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Social Network Optimization for Microwave Circuits Design

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Abstract—This paper presents the Social Network Optimization, a new population based algorithm inspired by the recent explosion of social networks and their capability to drive people's decision making process in everyday life. Early experimental studies have already proven the SNO effectiveness in the optimized design of planar and conformal antennas. Here this novel optimization procedure is described in detail, tested and compared with other traditional evolutionary algorithms, and finally used for the design of different microwave circuits.

1. INTRODUCTION

In recent years several procedures have been implemented for microwave circuits design and optimization [1].

Filtering structures with high performance requirements are essential in many synthesis problems and can be often properly designed only using advanced optimization techniques [2]. In [3] a general approach to the synthesis of cross-coupled resonator filters using an analytical gradient-based optimization technique is proposed considering the gradient of the cost function with respect to changes in the coupling elements between the resonators which is determined analytically. Several other techniques and methodologies are available for designing microwave filters and a good overview on their optimization can be found in [4, 5]. Design procedures generally consist of two steps, a preliminary synthesis carried out using lumped-element network and a suitable equivalence between the synthesized network and the actual distributed structure. This second step, which enables the physical dimensioning of the structure, is today exploited by different evolutionary optimization techniques. Their general aim is to find a global maximum or minimum in a suitably defined solution domain [6], and in this context Genetic Algorithms (GA) are perhaps the most famous evolutionary algorithm developed since late 80s [7] inspired by biology and genetics.

First attempts using GA can be found more than thirty years ago [8] and then recovered with hybrid coding to design compact dual-band bandpass filters with microstrip lines [9]. In this last paper the hybrid optimization technique is proposed in a scheme capable of searching at the same time an appropriate circuit topology and the corresponding electrical parameters with dual-band characteristic.

In this paper, we propose a novel population based algorithm inspired to a social network's metaphor. In the last decade, the diffusion of connected multimedia platforms and social networks have affected different research fields as for example computer science, economy and sociology creating novel paradigms inspired by social networks with interesting results related to pervasive diffusion of heterogeneous data and an increasing capacity in computation and information exchange [10].

To address this complexity, after creating a hybrid method between GAs and Particle Swarm ten years ago [11], the authors recently created the Social Network Optimization (SNO) algorithm, as a population based algorithm inspired to the social network knowledge sharing and decision making

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process. First steps of this algorithm have been used in a student project which aimed to develop a low-cost rocket system to establish a new European altitude record [12]. In this student competition activity, part of the design work regarded an optimized antenna suitably developed for the telemetry system of the experimental rocket.

A preliminary description of this algorithm has already been presented in [13]. However, here a more comprehensive and detailed structured version of the algorithm is presented with a full performance evaluation and a comparative study with other evolutionary algorithms. In particular, this manuscript will give a detailed description on SNO and its operators in Section 2; a preliminary numerical analysis on its performances versus other well-assessed optimization procedures is reported in Section 3, followed by the results of the application of SNO in the optimization of two well known microwave circuits, namely a wide-band matching circuit and a microstrip line band pass filter, which will be reported in Section 4.

2. SOCIAL NETWORK OPTIMIZATION

The optimization process of engineering problems in many fields of science is a complex task since the interaction between multiple physical parameters and not trivial boundary conditions affects the structure of the objective function and related algorithm convergence. In order to face this complexity, the authors introduced a new algorithm called SNO, first presented in [12] in a simplistic way and further developed to enhance its performance, essentially built as a population based algorithm inspired to the social network knowledge sharing and emulating the decision making process recently introduced by these networks.

In this algorithm, in fact, each individual represents a social network member characterized by a proper social environment (a specific position in the solution space), a proper character, a personal reputation recognized by his group and a personal interest which can be compared to a sort of taste (or liking) shared among his relational network. The personal interest can be seen as preferred direction in the space domain due to both stronger and weaker characters or particular opinion leaders.

The flow chart in Figure 1 represents how SNO changes the characteristics of the people during run time. It also summarizes the main aspect of SNO that will be explained in the followings, such as status, memory, ranking groups and influencers.

A preliminary analysis of SNO performances over standard benchmark functions commonly used to test evolutionary optimization algorithms was presented in [13]. Here a more complete study is presented in order to fully evaluate effectiveness and robustness of such algorithm. The first results after a comparative study confirm the ability of the algorithm to address complex and high dimension optimization functions.

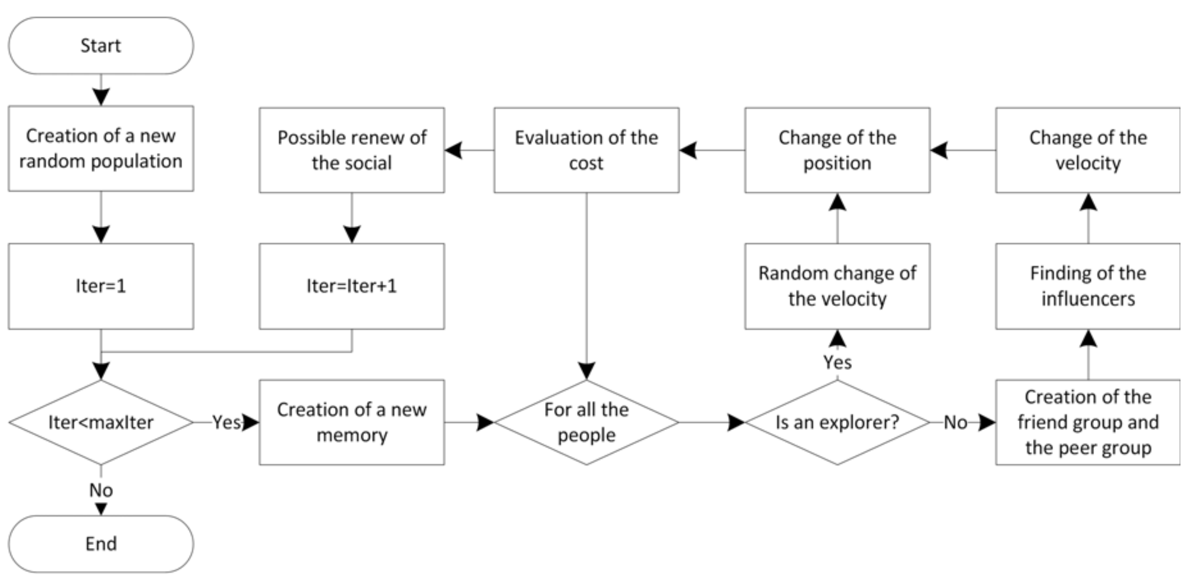

Figure 1. Flowchart description of basic SNO operations.

2.1. Working Principles

In the SNO population, each single individual has his personal life style as in the any day life of every person. Besides, any single person, which accumulates experience during his or her life, can be influenced by interaction with other members of the social network, in particular by some opinion leaders that frequently have eccentric characters. Thus each person is described by the surrounding social environment and its personal character, and both the elements change over time due to aging and multiple interactions. The combination of social environment and personal attitude or taste can be considered as experience which leads to actions in our lives and can certainly evolve over time in a dynamic context. Moreover, nowadays this life experience is often shared in social networks in order to avoid mistakes, suggest places to visit, and express likes and dislikes. Therefore, the social network has two main impacts: knowledge sharing and influence on other people's choice, which means that in the social network environment all the statuses shared and previously evaluated by other people can influence the way a person choose and act in the future.

The SNO operators also emulate the past experiences that are *posted* on common social networks, and we call this characteristic as memory. In fact, when a person goes into a social network to make a conscious and well referenced choice, he is influenced not only by his present experience and other people's suggestions, but also by his past experience and personal inclination. People interact with other members of certain groups, and these groups gather people with similar behavior or people that are experiencing or have similar statuses in the past. In this way, a person is influenced by friends (people which have lived similar statuses) and by counterparts. Such groups are certainly dynamic and time variant: when people change, they tend to pass from one group to another, but they do not necessarily lose their personal tastes.

Through interaction in the social network, people may change their character, and this change sometimes tends to help them to live experiences similar to the experiences lived by other people whom they consider extremely interesting. People able to create trends, e.g., in the fashion sector, are recognized in their groups by other people using a sort of estimation ranking they obtain from the others. They are also explorers or anticipators with strong characters, not easily influenced by other members of the social network, and they change their characters in a random and not predictable way. Their strong characters describe them as influencers. Nevertheless, they are members of some groups within the social network, so their positive and negative experiences are evaluated and posted on the social network to influence other people more than "normal" people. Their experience is commonly published in website with unbiased rankings, reviews and advice as for popular hotel or vacation websites.

Finally, there are other mechanisms borrowed from social networks represented by different operators as for example a boring effect. In this case, when a social network is considered boring, it tries to renew itself, and if it is not enough, a social network closes, and a new one opens as described in the following subsection.

2.2. SNO Main Operators

To emulate social networks' behavior, different operators have been introduced in SNO algorithm. In this section, we describe the main ones in order to clarify the algorithm behavior. The most important operator is the personal character $\bar{c}$ whose role explains the interaction between people among a social group.

In the social network metaphor, this mechanism can be explained as follows: the character of a person changes over time, and a person tends to maintain his character, but it is also influenced by other people's taste and previous choices. The influence can be even higher when the distances between the statuses lived by different people is greater.

The area of friends represents the area in which people who have similar experience, and tastes can be considered friends. Finally, the random change is a natural tendency to find something new in life avoiding a boring effect, and it is typical of common people who cannot be defined as explorers or opinion leaders.

SNO is a population-based algorithm. The population of SNO represents all the members of a social network. Each person is characterized by:

- the status currently lived, that represents a position in the space of the solution;

- their character, that is the inclination to change the status and so represents a velocity on the space of the solution;
- a cost related to the status, that is the fitness of the solution contained in the status;
- their influence, that is the capability to influence other people.

All the characteristics of a person change over time. A few percentage of the population is composed by some particular people: the explorers. They are influenced by none, and they have a higher influence power than normal people. Finally, their character is more pronounced than normal characters. The social network has a memory in which only the statuses with a good evaluation are contained and ranked. Each information stored in the memory contains:

- the status and its evaluation;
- character of the person who has lived the status;
- influence of the person;
- time in which the information is stored.

In the social network, people are divided into several groups. There are only two kind of groups:

- friend groups, that collect people with similar statuses;
- peer groups, that collect people with similar character.

The social network has then two processing mechanisms to avoid stagnation:

- elimination of the oldest statuses contained in the memory;
- renewal.

At each iteration, the members of the social network are divided into groups, depending on their status (group of friends) and character (groups of peer). Each member chooses one influencer in the same group, with the exception of the explorer, which has no influencers.

A member of the social network can see only the statuses contained in the memory of the social, and so only past statuses can influence people. As said before, the statuses lived by explorers have an higher influence rate than other statuses.

After the choice of the influencer, the characters of all normal people are modified in order to live statuses similar to the statuses lived by the influencer. The character is modified by this formula:

$$\bar{c}(t+1) = A \cdot \bar{c}(t) + B \cdot (\bar{s}_{t1} - \bar{s}(t)) + C \cdot (\bar{s}_{t2} - \bar{s}(t)) \tag{1}$$

where the meaning of variables is reported in Table 1.

Table 1. Some SNO operators.

Name	Meaning
$\bar{c}$	Character of a person
$\bar{s}$	Current status of a person
$(\bar{s}_{i1})$, $(\bar{s}_{i2})$	The statuses of the two influencers
A	Inertia parameter
B, C	Attraction parameters, depending on the influence of the influencer

The character of explorers changes randomly over time. At each iteration, the status of people changes due to their character. After that, new statuses are evaluated, so the memory of the social network can be updated, adding new good statuses and deleting statuses old enough. If the social is too boring, it can try to renew itself, deleting the most part of the statuses in the memory. During the renewal, some members of the social network leave the social, and new members are created.

In the next section first numerical results will be reported in order to prove the effectiveness of such a new algorithm with respect of common benchmark functions.

3. SNO NUMERICAL VALIDATION

SNO algorithm has been implemented in the Matlab environment taking inspiration from the work on Biogeography-Based Optimization (BBO) by Simon [14], for the ease of comparison, in particular, with the benchmark functions and optimization algorithms made available on his website, as described below.

SNO was tested and compared with other optimization algorithms in a preliminary trial campaign on different benchmark functions in order to assess its capabilities in terms of convergence, computational cost and reliability. The obtained results prove that it is a promising optimization tools for different potential applications.

In particular, Figure 2 shows the mean value (over 50 trials) of the curves of convergence vs. the number of cost function computations N_{comp} in the case in which the SNO is applied to the Ackley function with dimension $N = 20$. The different curves are obtained considering for all of them the same value of $N_{comp} = 20000$, but varying the number of iterations and consequently the population size, since $N_{comp} = N_{iter} \times N_{pop}$, where N_{iter} is the number of iterations and N_{pop} the number of individuals in the population. The figure shows very well a peculiarity of the implemented algorithm, which is most effective when the population size is big, while the optimal value for the number of iterations that could be derived from this plot is $N_{iter} = 20$, since after this value the algorithm tends to stagnate, in good accordance with the Social Network mimicking.

The increase of the speed of convergence with the population size is also confirmed by the curves plotted in Figure 3, which are the average (over 50 trials) curves of convergence for different populations size vs. N_{iter}.

For what concerns the reliability of the algorithm, it has been investigated considering the dispersion in results, rather than average, taking 50 trials of 40 iterations each and with a population of 500 individuals. In Figure 4, the curves related to the application of the SNO to the Ackey function are plotted. It can be deduced that the SNO shows a quite uniform behavior, and the dispersion of the final cost value has a reduced spread.

Finally, in order to compare the SNO with the most popular and performing optimization techniques, the selected different algorithms have been applied to several benchmark functions. In Figures 5–7, the average (over 50 trials) curves of convergence obtained with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) [15], Differential Equation (DE) approach [16], BBO [14], StudGA [17] and SNO applied to the Ackley, Griewank and Schwefel benchmark functions are plotted vs. N_{comp}. In all the cases, the SNO outperforms the other schemes, and this proves that it has good exploration and exploitation capabilities, making it able to face different cost functions, and is suitable for different engineering applications.

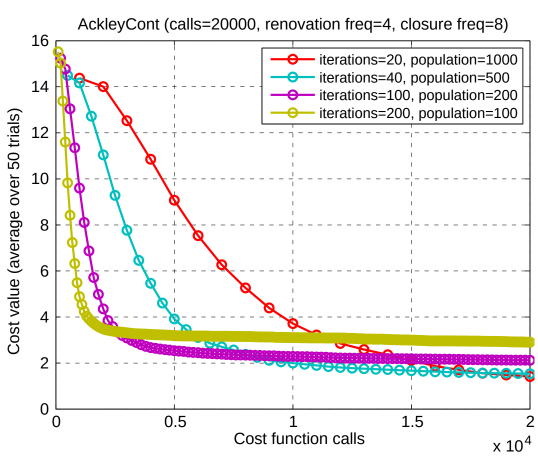

Figure 2. Average value of the curves of convergence computed assuming $N_{comp} = 20000$, but varying N_{iter} and N_{pop}.

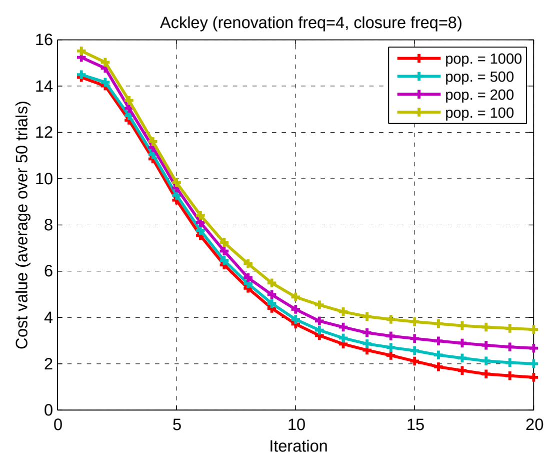

Figure 3. Mean value of the curves of convergence vs. N_{iter} and for different values of N_{pop}.

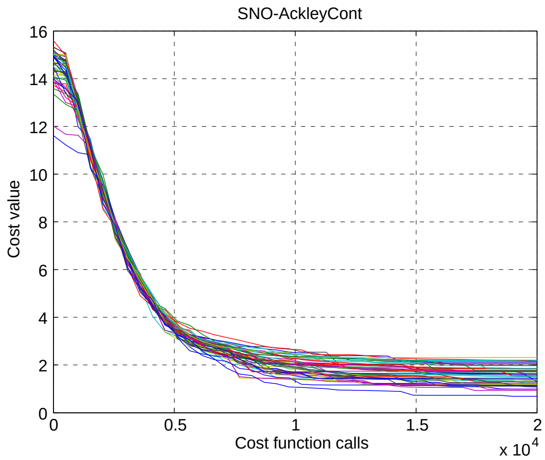

Figure 4. Best agent behavior over 50 trials, considering $N_{pop} = 500$.

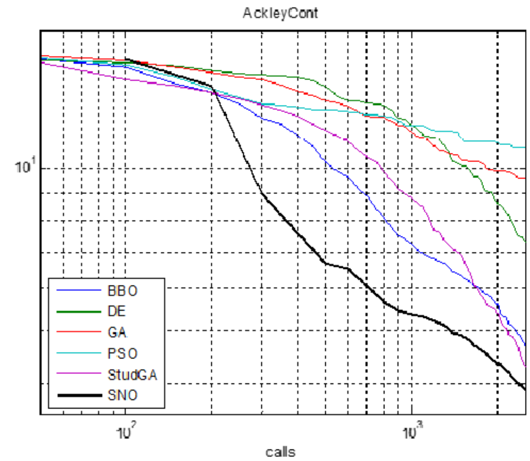

Figure 5. Average curves of convergence vs. N_{comp} obtained applying different optimization techniques to the Ackley function.

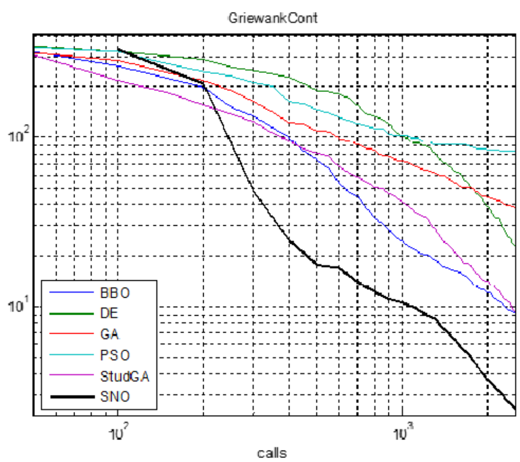

Figure 6. Average curves of convergence vs. N_{comp} obtained applying different optimization techniques to the Griewank function.

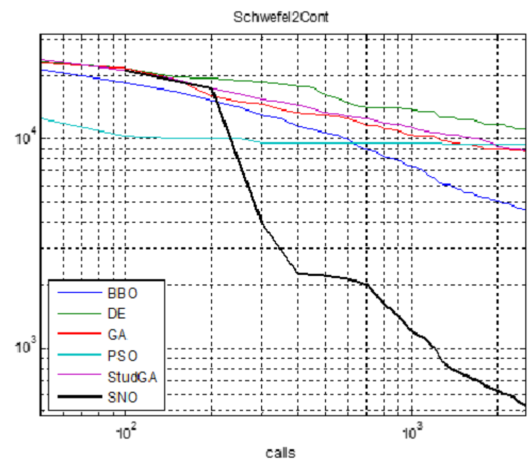

Figure 7. Average curves of convergence vs. N_{comp} obtained applying different optimization techniques to the Schwefel function.

4. SNO-BASED DESIGN OF MICROWAVE CIRCUITS

In view of the encouraging results obtained with the benchmark functions, the SNO has been applied to more realistic problems, i.e., the optimization of different microwave circuits. In particular, in the followings the results relative to two different microstrip two-port networks, i.e., a broadband matching circuit and a pass-band filter, realized with a cascade of $\lambda/2$ pieces of line, are reported, showing the good performances of the SNO also in practical problems.

4.1. Wide-Band Matching Circuit

As a first structure we considered a quite simple problem, but significant from the practical point of view: the optimized design of a wide-band matching circuit, i.e., a multisection matching transformer, consisting in a cascade of N $\lambda_g/4$ (being λ_g the guided wavelength) microstrip sections [18]. It is well-known that, properly choosing the equivalent characteristic impedance of each line section, it is possible to obtain an in-band maximally flat behavior of the reflection coefficient (binomial matching

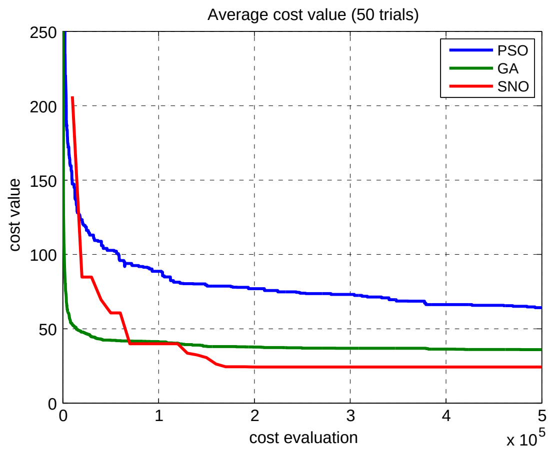

Figure 8. Comparison of PSO, GA and SNO in the optimization of the Wide-band matching circuit (Average over 50 trials).

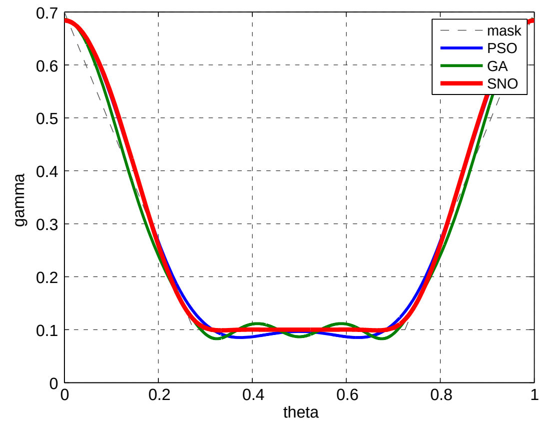

Figure 9. Resulting S_{11} for the Wide-band matching circuit optimization.

transformer) or maximally enlarge the bandwidth, keeping constant the number of sections, at the price of the presence of an in-band ripple (Chebyshev multisection transformer). The idea here was that of trying to see if, designing the transformer with an optimization algorithm, it is possible at the same time to maximize the bandwidth and to minimize the ripple.

To validate the SNO, its performances have been compared also with those of the PSO and the GA, applied to the same optimization problem: in Figure 8 the curves of convergence of the three considered optimization algorithms vs. number of cost evaluations are reported, showing a better convergence behavior of the SNO with respect to the GA and the PSO. It is worth to note that the number of cost evaluation required by the SNO to reach the optimal solution is much lower than the maximum number considered here, proving also a reduced computational cost of the SNO compared to that of the PSO and of the GA. The goodness of the solution obtained with the SNO is finally remarked by Figure 9, that reports the S_{11} frequency response for the structures optimized with the three algorithms, showing that the solution obtained with the SNO outperforms the other two ones both from the point of view of the bandwidth and the in-band ripple.

4.2. Wide-Band Pass-Band Filter

The second structure that has been considered is a pass-band filter consisting in a cascade of N pieces of microstrip line, each characterized by electrical length equal to $\lambda_g/2$ at the central frequency, but with a different width. The first reason for choosing this filter is that in the past years the authors have already used this structure as an example of applications of optimization algorithms [19, 20], and therefore results for comparing the SNO with other algorithms were already available. Additionally, this structure could be modeled as a cascade of an equivalent transmission lines, all with the same electrical length, but with varying characteristic impedance. If each line section is characterized by its chain matrix, that of the entire cascade is given, as shown in [20] and reported here for the sake of completeness, by the product of the single matrices, and finally the S_{21} of the filter could be written as a function of the entire structure chain matrix elements A_{tot}, B_{tot}, C_{tot} and D_{tot}

$$S_{21} = \frac{2\sqrt{Z_{out}Z_{in}}}{A_{tot} + B_{tot}/Z_{in} + (Z_{out}/Z_{in})\,(C_{tot}Z_{in} + D_{tot})} \tag{2}$$

where Z_{out}, Z_{in} are the reference impedances at the output and input ports of the filter.

In the filter optimization, the free parameters are the widths of different microstrip sections (i.e., the characteristic impedance of the equivalent transmission lines), while the cost function mathematically models the following three constrains:

- bandwidth at least equal to a fixed threshold;

Table 2. Resulting microstrip filter parameters after 216 k cost function evaluations with SNO and PSO.

N	Opt. alg.	No. iter	band (%)	$\lvert S_{21}\rvert$ (dB)	ripple max (dB)	ripple avg (dB)
15	SNO	30	61.8750	−60.0719	−0.9163	−0.1556
15	SNO	50	61.8750	−60.0019	−0.8339	−0.1557
15	SNO	100	61.8750	−60.0015	−0.7512	−0.1587
15	PSO (*)	3000	61.8375	−60.0277	−0.9682	−0.2104
17	SNO	30	63.1250	−64.4259	−0.3222	−0.0046
17	SNO	50	62.5000	−71.4289	−0.1337	−0.0106
17	PSO (*)	3000	62.7250	−63.0175	−1.0406	−0.4991

* *results from [20].*

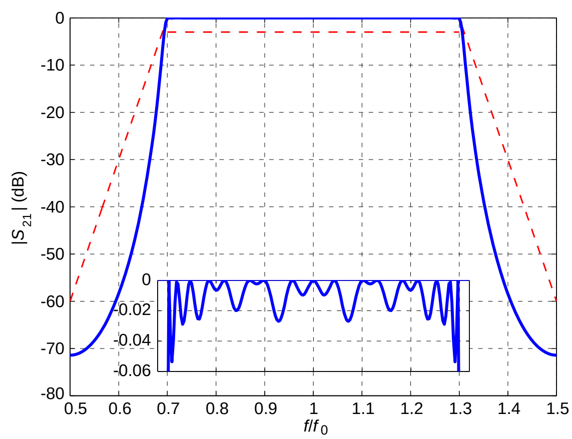

Figure 10. Transfer function for the 17-cell filter, obtained with the SNO (inset: details on the in-band ripple).

- minimization of the in-band ripple;
- maximization of the out of band rejection.

Table 2 reports the average (over 50 trials) values of the filter parameters obtained by the SNO with different sets of population and iterations, keeping constant the number of 216,000 function evaluations (to compare with the previous results from [20], reported in the last row for the sake of completeness). From the point of view of the maximum and mean ripple, the SNO outperforms the PSO [20], and in any case it guarantees a bandwidth within the specification. One of the corresponding filter transfer functions obtained with the SNO is shown in Figure 10, together with the considered mask. It is interesting to observe that the advantage in using the SNO instead of the PSO is slightly higher for $N = 17$, and this seems to confirm the good performances of the SNO also when the problem complexity increases.

5. CONCLUSION

In this paper, the authors present and employ a new optimization approach, named Social Network Optimization (SNO), which emulates the evolving properties of social networks. The proposed technique is applied firstly to several benchmark functions for a first trial campaign which demonstrates its effectiveness and robustness, and then to the optimized design of different microwave circuits. The obtained results prove the effectiveness of the SNO both in terms of convergence capability and reliability, and show that in many cases it outperforms other well-assessed optimization algorithms.

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