Triple-band Inverted-F Antenna Using QR-OBL TLBO Algorithm for RF Energy Harvesting Applications

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***Abstract*—Radio Frequency Energy Harvesting (RF EH) is one of the popular emerging techniques in wireless sensor networks that can sufficiently supply low power electronic circuits. With the evolution of Internet of Things (IoT) technology, which exhibits an exponentially positive growth rate over the last years, RF EH can play a primary role in the next-generation wireless networks. In this paper, we apply an optimization technique by utilizing the Quasi-Reflected (QR) variant of Opposition Based Learning (OBL) technique in Teaching Learning Based Optimization (TLBO) algorithm to design a triple-band Inverted-F antenna (IFA) for RF energy harvesting applications. The proposed antenna is operating in the cellular communication frequency bands of EGSM-900 and GSM-1800, as well as at the Long Term Evolution (LTE) telecommunication networks frequency band of LTE-2600. Simulation results demonstrate that the designed antenna has features of operation which make it suitable for RF EH applications.**

***Index Terms*—RF energy harvesting, Quasi-Reflected Opposition Based Learning, Teaching Learning Optimization Algorithm, Inverted-F antenna, optimization method.**

I. Introduction

Recently, the expansion of Internet of Things (IoT) has brought smart communication networks into daily life. The devices connected to these networks need to exhibit autonomous electric power operation. Batteries use was a good choice, but a foreseeable problem is the cost and the difficulty of their maintenance and replacement [1]. Drawing electric energy from Radiofrequency (RF) power resources present all the time in the environment would be a promising solution to this problem. The ambient power is a product of human wireless communication activities and so, the concept of a RF energy harvesting system seems to be a very interesting alternative to batteries for sensors' autonomous power operation.

The basic equipment for harvesting ambient RF power, includes an antenna which captures the incident RF power, a rectifier, potentially a matching network between them, a DC power storage unit, and if necessary, a power management unit. The role of the antenna is crucial for the effectiveness of the entire system, as all the rest units process and manage just the amount of energy that the antenna obtains to gather. Consequently, the suitable design of the antenna in order to have high gain and generally sufficient characteristics of operation is very important.

Optimization techniques are often used to find out the suitable antenna layout and size in order to all the operation requirements be satisfied. Traditional optimization techniques which depend on linear and dynamic programming often fail to solve large scale optimization problems. Therefore, meta-heuristic optimization algorithms have been developed. The most popular of them are based on the theory of evolution and imitate nature's behavior.

This paper focuses on a triple-band antenna approach for RF energy harvesting applications, with antenna design parameters being calculated by a meta-heuristic optimization algorithm called Teaching Learning Based Optimization (TLBO) algorithm [2]. To enhance the optimization process, we apply the Quasi-Reflected (QR) variant [4], [5] of the Opposition Based Learning (OBL) technique [3] to the selected algorithm. The remainder of the paper is as follows. In Section II, a brief description of the TLBO algorithm in combination to QR Opposition Based Learning variant is outlined. Section III describes the optimal design of the selected IF antenna obtained by the utilization of the QR-OBL TLBO algorithm. Section IV summarizes the main results of the proposed antenna, whereas Section V concludes the paper.

II. Algorithm Description

Teaching Learning Based Optimization (TLBO) is a nature-inspired algorithm which uses a population-based method to obtain a global solution to a given optimization problem [2]. Compared to other optimization techniques, TLBO does not require any algorithm parameters to be adjusted. The population in TLBO is classified into a group of 'learners' and a 'teacher'. As the definitions imply, the members of the TLBO population that belong to the 'learners' group improve their fitness values (i.e. learning) from the 'teacher'. Accordingly, the 'teacher' population member, as also the word imply, achieve the best fitness score at each iteration of the optimization process. TLBO algorithm process is classified into two different phases, the 'teacher' phase and the 'learner' phase. Once again, as the definitions of the phases imply, in the 'teacher' phase, the 'teacher' update the fitness function of the 'learners' group by trying to increase their mean value. Consequently, in the 'learner' phase, the 'learners' group of the population update their fitness value based on an interactive process.

To further analyze the TLBO algorithm, let us consider as NP the population number of TLBO, NIt the number of iterations, and ND the number of decision variables (in our case it is the vector of design variables of the proposed antenna). The total population (pop) can be expressed as

$$pop = \begin{bmatrix} z_{11} & z_{12} & z_{13} & \cdots & z_{1,ND} \\ z_{21} & z_{22} & z_{23} & \cdots & z_{2,ND} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{NP,1} & z_{NP,2} & z_{NP,3} & \cdots & x_{NP,ND} \end{bmatrix} \tag{1}$$

During the 'teacher' phase, the position vector (vector that contains the values of the decision variables in the given optimization problem) of each member of the population is updated by

$$\vec{Z}_{i,j}^{new} = \vec{Z}_{i,j}^{old} + \vec{Z}_{i,j}^{diff} \tag{2}$$

where $\vec{Z}_{new}$ is the new position vector, $\vec{Z}_{old}$ is the old position vector, and $\vec{Z}_{i,j}^{diff}$ is the difference between the teacher position vector and the average of the learners position vectors, which is given by

$$\vec{Z}_{i,j}^{diff} = rnd \times \left(\vec{Z}_{i,j}^{best} - P_c \vec{Z}_{i,j}^{avg}\right) \tag{3}$$

where $\vec{Z}_{i,j}^{best}$ is the position vector of the teacher (i.e. the position vector with the highest score achieved among the members of the population), $\vec{Z}_{i,j}^{avg}$ is the average of position vectors of the learners in the population, rnd is a randomly selected number $\in [0,1]$, and P_c is a two-state coefficient (values 1 or 2). In (1) - (3), the indices are extended as $i = 1, 2, \cdots, NIt$, $j = 1, 2, \cdots, NP$, and $k = 1, 2, \cdots, ND$.

During the 'learner' phase, the position vector of each member of the population is updated by an interactive process between the learners of the population. Detailed description of the 'learner' phase, as well as an overall description of the Teaching Learning Based Optimization process is outlined in Algorithm 1.

Algorithm 1 Overall description of TLBO algorithm.

Define number of iterations NIt, number of population NP, and number of decision variables ND
Initialize population matrix pop
Initialize position vectors for each member of the population
for $j = 1 : NP$ **do**
  Compute $\vec{Z}_{i,j}$
  Compute objective function $F(\vec{Z}_{i,j})$
end for
for $i = 1 : NIt$ **do**
  Compute the average position vector of the population $\vec{Z}_{i,j}^{avg}$
  Select the population member with the best position vector (i.e the 'teacher' in the population) $\vec{Z}_{i,j}^{best}$
  Initialize 'teacher' phase
  for $j = 1 : NP$ **do**
    Define two-state coefficient F_c
    Compute $\vec{Z}_{i,j}^{diff}$ from (3)
    Compute $\vec{Z}_{i,j}^{new}$ from (2)
    Evaluate $F(\vec{Z}_{i,j}^{new})$
  end for
  Initialize 'learner' phase
  for $j = 1 : NP$ **do**
    Choose two members of the population (learners) $\vec{Z}_{i,m}$ and $\vec{Z}_{i,n}$, where $m \neq n$ $(m, n = 1, 2, \cdots, NP)$
    Compute $P_s = \vec{Z}_{i,m} - \vec{Z}_{i,n}$
    if $F(\vec{Z}_{i,m}) < F(\vec{Z}_{i,n})$ **then**
      $P_s = -P_s$
    end if
    $\vec{Z}_{i,j}^{new} = \vec{Z}_{i,j}^{old} + rnd \times P_s$
    Evaluate $F(\vec{Z}_{i,j}^{new})$
  end for
end for

Opposition-Based Learning (OBL) is a novel computational approach in artificial intelligence, which is inspired by the opposite attributes among members in a population [3]. The main idea in OBL technique is to build and evaluate both the current and the opposite population in an optimization process.

Let us suppose that the number $z \in R$ is defined in the interval $[c, d]$. The opposite number z^* can be expressed as

$$z^* = c + d - z \tag{4}$$

Extending the above definition, if we consider $\vec{Z}_{i,j}$ as the position vector of each member in a population, then we can define as $\vec{Z}_{i,j}^*$ the opposite position vector of the population. In literature, several OBL variants have been applied to various optimization problems [4], [5]. In our case, we have selected to utilize Quasi-Reflected Opposition Based Learning (QR-OBL), because it has the highest expected probability to converge to the optimal solution among all other OBL variants

[6]. It can be expressed as

$$\vec{Z}^*_{i,j} = \begin{cases} rand(\vec{Z}_{i,j}, P_m), & if \ \vec{Z}_{i,j} < P_m \\ rand(P_m, \vec{Z}_{i,j}), & otherwise \end{cases} \tag{5}$$

where, once again, $\vec{Z}_{i,j}$ is the position vector, $\vec{Z}^*_{i,j}$ is the opposite position vector, and P_m is given by

$$P_m = \frac{c+d}{2} \tag{6}$$

III. Antenna Design

In this paper, we apply the QR-OBL TLBO algorithm to find an optimal solution in the design of a triple-band IF antenna, operating in the frequency bands of EGSM-900, GSM-1800, and LTE-2600. The proposed antenna is designed on a single layer and is consisted of two inverted-F designs. These two IF designs are coupled by a stripline, which acts as a feeder to the antenna (a source is edged at the stripline). Fig. 1a illustrates the proposed IF-antenna, whereas the two inverted-F designs are distinguished. The proposed antenna is placed on an FR-4 substrate (relative permittivity $\epsilon_r = 4.4$, $thickness = 1.6mm$, $L_{sub} = L_{ground} = 102mm$, $W_{sub} = 56.33mm$). In this antenna design, we utilize the partial ground technique to set the ground plane. Fig. 1b depicts the bottom view of the proposed antenna. We can easily note that the dimensions between the substrate and the ground plane are differentiated to the width of the latter one ($W_{ground} = 10mm$).

Table I lists the optimal values (best solution in the optimization process) of the proposed antenna design parameters obtained by the utilization of QR-OBL TLBO algorithm. The given algorithm has been applied in conjunction with a commercial electromagnetic field simulator (HFSS, © 2020 ANSYS, Inc.) to obtain the optimal values of the proposed antenna. The objective function, which is to minimize the S_{11} parameter of the inverted-F antenna at the previously mentioned frequency bands, can be expressed as

$$\begin{aligned} & F(\vec{Z}_{i,j}) = \\ & max\big(S_{11}^{0.94GHz}(\vec{Z}_{i,j}), S_{11}^{1.84GHz}(\vec{Z}_{i,j}), S_{11}^{2.64GHz}(\vec{Z}_{i,j})\big) \\ & +\Psi \times max\big(0, S_{11}^{0.94GHz}(\vec{Z}_{i,j}) - L_{dB}\big) \\ & +\Psi \times max\big(0, S_{11}^{1.84GHz}(\vec{Z}_{i,j}) - L_{dB}\big) \\ & +\Psi \times max\big(0, S_{11}^{2.64GHz}(\vec{Z}_{i,j}) - L_{dB}\big) \end{aligned} \tag{7}$$

where $\vec{Z}_{i,j}$ is the position vector of the design parameters to be optimized (12 parameters), $S_{11}^{0.94GHz}$, $S_{11}^{1.84GHz}$, and $S_{11}^{2.64GHz}$ are the S_{11} parameters of the proposed IF antenna, L_{dB} is the arbitrarily selected S_{11} limit in dB, and Ψ is a penalty factor (in our case, we set $\Psi = 1E+10$).

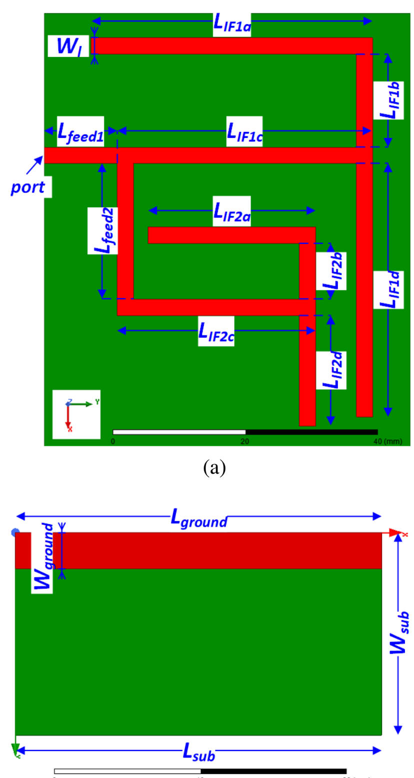
IV. Numerical Results

Fig. 2 shows the S_{11} magnitude of the proposed IF antenna vs frequency. From the presented graph, we can derive that the proposed antenna operates satisfactorily in the EGSM-900, GSM-1800, and LTE-2600 cellular communication frequency bands. The inverted-F antenna has a triple-frequency tuning operation (-30.58 dB at 0.94 GHz, -39.56 dB at 1.84 GHz, and -26.69 dB at 2.63 GHz) within the downlink of the previously mentioned cellular communication frequency bands (green shaded areas in graph). It is worth mentioning that the operational bandwidth (-10 dB bandwidth) of the obtained antenna surpasses the downlink communication frequency bands of interest.

Fig. 3 illustrates the obtained input impedance of the proposed antenna versus frequency. It is noticeable that the input impedance of the inverted-F antenna in the frequency bands of interest (EGSM-900, GSM-1800, and LTE-2600) is close to the input impedance of the port ($50 + j0$ Ohms). Fig. 4 portrays the realized gain of the best antenna geometry obtained by QR-OBL TLBO algorithm. From the presented graphs, we can conclude that the proposed antenna exhibits

TABLE I
Optimal values (best solution) of the antenna design parameters obtained by the QR-OBL TLBO algorithm.

Parameter	Value (mm)	Parameter	Value (mm)
L_{feed1}	11.20	L_{feed2}	20.92
L_{IF1a}	43.40	L_{IF1b}	14.35
L_{IF1c}	39.32	L_{IF1d}	39.00
L_{IF2a}	25.80	L_{IF2b}	8.67
L_{IF2c}	30.05	L_{IF2d}	17.00
W_l	2.50	W_{ground}	10.00



(a)

(b)

Fig. 1. Geometry of the proposed IF-antenna: (a) top view (the substrate of the antenna is partially displayed), (b) bottom view.

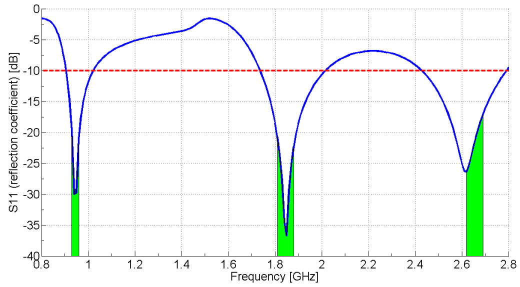


Fig. 2. $S11$ parameter (reflection coefficient) versus frequency of the best antenna geometry obtained by QR-OBL TLBO algorithm (blue solid line: $S11$ parameter, red dash line: -10 dB limit, and green shaded areas: downlink communication frequency bands of EGSM-900, GSM-1800, and LTE-2600).

high gain values toward directions inside extended areas of the surrounding space. Due to this performance, the antenna can gather effectively power from waves coming from these areas and it is valid especially for the two lower frequency bands. The maximum gain value obtained is 6.46 dBi at 0.94 GHz, 9.29 dBi at 1.84 GHz, and 10.02 dBi at 2.64 GHz.

V. Conclusion

In this paper, we have presented a modified inverted-F antenna operating in the cellular communication frequency bands of EGSM-900, GSM-1800, and LTE-2600, as the most important part of an RF energy harvesting system. The geometry of the proposed antenna was achieved by the utilization of QR-OBL TLBO algorithm. From the presented numerical results, we can conclude that the antenna operates satisfactorily in the previously mentioned frequency bands of interest, exhibits broadside beamwidth operation, and achieves high gain values. Future work includes the fabrication and the experimental evaluation of the antenna prototype.

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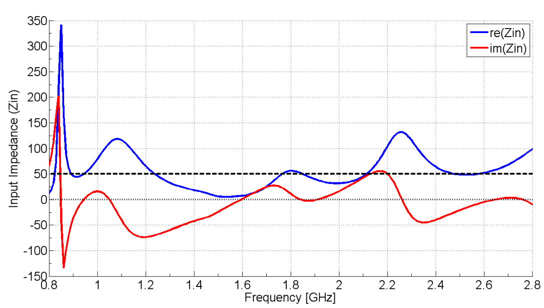
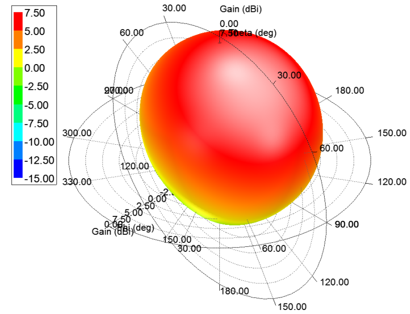
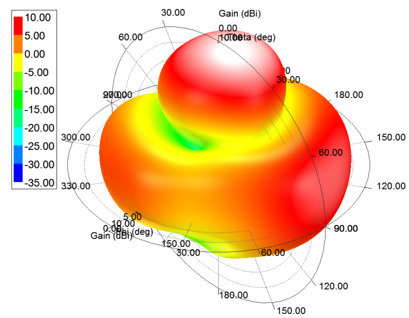


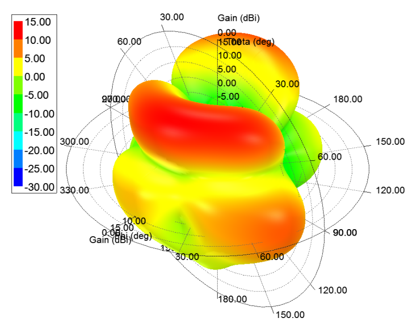
Fig. 3. Input Impedance (Zin) versus frequency of the best antenna geometry obtained by QR-OBL TLBO algorithm (blue solid line: Real part ($Re(Zin)$) of input impedance, red solid line: Imaginary part ($Im(Zin)$) of input impedance, black dot line: $Zin = 0$, and black dash line: $Zin = 50$.



(a)



(b)



(c)

Fig. 4. Realized gain of the best antenna geometry obtained by QR-OBL TLBO algorithm: (a) 0.94 GHz, (b) 1.84 GHz, and (c) 2.64 GHz (color scale in dB).

References

[1] A. Harb, "Energy harvesting: State-of-the-art," Renewable Energy, Elsevier, vol. 36(10), pages 2641-2654, 2011.

[2] R.V. Rao, V.J. Savsani, D.P. Vakharia, "Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems," Computer-Aided Design, Volume 43, Issue 3, 2011, Pages 303-315.

[3] Lei Peng and Yuanzhen Wang, 2010, "Differential Evolution using Uniform-Quasi-Opposition for Initializing the Population," Information Technology Journal, 9: 1629-1634. doi: 10.3923/itj.2010.1629.1634

[4] Qingzheng Xu, Lei Wang, Na Wang, Xinhong Hei, Li Zhao, "A review of opposition-based learning from 2005 to 2012", Engineering Applications of Artificial Intelligence, Volume 29, 2014, Pages 1-12. doi:10.1016/j.engappai.2013.12.004

[5] W. Wang, H. Wang, H. Sun and S. Rahnamayan, "Using opposition-based learning to enhance differential evolution: A comparative study," 2016 IEEE Congress on Evolutionary Computation (CEC), Vancouver, BC, 2016, pp. 71-77. doi: 10.1109/CEC.2016.7743780

[6] M. Ergezer, D. Simon and D. Du, "Oppositional biogeography-based optimization," 2009 IEEE International Conference on Systems, Man and Cybernetics, San Antonio, TX, 2009, pp. 1009-1014. doi: 10.1109/ICSMC.2009.5346043