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An improved clonal selection algorithm using a tournament selection operator and its application to microstrip coupler design

Ezgi DENİZ ÜLKER*
Department of Computer Engineering, Faculty of Engineering, European University of Lefke, Lefke, Northern Cyprus

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Abstract: The clonal selection algorithm (CLONALG) is a nature-inspired metaheuristic algorithm that has been applied to various complex optimization problems from different fields of study. Tournament selection (TS) is a selection operator that is mainly used in genetic algorithms. In this paper, a novel improved clonal selection algorithm by using the TS operator (ICSAT) is introduced. To observe the improvement, ICSAT was first tested on selected benchmark functions and then to validate its efficiency ICSAT was applied to a microstrip coupler design problem. Although showing some disadvantages that generally exist in all modified algorithms, it is observed that ICSAT has a significant improvement on the performance of CLONALG and can be a good candidate for real case optimization problems.

Key words: Clonal selection algorithm, improved metaheuristics, microstrip coupler design, tournament selection operator, optimization

1. Introduction

Over the last few decades, artificial immune systems and their applications have been preferred by many researchers from different fields of research areas [1–5]. The clonal selection algorithm (CLONALG) is a subfield of artificial immune systems that mimics the immune system of an organism in the way of antibodies reacting to an intruding antigen [5,6]. CLONALG was initially proposed to solve pattern recognition tasks by De Castro and Von Zuben [7]. After that, it was adapted to optimization tasks from various fields [8–11]. However, there is no algorithm that performs superiorly for all types of problems. Some optimization algorithms produce better results for some problems, while performing unsatisfactorily for others [12]. Instead of introducing new algorithms for optimization problems, applying certain modifications to the algorithms or their hybrid versions according to given problems may produce better results [13–17].

In this paper, tournament selection (TS), which is generally preferred in genetic algorithms as a selection operator [18,20], is used to improve the performance of the standard CLONALG. Due to its ease of implementation and efficiency, TS has a wide range of applications that can be accommodated via optimization algorithms [16,19,21]. As another advantage, TS increases the diversity by giving an opportunity to all members in the population to be selected. The main drawback of TS is that because of consideration of all individuals, convergence speed may be decreased. In this paper, improvements are done on crucial steps of CLONALG, which are selection and mutation processes. In CLONALG, the antibodies that have inadequate affinity values

*Correspondence: eulker@eul.edu.tr

are discarded from the population and are selected according to their affinity values. In ICSAT, selection and mutation processes are handled by the TS operator. The antibodies that have inadequate affinity values are considered, which avoids loss of performance caused by elimination of antibodies. A performance comparison test for ICSAT and CLONALG is first studied on benchmark functions, and then the performance of ICSAT is validated for the design of a microstrip coupler. A microstrip coupler circuit design problem is used to demonstrate the performance and effectiveness of the ICSAT algorithm. Using graphical results and formulas, the design of microstrip couplers, which is known as a complex and nonlinear problem with three variables, can be achieved to a certain extent. However, with the aid of optimization algorithms, the dimensions of the structure are optimized and more precise values can be obtained, which leads to better performance.

The rest of the paper is organized as follows: Section 2 gives the details of the standard clonal selection algorithm (CLONALG) and the improved version of it by using the TS operator (ICSAT). Section 3 presents performance analysis results of CLONALG and ICSAT on selected benchmark functions. Section 4 proposes a real case problem for designing a microstrip coupler and the results obtained by ICSAT. In section 5, the concluding remarks are given.

2. Evolutional and computational aspects of the standard CLONALG and ICSAT

Clonal selection theory was derived from Darwin's theory and contains the major steps of evolution, such as diversity, genetic variation, and natural selection [22]. The main aim of evolution is to improve the ability of an organism to survive and to adapt to a challenging environment [23]. The standard CLONALG was originally proposed by De Castro and Von Zuben in 2000 by mimicking the adaptive immune system [7].

When any organism is invaded by an antigen (Ag), bone-marrow cells (*B lymphocytes*) produce antibodies (Abs). Abs are aimed to recognize Ags and to bind to them. Each *B lymphocyte* cell produces a unique type of Ab that is also specific for the Ag. After that, with a signal from the T-helper cells, the Ag activates the *B lymphocytes* to divide (proliferate) and to transform (differentiate) into plasma cells. The cell division process generates clones and *B lymphocytes* can also transform into long-lived B memory cells. The B memory cells are located in the blood, tissues, and lymph. When the organism is exposed to the same antigen again, high affinity Abs can be produced. CLONALG steps are constructed according to the clonal selection theory in Figure 1.

Step 1: Initialization of a set of antibodies (Ab) by B lymphocyte cells.
Step 2: Definition of the objective function, antigen (Ag), that is needed to be optimized.
Step 3: Calculation of affinity values for each Ab.
Step 4: Selecting *n* number of Abs from the best affinity values.
Step 5: Cloning the Abs proportionally to their affinity values (Proliferating).
Step 6: Selecting *n* number of Abs from the best affinity values and applying a mutation proportionally according to their affinity values (Differentiating).
Step 7: Recalculation of affinity values for new mutated Abs.
Step 8: Introducing new *n* number of Abs to the population by discarding *n* number of the worst affinity elements.
Step 9: Repeat steps 3-8 until a stopping criterion is met.

Figure 1. Steps of CLONALG.

As in all evolutionary algorithms, the selection operator plays a crucial role in CLONALG. Researchers pay attention to the importance of selection operators for the performances of evolutionary algorithms [24–27]. Tournament selection (TS) is used as a selection operator for CLONALG, which is aimed at improving the performance of the algorithm. TS is generally preferred as a selection operator in a genetic algorithm and it increases the diversity by giving a probability to all individuals to be selected in the population. The major steps of the TS operator are as follows:

- In TS, the group size (G_{size}) should be initialized where $G_{size} < N$ (population size).
- The TS operator selects the G_{size} number of individuals randomly among the N number of individuals, compares the individuals, and selects the winner for the next generation.

When the TS operator is used with high selection pressure in which G_{size} is selected as a very big number, diversity will decrease, but convergence speed will increase [16], and vice versa. For $G_{size} = N$, the best individual will be selected at each time. For $G_{size} = 1$, each member in the population has the same probability to be selected. According to Darwin's rule of evolution theory, the best individuals have higher probability rates to survive. Because of this theory, G_{size} is not selected as 1. In this paper, different values of G_{size} are selected and the effect of selection pressure on the performance of ICSAT is observed.

In CLONALG, the selection process is expressed as selecting n number of best affinity elements from the population (N). Selection among the best ones will lead to faster convergence. It is assumed that elimination of an antibody that has the worst affinity avoids premature convergence, and introducing new random antibodies increases diversity. However, introducing new random antibodies to the population may cause low convergence. In CLONALG, when the antibody that has the worst affinity is eliminated from the population, some desired attributes of it are eliminated as well.

ICSAT aims to preserve the desired attributes of antibodies that are discarded from the population. Antibodies are selected not only from the best affinity elements, but from all the elements in the population. The TS operator handles the selection and mutation processes. G_{size} number of antibodies is selected randomly from the population and the winners of the tournament are considered for the next generation. An antibody that is selected by the TS operator can be selected again for the next generation. This may decrease the diversity but, since the antibody is the winner of the tournament, the convergence speed may increase. G_{size} affects the performance of ICSAT, which is directly related to selection pressure. Selection pressure drives natural selection, which is defined as any organism's particular characteristics being either eliminated or surviving. When particular characteristics of organisms are against the conditions, then they are not passed on to the next generation. According to the TS operator used in ICSAT, the randomly selected G_{size} number of individuals compete against each other and the characteristics of the winners are preserved for the next generation. Also, in ICSAT, a common mutation rate is applied to the winners. The next generation's characteristics change according to the environmental conditions and the survival rate of the population increases.

During the mutation process, a common mutation rate is applied to the antibodies that are selected by TS. In the original algorithm, after the mutation process, nonstimulated antibodies are discarded from the population and new antibodies are added randomly. In ICSAT, nonstimulated antibodies are selected by TS and a common mutation rate is applied to the winners of the tournament. It is aimed to keep their potentials within the population by applying a small rate of mutation without introducing new antibodies. Replacement is performed if the mutated antibodies are better than unmutated ones. The detailed steps of ICSAT and the differences between the algorithms are given in Figure 2. Improvements on the main processes of CLONALG are shown in italics in Figure 2.

3. Experimental results and discussion

3.1. Testing with benchmark functions

ICSAT is applied to five selected benchmark functions to observe its performance. The selected benchmark functions are shown in Table 1 and they are classified as unimodal and multimodal. In a multimodal benchmark

Step 1: Initialization of a set of antibodies (Ab) by B lymphocyte cells.
Step 2: Definition of the objective function, antigen (Ag), that is needed to be optimized.
Step 3: Calculation of affinity values for each Ab.
Step 4: *Competition of randomly selected G_{size} number of Abs from the population and keeping the winner for the next generation.*
Step 5: *Selecting G_{size} number of Abs randomly from the population and applying a mutation to the winners of the tournament.*
Step 6: Recalculation of affinity values for new mutated antibodies.
Step 7: *Selecting G_{size} number of Abs randomly among the n number of the worst affinity values and applying an equal mutation rate to the winners of the tournament.*
Step 8: *Replacing the Abs if the affini ty value of the mutated Ab is better than the affinity value of the same Ab that is not mutated.*
Step 9: Repeat steps 3-8 until a stopping criterion is met.

Figure 2. Steps of ICSAT.

problem, many local optimum points exist. Therefore, the final result obtained by the algorithm is crucial for the algorithm. In a unimodal benchmark function, since there is only one optimum point, the convergence rate is a distinguishing characteristic for the algorithm.

Table 1. Benchmark functions selected for experiments.

Function name	Characteristic	Function expression	Range	Optimum point
Sphere	Unimodal	$\sum_{i=1}^{D} x_i^2$	[–100, 100]	0
Rosenbrock	Unimodal	$\sum_{i=1}^{D}\left[100\left(x_{i+1}-x_i^2\right)^2 + (x_i-1)^2\right]$	[–30, 30]	0
Schwefel	Multimodal	$\left[\sum_{i=1}^{D} -x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)\right]$	[–500, 500]	–12,569.5
Rastrigin	Multimodal	$\sum_{i=1}^{D}\left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$	[–5.12, 5.12]	0
Ackley	Multimodal	$\left[-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e\right]$	[–32, 32]	0

The experimental results are given as average and best value of a function. The values are collected over 30 independent runs. The number of the population (N) is fixed to 100 and the dimension (D) is set to 30. The algorithms were simulated using Windows 7 on an Intel i5 processor with 4 GB of RAM using the C++ language. Stopping criteria are selected as a fixed number of iterations. In order to observe the effects of modifications, different numbers of iterations are applied to CLONALG and ICSAT. For the proposed algorithm ICSAT, the population size for TS (G_{size}) is selected as 5 and 15 by observational experiments. In Tables 2–6 average and best results obtained by CLONALG and ICSAT with different G_{size} values for TS are given. In general, CLONALG and its improved algorithm ICSAT are capable of finding the optimum points of given functions. Even for 5000 iterations, the algorithms converge or reach the global optimum points for almost all benchmarks.

Experimental results of the sphere function are shown in Table 2, and the convergence graph of average affinity values is plotted in Figure 3. It is observed that the proposed algorithm ICSAT is capable of finding the optimum point. When the population size (G_{size}) for TS is selected as 15, ICSAT performs well. However, in terms of solution quality, CLONALG performs slightly better than ICSAT (15).

Table 2. Experimental results of the sphere function.

Number of iterations		CLONALG	ICSAT (5)	ICSAT (15)
5000	Best	117.79E-10	10,872.1	259.5E-4
	Avg.	124.9E-9	12,523.7	352.4E-3
10,000	Best	1.16E-24	8562.9	118.9E-11
	Avg.	1.95E-23	9920.9	126.73E-10
50,000	Best	6.25E-44	0.23E-11	2.15E-39
	Avg.	0.89E-42	1.95E-10	3.24E-38
100,000	Best	1.03E-62	0.02E-24	0.11E-43
	Avg.	0.512E-60	4.23E-23	3.82E-40

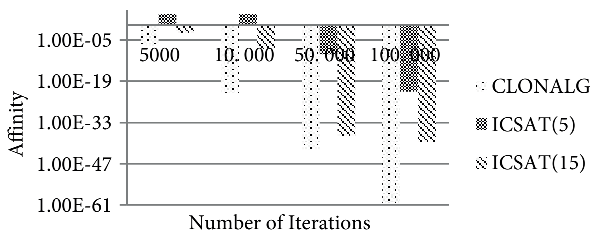

Figure 3. Convergence graph for sphere function.

Table 3 shows the experimental results of the Rosenbrock function. Average affinity values obtained by the algorithms are shown in Figure 4. It can be found that after 50,000 iterations, the algorithms converge to the global optimum point, but considering the solution quality, ICSAT (15) performs better than CLONALG.

Table 3. Experimental results of the Rosenbrock function.

Number of iterations		CLONALG	ICSAT (5)	ICSAT (15)
5000	Best	9.27	18.3	8.49
	Avg.	17.85	29.7	13.49
10,000	Best	5.02	8.24	0.0034
	Avg.	15.24	14.8	2.38
50,000	Best	3.81E-10	1.7E-4	2.44E-11
	Avg.	19.7E-8	0.031	3.27E-9
100,000	Best	1.27E-19	9.75E-6	0.79E-26
	Avg.	4.78E-15	0.29E-4	1.48E-23

The results for the Schwefel function are given in Table 4, and average affinity values for each algorithm are shown in Figure 5. As the final results show in Table 4, all algorithms reached the global optimum point. However, CLONALG reached the global optimum point faster than ICSAT. For this multimodal function, the performance of ICSAT for a low number of iterations is not satisfactory, but after 50,000 iterations, the global optimum point of Schwefel is found.

The experimental results of the Ackley function are given in Table 5. The convergence graph of average affinity values for the algorithms is shown in Figure 6. Even after 5000 iterations, all algorithms converged to

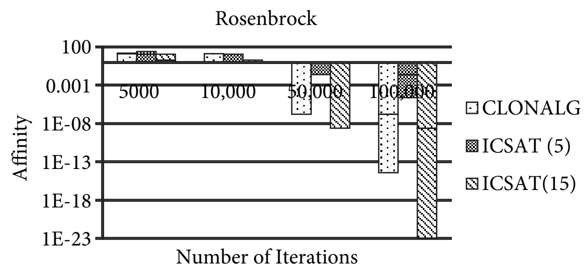

Figure 4. Convergence graph for Rosenbrock function.

Table 4. Experimental results of the Schwefel function.

Number of iterations		CLONALG	ICSAT (5)	ICSAT (15)
5000	Best	0.376E-6	0.12E-4	0.75E-10
	Avg.	1.487E-5	0.079	0.00609
10,000	Best	–12,569.5	–4697.8	6.48E-6
	Avg.	–12,569.7	–3249.6	7.597E-6
50,000	Best	–12,569.5	–12,569.5	–12,569.5
	Avg.	–12,569.5	–11,442.9	–12,569.5
100,000	Best	–12,569.5	–12,569.5	–12,596.5
	Avg.	–12,569.5	–12,569.5	–12,569.5

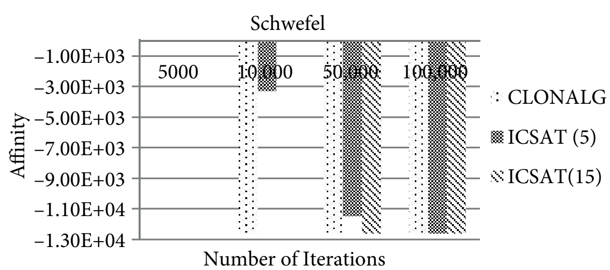

Figure 5. Convergence graph for Schwefel function.

this function's global optimum point. In terms of solution quality, ICSAT (15) produces much better results than the standard algorithm.

Table 5. Experimental results of the Ackley function.

Number of iterations		CLONALG	ICSAT (5)	ICSAT (15)
5000	Best	2.49E-5	0.24E-3	0.38E-11
	Avg.	8.59E-4	0.1147	0.464E-9
10,000	Best	1.21E-12	1.36E-7	0.12E-31
	Avg.	6.78E-12	8.38E-5	0.124E-29
50,000	Best	9.47E-16	1.44E-16	5.49E-42
	Avg.	3.23E-14	1.44E-16	6.29E-40
100,000	Best	0.29E-23	1.44E-16	0.075E-43
	Avg.	1.12E-20	1.44E-16	1.289E-40

In Table 6, experimental results for the Rastrigin function are given. According to the convergence graph shown in Figure 7, after 50,000 iterations, CLONALG and ICSAT (5) converge to the global optimum point

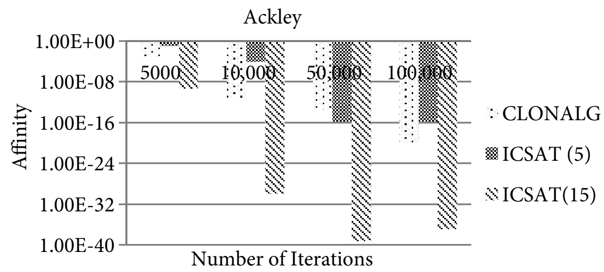

Figure 6. Convergence graph for Ackley function.

of the Rastrigin function. It can be seen from Table 6 that in terms of solution quality ICSAT (15) performs better than the others.

Table 6. Experimental results of the Rastrigin function.

Number of iterations		CLONALG	ICSAT (5)	ICSAT (15)
5000	Best	9.84	8.72	0.11E-3
	Avg.	11.04	15.21	0.0241
10,000	Best	6.23	5.48	2.67E-5
	Avg.	9.72	11.38	3.45E-4
50,000	Best	0.027	0.0032	0.65E-12
	Avg.	0.042	1.98	1.28E-8
100,000	Best	0.49E-28	1.52E-20	0.37E-32
	Avg.	8.51E-23	7.38E-18	7.45E-29

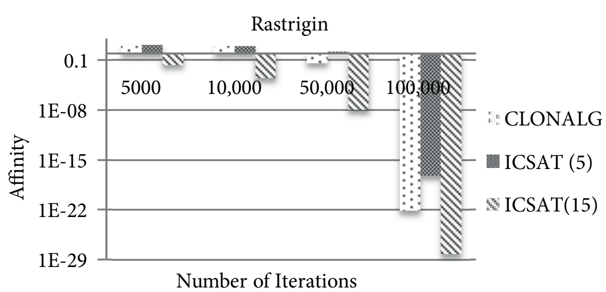

Figure 7. Convergence graph for Rastrigin function.

Considering all experimental results obtained by the algorithms, it can be concluded that the proposed algorithm ICSAT is capable of finding optimum points of different characteristics of given benchmark functions that can be optimized by the standard CLONALG. When the comparison results obtained by ICSAT (5) and CLONALG are studied, for all benchmark functions, the solution quality of CLONALG is better than the solution quality of ICSAT (5). It is also found that selecting the tournament group size (G_{size}) is directly related to the performance of the algorithm. When the results of ICSAT (5) and ICSAT (15) were analyzed, both of them obtained optimum points or approached the optimum points of benchmark functions. However, in terms of convergence rate, ICSAT (15) outperformed ICSAT (5).

ICSAT aimed to outperform CLONALG by modifying the main operators of CLONALG using the TS operator; according to the results, except for the sphere function, the solution quality of ICSAT (15) is better than the solution quality of CLONALG. It is also seen that ICSAT (15) provides better results, except for the

Schwefel function in the early stages of optimization. However, in the later iterations, ICSAT (15) has the same solution quality as CLONALG for the Schwefel function.

It is worth noting that according to the no free lunch theorem [12], an algorithm does not exist that outperforms for all problems. In modified algorithms, suppression of undesired characteristics or improvement of desired characteristics may provide some advantages and disadvantages. Therefore, as in all modified algorithms, our proposed algorithm ICSAT (15) has its own advantages and disadvantages according to given problems to be solved.

3.2. Optimizing the microstrip coupler

The proposed algorithm ICSAT is adapted to a microstrip coupler design problem to test its effectiveness in practical applications. Directional couplers are passive microwave components that are usually used for either power combining or power division. The design of a microwave microstrip coupler circuit using particle swarm optimization was studied in [28]. Similar work for the design of a hybrid coupler using a jumping gene evolutionary algorithm was demonstrated in [29]. The structure of a microstrip coupler can be designed by using two parallel unshielded transmission lines with width w and spacing s that are fabricated on a grounded dielectric substrate with thickness H. The power can be coupled between these lines due to the interaction of electromagnetic fields of each transmission line [30]. This is demonstrated in Figure 8.

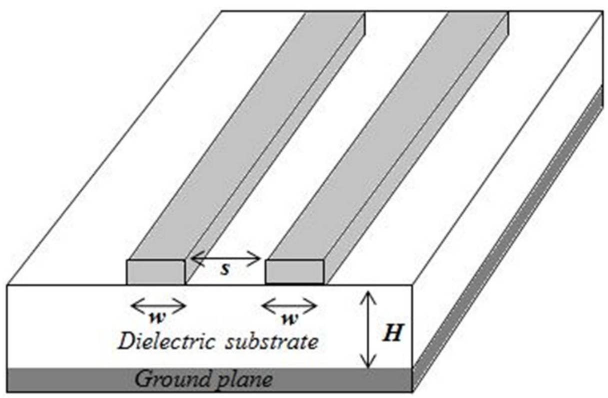

Figure 8. 3D view of a microwave microstrip coupler.

Mathematical models that represent the coupling between the transmission lines have been analyzed and refined over the years. They are based on the equations derived by Akhtarzad et al. [31]. The coupling value is directly related to finding the optimum values of w, s, and H for a given substrate with known dielectric constant (ε_r). The objective function, which is the coupling 'C', can be computed with a series of steps. First, the ratio of w to H for even and odd mode values (valid for substrate dielectric constant values less than 6) can be determined as follows, respectively:

$$\frac{w}{H}_{se} = \frac{2}{\pi}\cosh^{-1}\left(\frac{2h-g+1}{g+1}\right) \tag{1}$$

$$\frac{w}{H}_{so} = \frac{2}{\pi}\cosh^{-1}\left(\frac{2h-g-1}{g-1}\right) + \frac{4}{\pi\left(1+\varepsilon_r/2\right)}\cosh^{-1}\left(1+2\frac{w/H}{s/H}\right) \tag{2}$$

$$g = \cosh\left(\frac{1}{2}\pi\left(s/H\right)\right) \tag{3}$$

$$h = \cosh\left(\pi\left(w/H\right) + \frac{1}{2}\pi\left(s/H\right)\right). \tag{4}$$

After the computation, even mode (Z_{oe}) and odd mode (Z_{oo}) impedances of the transmission line can be obtained by using the w to H ratio for even and odd modes respectively in the equation below:

$$Z_o = \frac{120\pi\left(1/\varepsilon_r\right)^{1/2}}{\left(w/H\right)_s + 0.882 + \left(\left(\varepsilon_r+1\right)/\left(\pi\varepsilon_r\right)\right) \bullet \left(\log_e\left(\left(\frac{w}{H}\right)_s + 1.88\right) + 0.758\right) + 0.164\left(\left(\varepsilon_r - 1\right)/\varepsilon_r^2\right)}. \tag{5}$$

In the design problem, a substrate with a dielectric constant value of 3.9 (which shows the permittivity characteristic of the substrate) is used, which means that the above equations are valid for this design. According to the obtained values Z_{oe} and Z_{oo}, the coupling coefficient C can be calculated as follows:

$$C = \frac{Z_{oe} - Z_{oo}}{Z_{oe} + Z_{oo}} \tag{6}$$

In the design problem, the coupling coefficient value is set to 0.2. Thirty independent sets of variables are generated, which in turn provide the values of the coupling coefficient C. G_{size} for the TS operator is selected as 15 and the number of the population is fixed to 100. In the algorithm, it is also restricted that the even mode (Z_{oe}) and odd mode (Z_{oo}) impedance values are to be between 15 Ω and 90 Ω as an extra optimization criterion. The obtained final results are used in a simulator to test the operation of the coupler.

Different sets of values that satisfy the given criteria are obtained by ICSAT for the design of the coupler. Among these values, two samples are selected and simulated in the Puff Microwave Simulator [32] to show the coupling coefficient. Sample values are provided in Table 7, and the coupling coefficient with frequency graph is given in Figure 9.

Table 7. Sample design values of coupler by ICSAT.

	w (mm)	s (mm)	H (mm)	Z_{oe} (Ω)	Z_{oo} (Ω)	C
Sample 1	11.871	3.414	7.5	70.33	46.88	0.19569
Sample 2	13.013	2.410	6.5	60.91	40.61	0.19888

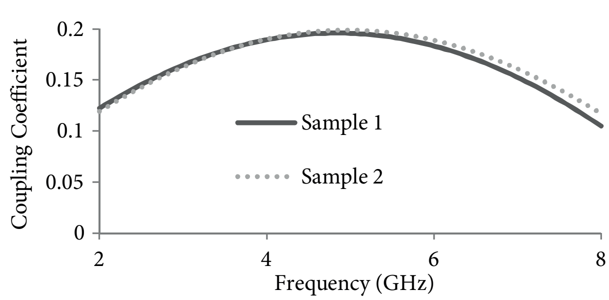

Figure 9. Frequency responses of two different samples of coupled lines.

As seen for both sample design values, the desired coupling is obtained at the design frequency of 5 GHz. For the first sample, the deviation from 0.2 is about 0.00431, which corresponds to 2.155% and is obtained in 10 iterations. For the second sample, the deviation from the desired value of 0.2 is about 0.00112, which corresponds to 0.56% and is obtained in 15 iterations. For real case optimization problems especially, the time required to optimize the problems is a distinguishing characteristic for the algorithms. Design values gathered by ICSAT are indications of an algorithm that performs well for real case optimization problems with a smaller number of iterations.

4. Conclusion

In this paper, a novel and improved clonal selection algorithm with a tournament selection operator, ICSAT, is proposed. Its efficiency is first tested with different characteristics of benchmark functions. Then it is applied to the microstrip coupler design problem. Modified algorithms generally produce better results because of the suppression of undesired characteristics or modification of main operators. As expected, the results denote that the modifications on the main processes by tournament selection operator provide good performance in terms of solution quality with a smaller number of iterations. The ICSAT algorithm is able to provide high solution quality even in the early stages of optimization. For almost all benchmark functions, even in 5000 iterations, ICSAT starts to converge to optimum points earlier than CLONALG. It is also seen that ICSAT obtained the desired coupling values of the microstrip coupler design problem in less than 20 iterations. The time required for optimization is crucial, especially for real case problems. Furthermore, the steps of ICSAT are quite easy to implement and it can be used as an effective optimization tool for real case optimization problems.

However, it is worth noting that the proposed algorithm has its own limitations. The ICSAT algorithm uses the potential of all antibodies in the population without elimination and without introducing new random antibodies. This causes low convergence for some benchmark problems, and it is avoided by increasing the population size (G_{size}) used for the tournament selection operator. G_{size} is the main control parameter of ICSAT that affects the performance of the algorithm. For future work, performance analysis can be done by changing the population size of the tournament selection operator.

References

[1] Dasgupta D. An Overview of Artificial Immune Systems and their Applications. Berlin, Germany: Springer, 1993.

[2] Harmer PK, Williams PD, Gunsch GH, Lamont GB. An artificial immune system architecture for computer security applications. IEEE T Evolut Comput 2002; 63: 252-280.

[3] Timmis J, Neal M, Hunt J. An artificial immune system for data analysis. Biosystems 2000; 55: 143-150.

[4] Dasgupta D, Forrest S. Artificial immune systems in industrial applications. In: Intelligent Processing and Manufacturing of Materials, Proceedings of the Second International Conference; 1999. New York, NY, USA: IEEE. pp. 257-267.

[5] De Castro LN, Timmis J. Artificial immune systems: a novel paradigm to pattern recognition. Lect Notes Com Sci 2002; 67-84.

[6] De Castro LN, Von Zuben FJ. Learning and optimization using the clonal selection principle. IEEE T Evolut Comput 2002; 6: 239-251.

[7] De Castro LN, Von Zuben FJ. The clonal selection algorithm with engineering applications. In: Proceedings of GECCO; 2000. pp. 36-39.

[8] Babayigit B, Akdagli A, Guney K. A clonal selection algorithm for null synthesizing of linear antenna arrays by amplitude control. J Electromagnet Wave 2002; 20: 1007-1020.

[9] Gao S, Dai H, Yang G, Tang Z. A novel clonal selection algorithm and its application to traveling salesman problem. IEICE T Fund Electr 2007; 90: 2318.

[10] Deniz E, Ülker S. Clonal selection algorithm application to simple microwave matching network. Microw Opt Techn Let 2011; 53: 991-993.

[11] De Castro LN, Von Zuben FJ. An evolutionary immune network for data clustering. In: Neural Networks, 2000, Proceedings of Sixth Brazilian Symposium; 2000. pp. 84-89.

[12] Wolpert DH, Macready WG. No free lunch theorems for optimization. IEEE T Evolut Comput 1997; 1: 67-82.

[13] Shangce G, Wei W, Fangjia L, Zheng T. Improved clonal selection algorithm combined with ant colony optimization. IEICE T Inf Syst 2008; 91: 1813-1823.

[14] Atay Y, Kodaz H. Optimization of job scheduling problems using modified clonal selection algorithm. Turk J Electr Eng Co 2014; 22: 1528-1539.

[15] Dandy GC, Simpson AR, Murphy LJ. An improved genetic algorithm for pipe network optimization. Water Resour 1996; 32: 449-458.

[16] Li G, Wang Q, Du Q. Improved harmony search algorithms by tournament selection operator. In: IEEE Congress on Evolutionary Computations; 2015. pp. 3116-3123.

[17] Liu B, Wang L, Jin YH, Tang F, Huang DX. Improved particle swarm optimization combined with chaos. Chaos Soliton Fract 2005; 25: 1261-1271.

[18] Blickle T, Thiele L. A mathematical analysis of tournament selection. In: Proceedings of the 6th International Conference on Genetic Algorithms; 15–19 July 1995. pp. 9-16.

[19] Miller BL, Goldberg DE. Genetic algorithms, tournament selection, and the effects of noise. Complex Systems 1995; 9: 193-212.

[20] Blickle T. Tournament selection. Evol Comput 2000; 1: 181-186.

[21] Qu BY, Suganthan PN. Novel multimodal problems and differential evolution with ensemble of restricted tournament selection. In: IEEE Congress on Evolutionary Computation; 2010. pp. 1-7.

[22] Cziko G. Without Miracles: Universal Selection Theory and the Second Darwinian Revolution. Cambridge, MA, USA: MIT Press, 1995.

[23] Engelbrecht AP. Computational Intelligence: An Introduction. New York, NY, USA: John Wiley & Sons, 2007.

[24] Bäck T. Selective pressure in evolutionary algorithms: a characterization of selection mechanisms. In: IEEE World Congress on Computational Intelligence, Proceedings of the First IEEE Conference on Evolutionary Computation; 1994. pp. 57-62.

[25] Blickle T, Thiele L. A comparison of selection schemes used in evolutionary algorithms. Evol Comput 1996; 4: 361-394.

[26] Bäck T, Hoffmeister F. Extended selection mechanisms in genetic algorithms. In: Proceedings of the 4th International Conference on Genetic Algorithms; 1991.

[27] Hancock PJ. An empirical comparison of selection methods in evolutionary algorithms. In: Fogarty TC, editor. Evolutionary Computing. Berlin, Germany: Springer, 1994. pp. 80-94.

[28] Ulker S. Particle swarm optimization to microwave circuits. Microw Opt Techn Let 2008; 50: 1333-1336.

[29] Zheng SY, Yeung SH, Chan WS, Man KF, Tang KS. Design of broadband hybrid coupler with tight coupling using jumping gene evolutionary algorithm. IEEE T Ind Electron 2009; 56: 2987-2991.

[30] Pozar DM. Microwave Engineering. 4th ed. New York, NY, USA: John Wiley & Sons, 2011.

[31] Akhtarzad S, Rowbotham TR, Johns PB. The design of coupled microstrip lines. IEEE T Microw Theory 1975; 6: 486-492.

[32] Wedge SW, Compton RC, Rutledge DB, Gerstlauer A. Puff: Computer Aided Design for Microwave Integrated Circuits, Version 2.1. Pasadena, CA, USA: California Institute of Technology, 1998.