A New approach for FSS Design in 3.5GHz Based on General Neural Network Model by using Multi-objective Sailfish Optimization Algorithm

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Abstract — **This work approaches a bioinspired hybrid multi-objective optimization technique associated with a general regression neural network as a proposal to synthesize the geometry and the dimensions of a frequency selective surface (FSS) for electromagnetic wave filtering in 5G applications. This new hybrid technique associates the bio-inspired algorithm known as the Sailfish Optimizer (SFO), together with a GRNN net to obtain the parameters for constructing the filter. In this study, the focus is on the application of the technique as a tool for the design and the synthesis of FSS, which has the shape of a square spiral unitary cell, printed on a fiberglass substrate plate (FR4). The objectives of the optimization process are to set the resonant frequency of the FSS to 3.5 GHz and the operating bandwidth to 0.8 GHz. It is reported a good agreement between the simulated and measured results.**

Index Terms — **Algorithm Bioinspired, Sailfish Optimizer, general regression neural network, frequency selective surfaces.**

I. INTRODUCTION

The mobile telephony market is one of the fastest growing in the segment of telecommunication services, which contributes to an increasingly polluted frequency spectrum. When proposing the fifth generation system, 5G, for mobile data communications, the development of equipment and devices with applications in new frequency bands opened a vast field. However, a higher speed rate to data transmission is desired when ascending in the frequency scale, and thus, to achieve a less explored frequency in order to avoid interferences by other communication radio systems [1]. However, with 5G expansion, the pollution of the electromagnetic spectrum perceived in the 4G system, which operates in frequencies close to the pattern IEEE 802.11, is an issue that deserves attention and new studies should consider it [2]. Frequency Selective Surfaces (FSS) are structures that have the function of limiting and controlling the frequencies used. An analysis of this type of structure demands high computational complexity, through techniques of full wave analysis, where the evaluation of the variation of a single parameter can cost large time intervals [3-4].

In this context, Bio-inspired computing (BIC) has been consolidated in computer science to solve the difficulties presented by traditional methods, with a great potential to be explored. BIC, which are computational techniques inspired by the behavior of biological systems in nature, serving as methodologies and approaches to present a set of efficient solutions to solve various types of problems from different areas of engineering and industry [5-6]. Aiming to accelerate the design processes of devices and circuits for wireless communication, or improve parameters of devices already designed, researchers continue to propose new metaheuristic algorithms, combining the main advantages of classic BIC algorithms with inspiration from biological systems not yet explored [7-15].

Talking about recent techniques, one might mention the algorithm called The Sailfish Optimizer (SFO), [16], described as a new metaheuristic that proposes to emulate the hunting behavior of a group of sailfish as predator and sardines as prey. The application of SFO in engineering problems is found in [17] and [18]. A scenario of possible interferences in bands of 5G together with satellite TV transmissions is the starting point driving this study. We can find in literature numerical analysis of coexisting satellite reception systems and possible interference problems in this 3.5 GHz band [19-21].

This paper presents a FSS design capable of enabling an alternative for the coexistence between 5G services in 3.5 GHz and television signals transmitted via satellite by Band C. To attend this objective, the tool to be used is a hybrid technique that uses a combination of the SFO bio-inspired algorithm and a General Regression Neural Network (GRNN), where the filter manufacturing parameters are delivered by this tool, being the strategy of multi-objective search in this algorithm an unprecedented contribution to solve the problem raised in this work. In a nutshell, the main contributions of this work are as follows:

- A new hybrid method known as the SFO modified algorithm (MSFO) optimizer is introduced using the newly proposed SFO metaheuristic.

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- The main contribution is the application of this methodology as a strategy for finding multi-objective solutions for these types of problems, using PSO+GRNN.

The following sections are elaborated as follows: the 2nd is dedicated to the use of GRNN; the 3rd is detailed the Sailfish algorithm; 4th presents the hybrid model using the two computational tools applied to search for solutions; 5rd presents the manufactured framework and measured results; and 6th part contains the conclusions.

II. NEURAL NETWORK APLIED TO FSS

GRNNs are based on non-parametric estimation, being a neural network derived from radial basis neural network, and have the advantage of using only part of the data to train the network, ensuring fast learning [22-23].

The network architecture in this study has four input nodes with the training parameters that describe the FSS project variables delivering two output nodes. The network has two input and output neurons and with the training data 121 hidden layers and two output layers were obtained, being used a Gaussian activation function in the hidden layer. The input nodes represent the chosen filter construction variables, being the periodicity of the cell (T), the spiral side (L), the relative permittivity of the substrate material (ε_r), and the height of the substrate (h). Fig. 1 illustrates the variables in the unit cell.

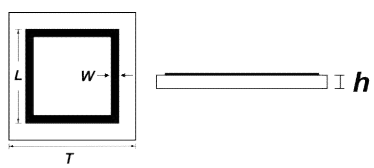

Fig. 1. ***Unit cell dimensions***

In the last layer, two vectors of dependent variables are delivered, where the resonance frequency (F_c) and bandwidth (BW) are the desired vectors and consequences of the iteration of the independent variables of the training layer. The input (x) and output (y) parameters are represented by the following vectors:

$$x = [T, L, \varepsilon_r, h]^t \quad (1)$$
$$y = [F_c, BW]^t \quad (2)$$

The network is taught to deliver the bandwidth and center frequency results through the database of periodicity values, square spiral side, substrate height and material permittivity. This learning creates conditions to obtain characteristics to help in the design of the FSS unit cell. The values of these parameters are shown in Table I.

TABLE I FSS PARAMETERS

FSS PARAMETERS	VALUE
Array Periodicity (mm)	Tx=Ty= [20:1:30]
Square loop dimensions (mm)	L=[18:1:28]
Loop width (mm)	W=1
Substrate height (mm)	h = 1,57
Substrate relative permittivity	ε_r= 4,4

From the data available in Table I, the calculations of the electromagnetic properties of the prototype are performed through computer simulations in the CST Microwave Studio ® software where the Finite Integral Technique (FIT) was defined to perform these calculations.

III. THE SAILFISH OPTIMIZER

SFO is an algorithm based on the behavior of the group of sailfish when hunting sardines [16]. It describes the use of two groups of populations, the prey and the predator, and thus it is possible to simulate the hunting behavior of a group and how it sets an alternating strategy in attacking predators. The following steps describe how the code works.

A. Initialization

The algorithm assumes each sailfish ($SF_{m,d}$) and each sardine ($S_{n,d}$) as a possible candidate for the solution that meets the objective function, being random the generation of the two populations and the assignment of the position to each solution in the search space according to the iteration.

The matrices representing the positions of the sailfishes and sardines as possible solutions in the search space are:

$$SF_{position} = \begin{bmatrix} SF_{1,1} & SF_{1,2} & \cdots & SF_{1,d} \\ SF_{2,1} & SF_{2,2} & \cdots & SF_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ SF_{m,1} & SF_{m,2} & \cdots & SF_{m,d} \end{bmatrix} \quad (3)$$

$$S_{position} = \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,d} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n,1} & S_{n,2} & \cdots & S_{n,d} \end{bmatrix} \quad (4)$$

m is the number of sailfish, n is the number of sardines and d is the number of variables. The idea is to understand that the sailfish position is the factor that carries more importance in the solution search (prey hunting), and the position of the sardine can favor the consummation of the solution choice. Then, the aptitude of each sailfish and sardine are obtained by calculating the fitness function and computed in a matrix.

$$f(sailfish) = f(SF_1, SF_2, SF_3, \dots, SF_m) \quad (5)$$
$$f(sardine) = f(S_1, S_2, S_3, \dots, S_n) \quad (6)$$

The following matrices represent the weights of each solution of both the sailfish and the sardines. This has importance in evaluating the best positioning of both.

$$SF_{fitness} = \begin{bmatrix} f(SF_{1,1} & SF_{1,2} & \cdots & SF_{1,d}) \\ f(SF_{2,1} & SF_{2,2} & \cdots & SF_{2,d}) \\ \vdots & \vdots & \vdots & \vdots \\ f(SF_{m,1} & SF_{m,2} & \cdots & SF_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{SF_1} \\ F_{SF_2} \\ \vdots \\ F_{SF_m} \end{bmatrix} \quad (7)$$

$$S_{fitness} = \begin{bmatrix} f(S_{1,1} & S_{1,2} & \cdots & S_{1,d}) \\ f(S_{2,1} & S_{2,2} & \cdots & S_{2,d}) \\ \vdots & \vdots & \vdots & \vdots \\ f(S_{m,1} & S_{m,2} & \cdots & S_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{S_1} \\ F_{S_2} \\ \vdots \\ F_{S_m} \end{bmatrix} \quad (8)$$

B. Elitism

SFO performs an elite selection of the best positions, in other words, it keeps the sailfish best position, in other words, it keeps the best position of the sailfish and the injured sardines after the attack, keeping it unchanged for a next generation and avoiding waste of good solutions. The elite position of the sailfish and the injured sardine have the highest fitness function at the i-th iteration, and are called $X^i_{elite\_SF}$ and $X^i_{injured\_S}$, respectively.

C. Hunting strategy and prey capture

The effectiveness of a group of sailfish attack is benefited by the strategy of alternating attack among members of a group. It is the execution of the exploration phase, where it is made the search for viable solutions over a large part of the search space, which evolves and refines the search to a smaller radius. Finally, the sailfish updates its position within a sphere created around the best solution, and this update is adjusted as follows:

$$X^i_{new_{SF}}{=}X^i_{elite\_SF} - \lambda_i \times \left(rand(0,1) \times \left(\frac{X^i_{elite\_SF} + X^i_{injured\_S}}{2} \right) - X^i_{old\_SF} \right) \quad (9)$$

In the Equation (5) the new position of the sailfish takes into account its old position ($X^i_{old\_SF}$), the best stored positions that are the result from the elitism process ($X^i_{elite\_SF}\ and\ X^i_{injured\_S}$), a random number from 0 to 1 ($rand(0,1)$) and a coefficient generated in each iteration (λ_i).

To emulate a process of losing energy from the prey with each attack, each sardine updates its position relative to the current best position of the sailfish and the strength of the attack in each iteration. In the algorithm this update is defined as follows:

$$X^i_{new\_S} = r \times \left(X^i_{elite\_SF} - X^i_{old\_S} + AP \right) \quad (10)$$

r is a random number from 0 to 1 and AP shows the amount of power of the sailfish attack at each iteration.

IV. THE HYBRID OPTIMIZER BASED ON SAILFISH MULTIOBJECTIVE ALGORITHM AND GENERAL REGRESSION NEURAL NETWORKS

Firstly, the generalized regression neural network was developed using the simulated data obtained through CST ®. This type of neural network is composed by a radial basis layer and a special linear layer. It differs from another neural networks which use sigmoidal functions.

This neural network represents the objective function F(.) of the hybrid optimization that must calculate bandwidth and frequency related with the following inputs: T and L.

A. The Modified Sailfish Optimizer for FSS design

The multi-objective optimization calculate more than one objective and the result is a trade off between the objectives. It was added to the Sailfish optimizer through Weighted Sum Method. The weight of an objective is chosen in proportion to the relative importance of the objective. This method uses the scalarization of a set of objectives into a single objective by adding each objective pre-multiplied by a user supplied weight [24].

In the SFO modified algorithm (MSFO), a neural network of radial basis function is run. The goal is to train the neural with set of input values T and L, and with output F and B. This network generated after training will be used in the fitness function to calculate F and B with the input of the population of sailfish and sardines representing T and L. The Pareto front is set by the decision maker.

The next step is to generate the position of sailfish and sardines, they are generated randomly. The result of each most internal iteration is the updated position of each sailfish related to an injured sardine and the elite sailfish. It must be cited that the updating position of sardine is then accomplished by selected sardine and elite sailfish depending on the power of sailfish attack.

All the time that that the process of updating the position of sailfish and sardines happened, they are evaluated by the fitness function. If any of the sardines become with best fitness function result than any other sailfish, the sailfish updates its position to this related sardine. Moreover, the position of elite sailfish and the injured sardine will be updated in each iteration of the algorithm. These steps are repeated in an iterative manner until the end of criterion is satisfied, i.e., Pareto front number is achieved. The best sailfish population is returned related to the Pareto number front.

V. COMPUTATIONAL AND EXPERIMENTAL RESULTS

Fig. 2 and Fig. 3 show the generalization capability of this network that has been implemented.

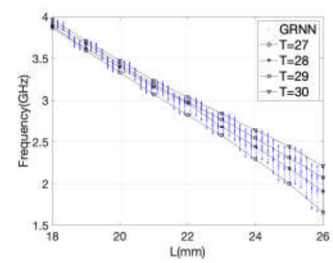

Fig. 2. ***Response of the GRNN to the Resonance Frequency of the FSS under study***

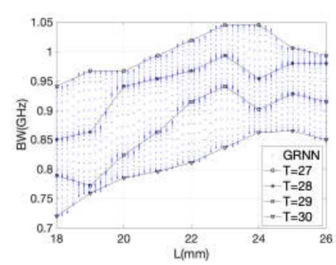

Fig. 3. ***Response of the GRNN to the Bandwidth of the FSS under study***

The computational time to generate data plotted in Fig. 2 and Fig. 3 was about 41.64 seconds. Computer configuration follows: Intel(R) Core(TM) i7-5500U CPU @ 2.40GHz 2.40 GHz RAM: 12,0 GB. With the progress of the iterations of the code execution, an example of the search for these solution candidates can be seen in Fig. 4. The point identified with a circle located further to the left is the worst solution candidate, while the best solution is identified with a square and the other candidates are represented by asterisks, where the best performing solution is close to the coordinates with the desired objectives ($F_r = 3.5\ GHz\ and\ WB = 0.8\ GHz$).

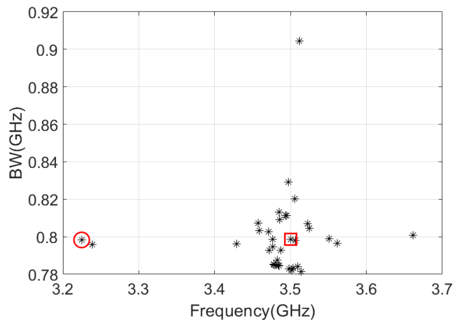

Fig. 4. ***Domination relationship of the cost function problem***

The Fig. 5 illustrates the solution after 500 iterations, and for each iteration the sets of possible solutions make up the Pareto front, where they consequently constitute a region of interest, where the algorithm proceeds by searching for a better solution.

Following the analys is we observe in Fig. 5 the evolution of the solution pattern for this structure, where we see a sharp decline in the value of the cost function over the iterations, where we have the solid line with the average fitness rate, while the dashed line shows each individual solution over the iterations.

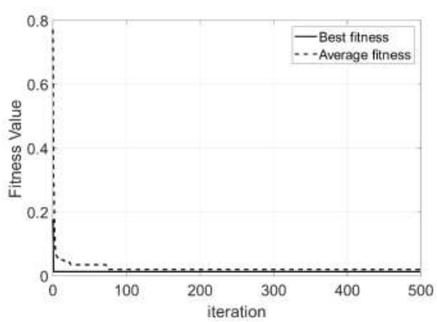

Fig. 5. ***Fitness evolution in the synthesis process for the optimized FSS.***

The use of GRNN+MSFO, delivers a feasible solution with the already optimized structure parameters, which are: $T_x = 30\,mm$, $L = 20{,}46\,mm$, $W = 1\,mm$, $h_s = 1{,}57\,mm$ e $\varepsilon_r = 4{,}4$. With these values the filter was built on the FR-4 plate with dimensions of 200 mm x 200 mm and subjected to measurements for validation purposes.

These measurements were made with an Agilent E5071C network analyzer, in conjunction with two SAS-571 horn antennas operating in a range from 0.7 to 18 GHz, as shown in Fig. 6. Then Fig. 7 illustrates a comparison of the results optimized with the hybrid GRNN+MSFO technique, together with the results from the CST full-wave software plus those obtained from the measurements.

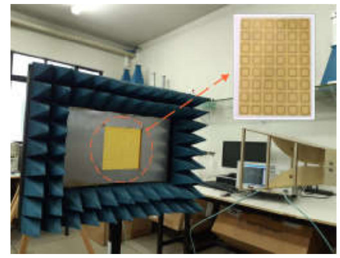

Fig. 6. ***FSS measurement setup***

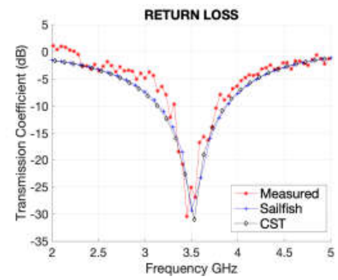

Fig. 7. ***Transmission coefficient of FSS with square loop elements, optimized using SFO algorithm.***

The data presented in Fig. 7 show good agreement between preliminary code and measured results, given the filtering of the resonant frequency at 3.5 GHz.

VI. CONCLUSION

In this work, was developed a hybrid bioinspired multi-objective technique combining a GRNN network and a MSFO optimization algorithm. The technique was applied to optimize the unit cell of an FSS, with the element shaped as a square spiral, for microwave filtering applications. The technique has been shown to be fast and accurate, contributing as a new application of SFO as a multi-objective, as a solution to this type of proposal and also as a viable tool for the development of broadcast circuits, including planar FSS. The preliminary results show the robustness of the code and with this it is possible to observe agreement in the results obtained for the desired resonance and bandwidth in an FSS, thus making the prototype viable as an alternative for the coexistence between 5G systems and television signals transmitted via satellite in C Band. A good agreement between them was observed, validating the proposed optimization technique.

For future studies, we can apply this methodology to different engineering problems, making a comparison with the use of other metaheuristic algorithms for multi-objective solutions.

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