Optimal Design of Colpitts Oscillator Using Bat Algorithm and Artificial Neural Network (BA-ANN)

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Abstract. Oscillators form a very important part of RF circuitry. Several oscillator designs exist among which the Colpitts oscillator have gained widespread application. In designing Colpitts oscillator, different methods have been suggested in the literature. These ranges from intuitive reasoning, mathematical analysis, and algorithmic techniques. In this paper, a new meta-heuristic Bat Algorithm (BA) is proposed for designing Colpitts oscillator. It involves a combination of BA and Artificial Neural Network (ANN). BA was used for selecting the optimum pair of resistors that will give the maximum Thevenin voltage while ANN was used to determine the transient time of the optimized pairs of resistors. The goal is to select, among the several optimized pairs of resistors, the pair that gives the minimum transient response. The results obtained showed that BA-ANN gave a better transient response when compared to a Genetic Algorithm based (GA-ANN) technique and it also consumed less computational time.

Keywords: Artificial Neural Network · Bat algorithm · Colpitts oscillator Genetic Algorithm · RF circuit · Transient response

1 Introduction

An electronic oscillator can be seen either as a circuit capable of converting dc signal to ac signal operating at a very high frequency or a device that generates ac signals of a given waveform such as sine, square, saw tooth, or pulse shape. It provides an AC output signal without necessarily requiring any externally applied input signal. It can also be described as an unstable amplifier.

There are different categories of oscillator depending on the output waveform, operating frequency range and the circuit components used. Based on circuit components used, the Colpitts oscillator falls under the LC type among others such as Clapp, and Hartley oscillators. Conventional methods of designing Colpitts oscillator involves either the use of the following: intuitive techniques, and analytical techniques for the determination of the values of the circuit components used. However, emerging trends in electronic circuit optimization involve the use of artificial intelligent techniques such

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as ANN, PSO, and GA among others [1–6]. In the next section, a brief review of related work where artificial intelligence have been applied in the design of Colpitts oscillator is presented.

The rest of this paper is organized as follows: Sect. 2 presents a review of related work, while the oscillator design is presented in Sect. 3. Section 4 presents resistor selection using artificial intelligence technique followed by results and discussion which are presented in Sect. 5. Conclusion and future recommendations are given in Sect. 6.

2 Related Work

Optimization techniques are fast gaining applications in the area of electronic circuit design. This is particularly due to the ability of most of these algorithm to mimic natural intelligence in animal. For example, in the design of dc-dc converter, three intelligent optimization techniques (GA, Scatter Search (SS), and Simulated Annealing (SA)) have been evaluated for optimality [7]. The converter efficiency in forward mode operation was derived and used as the optimization objective function. The optimal parameters of the converter obtained from Genetic Algorithm method was compared with those obtained using SA and SS intelligent techniques. The waveform resulting from the three approaches both in forward and backup modes were close to the ideal waveform of the converter. However, SS outperformed GA and SA in terms of execution time.

Similarly, radio frequency varactor circuit design has also been improved using optimization techniques. For example, an optimization method for design of RF varactors was proposed by [8]. Generally, varactor behavior is characterized by some set of supporting equations based on technical parameters. Consequently, this makes the accuracy of the results obtained from RF varactor design adaptable to any technology. GA optimization methodology was used to particularly achieve the varactor circuit design. An interesting feature of GA is that it is able to handle continuous as well as discrete variables, thus providing the possibility of adapting it to both technological and layout constraints. A set of working examples for UMC130 technology were used to justify the validity of the proposed model. The results obtained, identified the likelihood of analytical method of varactor design, enhanced with a GA optimization technique [8]. The accuracy of the obtained results was evaluated in comparison with a HSPICE simulator. Similarly, an optimal LC-VCO design using evolutionary algorithm (GA) was proposed by [9]. Considering the challenge in designing the on-chip LC tank, an optimization technique was used. To overcome phase-noise limitation, the approach sought to minimize both VCO phase noise and power consumption. The validity of the results obtained was also verified using HSPICE/RF simulation thus showing GA as a potential algorithm for designing an accurate and efficient oscillator. The same authors went further to compare the performance of three popularly known meta-heuristic algorithms (GA, PSO, and SA) for LC-VCO design [10]. The results obtained showed that GA, despite being the fastest algorithm, gave the worst deviation from the final solution. However, PSO showed a trade-off between convergence and computational time. In addition, PSO also requires less parameter adjustment than GA and SA, while SA gave the best solution.

A neuro-genetic framework for centering of millimeter wave oscillators have been proposed in the literature [11]. Neural Network was used for circuit modeling while GA for parameter optimization. The authors focused on yield enhancement using Monte Carlo based method. The proposed method was used for a design centering on 30 GHz cross-coupled VCO as well as a fixed frequency 60 GHz oscillator. The results obtained showed significant yield improvement from 8% to 91% for 30 GHz and 7% to 70% for the 60 GHz oscillator.

Various intelligent techniques for analogue electronic circuit design were presented by [6, 12], with PSO being the best followed by GA in terms of frequency response and power consumption reduction. A new hybrid artificial intelligence technique for the design of Colpitts oscillator was proposed. The approach involved optimization of the Thevenin resistors of a common based Colpitts oscillator using a combination of Genetic Algorithm (GA) and Artificial Neural Network (ANN) [4, 5]. GA was used for selecting the pair of resistors that gives the maximum Thevenin voltage while ANN was used to determine the transient time of the optimized couple of resistors. From the results obtained, it was reported that the selected resistor pair for the Colpitts oscillator has shortest transient time and stable dc during long-term operation. From the foregoing it could be seen that state-of-the-art researches have shown the benefits in using artificial intelligence methods for circuit design optimization. Thus, in this paper, an approach involving the use of Bat Algorithm (BA) is introduced in combination with ANN. A performance analysis of this approach was also conducted and results obtained were compared with a previous approach to the same problem. In the rest of this paper, we present brief discussion on the Colpitts oscillator design, followed by the proposed resistor selection algorithm for the Colpitts oscillator. Finally we present our results, and compare with previous similar work, and then conclude the paper.

3 Oscillation Design Methodology

Transient time is the time taken for a circuit to move from one steady-state to another steady-state. It is the time taken for the circuit to settle down when turned ON/OFF. It is of utmost for a circuit to have small transient time as such delay in time determines how soon the final output level is reached. In this section, the design of Colpitts oscillator is presented with the goal of achieving minimum transient time using optimization technique. Figure 1, shows the circuit diagram of the Colpitts oscillator whose design is to be optimized using the combination of optimization technique and artificial intelligence (AI) approach. It is a common base Colpitts oscillator consisting of a voltage divider network using R_1 and R_2, an emitter bypass resistor R_3, two coupling capacitors C_3 and C_4, and an LC tank comprising C_1, C_2 and L_2.

The oscillator was designed around a BJT transistor whose base is connected to the LC tank as feedback via a coupling capacitor C_3. The oscillating frequency of the oscillator can be obtained as in Eq. (1).

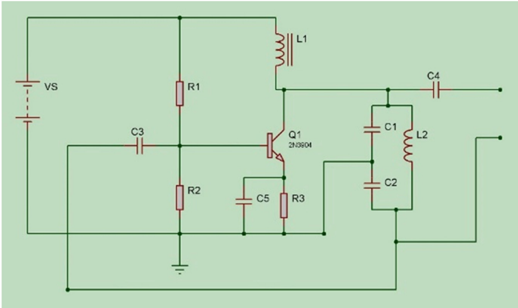

Fig. 1. Circuit diagram of common base Colpitts oscillator

$$f = \frac{1}{2\pi\sqrt{LC_{eqv}}} \tag{1}$$

where C_{eqv} is the parallel combination of C_1 and C_2 and given as

$$C_{eqv} = \frac{C_1 C_2}{C_1 + C_2} \tag{2}$$

As obtained [4, 5], using large signal analysis, the equivalent Thevenin resistance R_{th} and voltage V_{th} are given respectively as

$$R_{th} = \frac{R_1 R_2}{R_1 + R_2} \tag{3}$$

$$V_{th} = \frac{R_2}{R_1 + R_2} V_{cc} \tag{4}$$

Similarly, from large signal analysis the dc operating point as well as the collector current I_c of the oscillator can be obtained. Thus, the collector current I_c is given as in Eq. (5).

$$I_c = \frac{V_{th} - V_{BE}}{R_E + \frac{R_{th}}{h_{FE}}} \tag{5}$$

Thus, it can be seen from Eq. (5) that I_c is directly proportional to the difference between the Thevenin equivalent voltage V_{th} and V_{BE}. V_{BE} is 0.69 at room temperature and can vary with change in temperature. A change in V_{BE} changes the difference between the V_{th} and V_{BE}, consequently affecting the collector current I_c. Therefore, a slight change in V_{BE} if V_{th} is small can affect the transistor operating point. Consequently, V_{th} should be selected relatively large with respect to V_{BE}. Therefore, the goal of the oscillator design is to maximize V_{th} in order to maintain stable dc operating point of the transistor while minimizing the transient response time. From Eq. (4), it can be seen that V_{th} depends on R_1, R_2, and the supply voltage V_{cc}. Since the V_{cc} is constant, maximizing V_{th} simply requires selection of the best combination of resistors R_1 and R_2 which maximizes the V_{th}. Resistors R_1 and R_2 do not only determine the Thevenin equivalent voltage, they also affect the quality of sine wave obtained from the oscillator. Thus, simulation using LTspice software was conducted to determine the range of resistor values that can give the required oscillator waveform [4]. Different combinations of R_1 and R_2 were utilized and the time taken for the waveform to achieve steady amplitude was recorded. Results obtained for this simulation [4, 5] was also used in this work to train the neural network model. Based on the results, resistance value range of 100 kΩ to 1 MΩ was identified as a suitable range for resistor selection. Thus, an artificial intelligent technique was employed to select the combination of resistors (R_1 and R_2) that gives the maximum Thevenin voltage and minimum transient time using the obtained range of resistance values as constraint.

4 Resistor Selection Using AI Techniques

GA is an evolutionary theory based algorithm that combines crossover, mutation and selection approach in searching for an optimal solution. It has found widespread applications in different fields of engineering and science. Recently, it was introduced in the design of Colpitts oscillator. However, due to its computational complexity, in this work, a new bio-inspired Bat Algorithm (BA) is proposed for the same purpose.

4.1 The Bat Algorithm

Bat Algorithm (BA) is a new bio-inspired algorithm introduced by Yang (2010) and has been established to be a very efficient algorithm for optimization [13]. BA is a recently introduced meta-heuristic algorithm, which imitates the echolocation behavior of bats to carry out global optimization. The excellent performance of this algorithm has been demonstrated among other very well-known algorithms such as GA and PSO [14]. Micro Bats use a type of sonar called echolocation to detect prey, avoid obstacles, and locate their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for reflection from the surrounding objects. The loudness of the released pulse varies from the loudest when searching for prey and to a quieter base when homing towards the prey.

Some important features of BA includes its ability to increase the assortment of the results in the population using frequency-tuning technique, automatic zooming such that it balances between exploration and mistreatment during the search process thus mimicking the changes of pulse emission rates and loudness of bats when looking for prey. BA is based on three idealized rules [13, 15]:

(1) Bats use the concept of echolocation to sense distance, as well as to differentiate between food/prey and background obstacles in some magical way
(2) They fly randomly with a velocity v_i at position x_i using a constant frequency $f_{\min}$, a variable wavelength λ and loudness A_0 while searching for their prey. The

wavelength (or frequency) of their released pulses can automatically be tuned in addition to tuning the rate of pulse emission $r \in [0, 1]$, in accordance to their closeness to their target.

(3) Though the loudness can fluctuate in many ways, it is assumed that the loudness changes from a large (positive) A_0 to a minimum fixed value $A_{\min}$.

Every individual Bat is associated with a velocity v_i^t at position x_i^t at iteration t in a search space or solution space of dimension d. At any given iteration t the current best Bat position (solution) at that iteration is denoted as x_*. The frequency f_i, velocity v_i and solution x_i are updated using Eqs. (6)–(8).

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \tag{6}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*)f_i \tag{7}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{8}$$

where $\beta \in [0\ 1]$ is a random vector drawn from a uniform distribution. After a solution is chosen from the current best solution, a new solution for individual Bat is obtained from Eq. (9) [16].

$$x_{new} = x_{old} + \in A^t \tag{9}$$

where $\in$ is a random number which can be drawn from a uniform distribution. The algorithm starts with initializing the individual Bat with a random frequency or wavelength within the maximum and minimum allowed value. Thus the BA is considered a frequency-tuned algorithm [14]. Bat algorithm was used for determining the optimal resistance values of the two resistors, while ANN was used to predict the transient response of the generated optimized pair of resistors.

4.2 Artificial Neural Network for Oscillator Transient Time Predicting

The use of Artificial Neural Networks (ANNs) for modeling non-linear and complex problems has been largely motivated by the ability of systems to mimic natural intelligence in learning from experience. ANNs learn from training data by creating an input-output mapping without the need to explicitly derive the underlying equations. It has found broad areas of applications including but not limited to areas such as: pattern classification, function approximation, optimization, prediction and automatic control, among others.

Individual link to a neuron has an adaptable weight factor allied with it. Each of the neuron in the network sums up its weighted inputs to give an internal activity level as:

$$a_i = \sum_{j=1}^{n} w_{ij}x_{ij} - w_{io} \tag{10}$$

where w_{ij} is the weight of the link from input j to neuron i, x_{ij} is the input vector (R_1 and R_2 in our case) number j to neuron i, and w_{io} is the threshold associated with unit i.

The internal activity a_i is passed through a nonlinear activation function ϕ to give the output of the neuron y_i

$$y_i = \phi(a_i) \tag{11}$$

The weights of the connections are adjusted during the training process to achieve the desired input/output relation of the network.

4.3 The Proposed BA-ANN Model

The flowchart of the proposed model is as shown in Fig. 2. It consists of two parts, the Bat optimization and the ANN part. BA was used to generate several optimum resistance combination for resistors R_1 and R_2, while ANN was used on the other hand to predict the transient response of the generated combinations. The combination with the minimum transient time will be selected as will be seen in the results section.

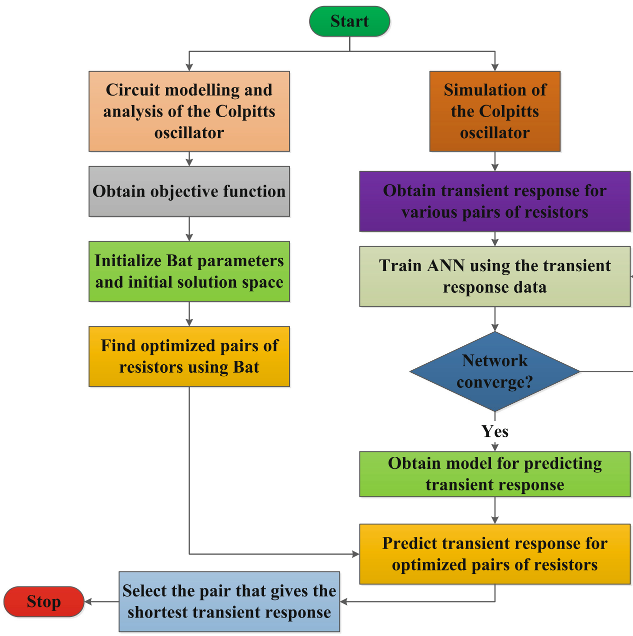

Fig. 2. Flowchart for selection of R_1 and R_2

BA requires an objective function f containing the parameters (R_1, R_2) to be optimized. The goal of the BA is to maximize the Thevenin equivalent voltage (V_{th}). Thus Eq. (4) is rewritten as:

$$f(R_1, R_2) = \frac{R_2}{R_1 + R_2} V_{cc} \tag{12}$$

Vcc is the supply voltage which was set to 12 V, R_1, R_2 were constrained to lower bound of 100 kΩ and upper bound of 1 MΩ which serve as the range that produced pure sine wave. BA was set to a population size and generation of 500, amplitude (A) of 0.6, and pulse rate (r) of 0.5. The minimum (f_{min}) and maximum (f_{max}) frequencies were set to 0 and 3 respectively. While BA searches for the optimum combination of resistance values, there is need to find the combination that gives the minimum transient time. Considering the time to compute transient response for the 500 generated combinations, ANN was used to study and understand the underlying relationship that exists between the resistance combinations and the transient response obtained from the circuit simulation. Consequently, ANN is able to forecast the transient time for the 500 pairs of resistors in just a single step.

5 Results and Discussion

This section presents the results obtained from the BA-ANN algorithm in comparison to previously obtained results using GA-ANN. Both the BA algorithm and ANN were implemented in MATLAB environment. ANN was implemented using the Neural Network toolbox. Back propagation was used with 2 input nodes, a single hidden layer containing three (3) neurons and a single neuron in the outer (output) layer. BA was first used to generate 500 optimized combination of resistors R_1 and R_2. The following parameters were used to tune the BA: A = 0.6, r = 0.5, and $f_{max} = 3$, etc. The generated population from the Bat optimization was fed into ANN to determine the combination of resistors with the minimum transient time. ANN first learned the relationship between the resistor combination and the corresponding transient time using the data obtained from simulation. Initial solution space was generated randomly between the minimum and maximum allowed values of resistors. Results obtained showed that BA converged in a very few number of iterations as can be seen from Fig. 3.

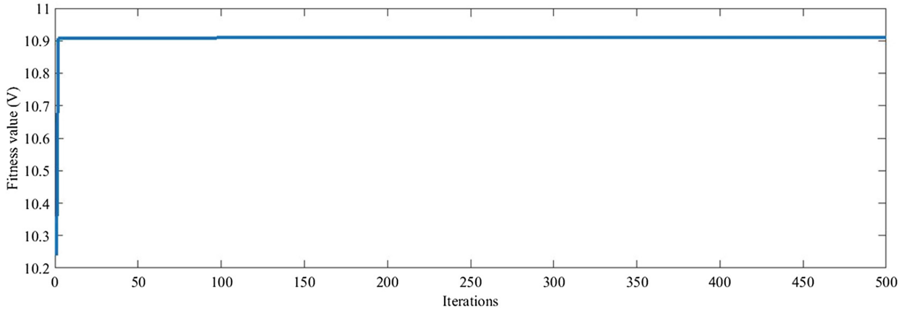

Fig. 3. Plot of fitness value against iteration obtained from Bat algorithm for the 500 optimized pairs of resistor value

The results also showed that irrespective of the initial solution space, BA always converge to the optimum solution. Some of the optimized values obtained are shown in Table 1.

Table 1. Some of the optimized resistor combination using BA

$\mathbf{R_1(k\Omega)}$	100.0	100.0	99.999	99.998	99.998	99.997	99.997	99.996	99.994
$\mathbf{R_2(k\Omega)}$	999.99	999.9	1000.01	999.9	1000.0	999.9	999.8	999/9	1000

On applying the 500 optimized resistor pair as input to the ANN model, a minimum transient time of 0.952 ms was obtained which occurred at $R_1 = 99.994$ kΩ and $R_2 = 1$ MΩ. The ANN model was also applied on the GA optimized values obtained by [5]. Table 2 shows the transient response obtained in comparison to the GA-ANN approach.

Table 2. Transient response predicted using AI for both GA and BA

$\mathbf{R_1(k\Omega)}$	$\mathbf{R_2(k\Omega)}$	T (ms), GA-ANN	T (ms) BA-ANN
100	958	1.27	0.939
100	979	1.29	0.946
100	986	1.30	0.948
100	986	1.30	0.948
100	910	1.22	0.925
100	1000	1.32	0.953
100	965	1.28	0.942

From Table 2, it can be seen that the minimum transient time of 0.925 ms occurred at $R_1 = 100$ kΩ and $R_2 = 910$ kΩ. Thus, it can be concluded that both GA and BA gave close range of optimized values, however, BA has a 31.89% reduction in computation time when compared to GA.

6 Conclusion

In this paper, a combination of Bat algorithm and Artificial Neural Network have been introduced for the design of Colpitts oscillator. The objective was to select the best combination of resistors that gives the Colpitts oscillator maximum Thevenin voltage with minimum transient response. BA was used to select the best combination of resistor values, while ANN predicts the transient time of the optimized resistance values. Obtained results was compared with similar work done using GA. Both GA and BA converge to an approximate solution, however, result from the proposed approach yielded 31.89% lesser transient response with less computation time. Future work includes application of the developed Colpitts oscillator for development of a GSM signal booster.

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