at the operating frequency (1.75 GHz), while controlling the antenna bandwidth. From our experience, we defined the cost-function as follows:

- $f_{\text{cost1}} = \begin{cases} 0, & \text{if } s_{11}(f) > -5 \text{ dB} \\ |s_{11}(f)| - 5, & \text{if } s_{11}(f) \leq -5 \text{ dB} \end{cases}$, $f = 1.66 \text{ GHz}$
- $f_{\text{cost2}} = \begin{cases} 0, & \text{if } s_{11}(f) \geq 50 \text{ dB} \\ 50 - |s_{11}(f)|, & \text{if } s_{11}(f) < 50 \text{ dB} \end{cases}$, $f = 1.75 \text{ GHz}$
- $f_{\text{cost3}} = \begin{cases} 0, & \text{if } s_{11}(f) > 5 \text{ dB} \\ |s_{11}(f)| - 5, & \text{if } s_{11}(f) \leq 5 \text{ dB} \end{cases}$, $f = 1.84 \text{ GHz}$

$$f_{\text{cost}} = f_{\text{cost1}} + f_{\text{cost2}} + f_{\text{cost3}}$$

Both algorithms are run for 10 times to estimate the average outcome of the optimization. The averaged-best found solutions versus the number of iterations are shown in Fig.5.
After 2000 iterations both algorithms converge to practically the same value. Nevertheless, the Tournament Selection PSO algorithm has faster convergence. Both algorithms found the solutions that satisfy our requirements. \( s_{11} \) parametr for one of those solutions is shown in Fig. 6.

IV. 3rd Optimization Problem

The third optimization problem is a broadside coupled filter, shown in Figs. 7-8. All the resonators are printed on different substrates and placed one above the other. The optimization parameters are the lengths of the resonators, \( L_1 \), \( L_2 \) and \( L_3 \), their width, \( W \) and the resonators’ offsets from the box, \( dX_2 \), and \( dX_3 \)(see Fig. 7). The optimization space is:

\[
\begin{align*}
1 \text{ mm} &\leq W \leq 2 \text{ mm} \\
3 \text{ mm} &\leq L_1 \leq 5 \text{ mm} \\
16 \text{ mm} &\leq L_2, L_3 \leq 18 \text{ mm} \\
1 \text{ mm} &\leq dX_2, dX_3 \leq 3 \text{ mm}
\end{align*}
\]

We want our filter to have \( s_{11} < -20 \text{ dB} \) for the band-pass frequencies, and we want to control its bandwidth. For that purpose, the cost-function is defined as:

\[
f_{\text{cost1}} = |s_{11} + 5|, \quad f = 6.835 \text{ GHz} \\
f_{\text{cost2}} = |s_{11} + 10|, \quad f = 6.840 \text{ GHz} \\
f_{\text{cost3}} = \begin{cases} 0, & \text{if } s_{11} \leq -20 \text{ dB} \\ 20 - |s_{11}|, & \text{if } s_{11} > -20 \text{ dB} \end{cases}, \quad f = 6.865 \text{ GHz} \\
f_{\text{cost4}} = \begin{cases} 0, & \text{if } s_{11} \leq -20 \text{ dB} \\ 20 - |s_{11}|, & \text{if } s_{11} > -20 \text{ dB} \end{cases}, \quad f = 6.905 \text{ GHz} \\
f_{\text{cost5}} = \begin{cases} 0, & \text{if } s_{11} \leq -20 \text{ dB} \\ 20 - |s_{11}|, & \text{if } s_{11} > -20 \text{ dB} \end{cases}, \quad f = 6.945 \text{ GHz} \\
f_{\text{cost6}} = |s_{11} + 10|, \quad f = 6.965 \text{ GHz} \\
f_{\text{cost7}} = |s_{11} + 5|, \quad f = 6.975 \text{ GHz} \\
f_{\text{cost}} = \sum_{i=1}^{7} f_{\text{costi}}
\]

\[
\begin{align*}
\varepsilon_{e_1} &= 2.33 & h_1 &= 0.51 \text{ mm} \\
\varepsilon_{e_2} &= 1.0 & h_2 &= 0.66 \text{ mm} \\
\varepsilon_{e_3} &= 2.33 & h_3 &= 0.51 \text{ mm} \\
\varepsilon_{e_4} &= 1.0 & h_4 &= 7.30 \text{ mm} \\
\varepsilon_{e_5} &= 2.33 & h_5 &= 0.51 \text{ mm} \\
\varepsilon_{e_6} &= 1.0 & h_6 &= 8.60 \text{ mm} \\
\varepsilon_{e_7} &= 2.33 & h_7 &= 0.51 \text{ mm} \\
\varepsilon_{e_8} &= 1.0 & h_8 &= 7.30 \text{ mm} \\
\varepsilon_{e_9} &= 2.33 & h_9 &= 0.51 \text{ mm} \\
\varepsilon_{e_{10}} &= 1.0 & h_{10} &= 0.66 \text{ mm} \\
\varepsilon_{e_1} &= 2.33 & h_1 &= 0.51 \text{ mm}
\end{align*}
\]
Both algorithms are run for 10 times. The averaged-best found solutions versus the number of iterations are shown in Fig. 9.

For the small number of iterations Tournament Selection PSO algorithm has faster convergence. After 1000 iterations it is outperformed by Classical PSO algorithm. Nevertheless, Tournament Selection PSO still finds a very good solution.

Both algorithms found the solutions that satisfy our requirements. $s_{11}$ parametar for one of those solutions is shown in Fig. 10.

V. CONCLUSIONS

We have applied Classical and Tournament Selection PSO algorithms to several multilayered media problems, in order to compare their performances. From the presented results, we see that the tournament selection significantly speeds-up the convergence of the PSO algorithm. Since the EM simulation is the most time-consuming part of the optimization, reducing the overall number of iterations (EM solver calls) is of a great significance.

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