Continuous CLA-EC

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***Abstract*—Standard CLA-EC which is introduced recently is an evolutionary computing model obtained by combining cellular learning automata (CLA) model and evolutionary computing (EC) model. Some drawbacks of this model are low convergence speed and low accuracy for some optimization problems. In this paper a new version of CLA-EC called Continuous Action Set CLA-EC or in short Continuous CLA-EC is proposed. In this new version, the finite action set learning automaton in each cell is replaced by a continuous action set learning automaton. To show the effectiveness of the proposed model it is tested on some function optimization problems. The results of experimentations have shown that the proposed Continuous CLA-EC comparing to standard CLA-EC has both higher accuracy and speed of convergence.**

Keywords—CLA-EC; Continuous CLA-EC; Evolutionary Algorithm; Cellular Learning Automata; Continuous Action Set Learning Automata; Optimization.

I. INTRODUCTION

Evolutionary Algorithms (EA) are inspired by Darwin's theory of natural evolution. In nature, the better species are evolved by means of natural selection and random variation. EAs follow this approach and simulate the natural selection and variation to evolve a better solution to a problem. Both selection and variation have their distinct role in EA evolution. Selection puts pressure on evolution of high quality solutions by selecting more suitable solutions from a population of solutions. Variation reproduces the next generation of population based on the selected more suitable solutions, and ensures the proper exploration of possible set of solutions. EAs are general–purpose non–linear optimization techniques and relatively easy to parallelize and to combine with existing optimization techniques and heuristics. Advantages such as these make EAs into attractive optimization algorithms.

Evolutionary computation (EC) uses iterative progress, such as growth or development in a population. This population is then selected in a guided random search to achieve the desired end. they are often applied to optimization problems where specialized techniques such as gradient based algorithms, linear programming, dynamic programming are not available or standard methods fail to give reasonable answers due to multimodality, non-differentiability or discontinuity of the problem at hand [1]. Evolutionary computation can be done in parallel. The basic idea behind most parallel EAs (PEA) is to divide their tasks into chunks and then solve the chunks simultaneously using multiple processors. This divide-and-conquer approach can be applied to EAs in many different ways, and the literature contains many examples of successful parallel implementations. There are four main types of parallel EAs: global single-population master-slave EAs, single-population fine-grained PEA, multiple-population coarse-grained EAs and hierarchical combinations [2]. More information about fine-grained PEAs can be found in [3][4][5].

Cellular learning automata (CLA) [6] which is introduced recently is a combination of the cellular automata (CA) [7] and learning automata (LA) [8]. CLA consists of a large number of simple components. The simple components of CLA which have learning capabilities, act together to solve a particular problem. The basic idea of CLA is to use learning automata to adjust the state transition probability of stochastic CA. In [9][10] A Fine Grained Evolutionary Algorithm based on Cellular Learning Automata called standard CLA-EC are reported. Standard CLA-EC is obtained by combining cellular learning automata (CLA) model and the evolutionary computing model. More information about Standard CLA-EC can be found in [10].

Some drawbacks of standard CLA-EC are low convergence speed and low accuracy for some optimization problems and using high number learning automata. In this paper a new version of CLA-EC called continuous CLA-EC or in short CCLA-EC is proposed. In this new version, the finite action set learning automaton (FALA) in each cell is replaced by a continuous action set learning automaton (CALA) [11][12][13]. For an r-action FALA, the action probability distribution is represented by an r-dimensional probability vector that is updated by the learning algorithm. For CALA, the action probability distribution is represented by a continuous function and this function is updated by learning algorithm at any stage. In standard CLA-EC, if the string genome contains of d gene then a problem with p parameters needs $p*d$ gene each of which assigned a finite action set learning automata (FALA). Therefore in total for a CLA-EC with n cell we need $n*p*d$ learning automata whereas in continuous CLA-EC, a problem with p parameters needs

only *n*p* learning automata. That is, in continuous CLA-EC for encoding each parameter of the problem we need just one CALA whose actions are chosen from real line. To show the effectiveness of continuous CLA-EC it is tested on some function optimization problems. The results of experimentations have shown that the proposed CCLA-EC comparing to standard CLA-EC has both higher accuracy and speed of convergence.

The rest of this paper is organized as follows. Section 2 briefly describes learning automata, cellular automata and cellular learning automata. Section 3 describes standard CLA-EC. Section 4 introduces the proposed CCLA-EC. The experimental results are given in Section 5. Section 6 is the conclusion.

II. Learning Automata, Cellular Automata and Cellular Learning Automata

In this section learning automata, cellular automata and cellular learning automata are briefly introduced.

A. Learning Automata (LA)

Learning Automata are adaptive decision-making devices that operate on unknown random environments. The LA can find optimal action from action set via interact with environments and improve performance for selecting next optimal action [8]. The LA can be classified into two main groups, Finite Action set Learning Automata (FALA) and Continuous Action set Learning Automata (CALA). More information about FALA can be found in [13]. For CALA, the action probability distribution is represented by a continuous function and this function is updated by learning algorithm at any stage. Like FALA, the CALA also use a probability distribution function to choose an action and the learning algorithm updates this function based on the reinforcement signal [11][12][13]. The action probability distribution at instant α_n is a normal distribution with mean μ_n and standard deviation σ_n. At each instant, the CALA updates its action probability distribution (based on its interaction with the environment) by updating μ_n and σ_n. The objective for CALA is to learn value of α_n at which normal distribution $N(\mu_n, \sigma_n)$ converges to the $N(\alpha^*,0)$ where α^* is optimal action.

B. Cellular Automata (CA)

A Cellular Automata (CA) is an abstract model that consists of a large number of simple identical cells with a local interaction. CA is a non-linear dynamical system in which space and time is discrete. It is cellular, because it is made up cells like points in the lattice or like squares of the checker board and it is automata, because it follows a simple rule. It is especially suitable for modeling natural systems that can be described as massive collection of simple objects locally interacting with each other [7].

C. Cellular Learning Automata (CLA)

Cellular Learning Automata (CLA) which is obtained by combining cellular automata and learning automata is a mathematical model for dynamical complex systems that consists of a large number of simple learning components. Any number of LA can reside in a specific cell. Reinforcement signal for every LA is computed according to CLA rule and actions of other LA residing in neighbor cells. For more information about cellular learning automata the reader may refer to [6].

III. Standard CLA-EC

Cellular learning Automata based evolutionary computing (CLA-EC) is obtained by combining cellular learning automata (CLA) model and evolutionary computing (EC) model [9][10]. In CLA-EC, similar to other evolutionary algorithms, the parameters of the search space are encoded in the form of genomes. Each genome has two components, model genome and string genome. Model genome is a set of finite action set learning automata (FALA). The set of actions selected by this set of learning automata determines the second component of the genome. Using a local rule, a reinforcement signal vector is generated for each cell and given to the set of learning automata residing in that cell. On the basis of the received signal, each learning automaton updates its internal structure according to a learning algorithm. Then, each cell in CLA-EC generates a new string genome and compares its fitness with the fitness of its own string genome. If the fitness of the generated genome is better than the fitness of the string genome of the cell, the generated string genome becomes the string genome of that cell. The process of generating string genome by the cells is repeated until a termination condition is satisfied. For more information about CLA-EC the reader may refer to [9][10].

IV. The Proposed Continuous CLA-EC (CCLA-EC)

In this section, a new version of CLA-EC which we call it continuous CLA-EC (CCLA-EC) will be proposed. In continuous CLA-EC unlike standard CLA-EC which uses finite action set learning automaton (FALA) in each cell, it uses continuous action set learning automaton (CALA) and hence genome strings has real representation rather than binary representation. In this model a set of CALA assigned to each cell of CLA model and each genome has two components, model genome and string genome. Model genome is a set of continuous actions learning automata. The set of actions selected by this set of learning automata determines the second component of the genome. In standard CLA-EC model, if the string genome contains *d* gene then a problem with *p* parameters needs *p*d* gene each of which assigned a finite action set learning automata (FALA). Therefore in total for a CLA-EC with *n* cells we need *n*p*d* learning automata whereas in continuous CLA-EC, a problem with *p* parameters needs only *n*p* learning automata. The architecture of a cell of continuous CLA-EC is shown in Fig.1. Each cell is equipped with m Continuous action set learning automata. The string genome determiner compares the new string genome with the string genome residing in the cell. The string with the higher quality replaces the string genome of the cell. Depending on the neighboring string genomes and the string genome of the cell, a reinforcement signal will be generated by the signal generator. In CCLA-EC model,

search space is Continuous then each string genome made from m CALA.

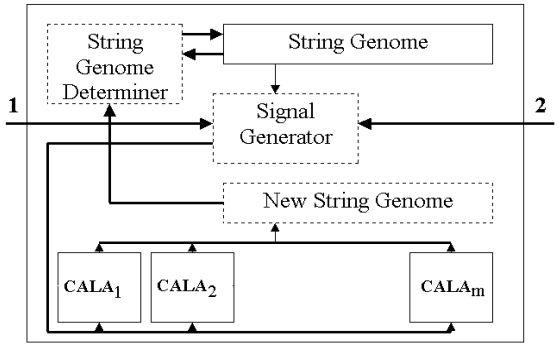

Figure1. The architecture of a cell in the proposed Continuous CLA-EC

Continuous CLA-EC model is iterative and the following steps for each cell *i* will be repeated until the termination criterion is met:

1- Every automaton *j* in cell *i* choose an action. That is, it draws sample $\alpha_n^{i,j}$ from normal distribution ($N(\mu_n^{i,j}, \sigma_n^{i,j})$).

2- Every Cell *i* generates a new string genome, $new^i = \alpha_n^{i,1}\, \alpha_n^{i,2} \ldots \alpha_n^{i,m}$ which is obtained by concatenating the value of actions of automata residing in cell *i* at step *n*.

3- Every cell *i* computes the fitness value *f*(.) of string genome new^i; if the fitness of this string genome is better than the one in the cell (ξ_n^i) then the new string genome new^i becomes the string genome of that cell. That is:

$$\xi_{n+1}^i = \begin{cases} \xi_n^i & f(\xi_n^i) \le f(new_{n+1}^i) \\ new_{n+1}^i & f(\xi_n^i) > f(new_{n+1}^i) \end{cases} \qquad (1)$$

4- Se Cells of the neighboring cells of cell *i* are selected and the set of selected neighbors of cell *i* be shown with $N_{se}(i)$. This Selection is based on the fitness value of the neighboring cells according to a selection strategy.

5- Based on selected neighboring cells, a reinforcement vector is generated. This vector becomes the input for the set of learning automata associated to the cell. $\beta_n^{i,j}$ is computed as follows, (equation 2)

$$\beta_n^{i,j} = \sum_{l \in N_{se}(i)} \left(\frac{w_I(\xi_n^{l,j} - \mu_n^{i,j})}{\sigma_n^{i,j}}\right) \qquad (2)$$

where $\beta_n^{i,j}$ is the reinforcement signal given to learning automaton *j* of cell *i at step n* and the set of selected neighbors of cell *i* be shown with $N_{se}(i)$. w_I is the normalized evaluation signal by Genome of cell i and $\xi_n^{l,j}$ is the action selected learning automaton j of cell i. $\mu_n^{i,j}$, $\sigma_n^{i,j}$ are mean and variance of normal distribution learning automaton *j* of cell i respectively.

6- The parameters of normal distribution of learning automaton *j* of cell *i* is updated using equation (3)

$$\overline{\sigma_{n+1}^i} = \max\{\ \overline{\sigma_n^i} + \sqrt{q * \overline{\sigma_n^i}} * N(0,1), \sigma_{min}\} \qquad (3)$$
$$\mu_{n+1}^{i,j} = \mu_n^{i,j} + \beta_n^{i,j} * \sigma_{n+1}^{i,j}$$

Where, q is set to 5.

The overall operation of Continuous CLA-EC is summarized in the algorithm of **Error! Reference source not found.**.

```
Initialize;
While not done do
   For each cell i in CCLA do in parallel
      Generate a new string genome;
      Evaluate the new string genome;
      If f(new string genome)> f(old string genome) then
         Accept the new string genome;
      End if
      Select Se cells from neighbors of cell i;
      Generate the reinforcement signal vector;
      Update parameters CALAs of cell i;
   End parallel for
End while
```

Figure2. Pseudo code for continuous CLA-EC

V. Simulation Results

This section presents simulation results for different function optimization problems and then compares the Proposed Continuous CLA-EC with Standard CLA-EC [10] and Continuous Genetic Algorithm (GAc) [19]. The Standard CLA-EC used for these simulations has a linear topology with wrap around connection and q cells, neighborhood radius r, the number of selected cells *se* and reward and penalty parameters for updating learning algorithm are set to 0.01 and 0.01. If the radius of neighborhood is one the neighbors of cell i are cell i-1 and cell i+1.

A CCLA-EC completely converges when all CALAs residing in all cells converge, i.e. the population (the set of string genomes residing in cells of CCLA-EC) remains unchanged. Each quantity of the reported results is the average taken over 20 runs. The population size (number of cells) varies from 3 to 47 with increments of four. In Proposed CCLA-EC, For the sake of convenience in presentation, we use CCLA-EC(CALA(θ_s),r,se,q) for refer to CCLA-EC algorithm with q cells, neighborhood radius r, the number of selected cells Se when using the CALA with distribution parameters θ_s. The algorithm terminates when all CALAs converge.

To show the performance of the proposed continuous CLA-EC, we have arranged several benchmark tests for optimization problems. Five benchmark DeJong's functions [16] and other benchmark tests are given in the table1. These functions have been used in order to compare our proposed method with other methods.

CCLA-EC versus Standard CLA-EC and Continuous Genetic Algorithm: To show the performance of CCLA-EC for real-valued function

optimization, we compare it with Standard CLA-EC [10] and GAc [19].

The GAc uses K tournament selection (k=3), arithmetic crossover and Gaussian mutation. Crossover and mutation is applied with probability 0.85 and 0.05 respectively. The parameters of Standard CLA-EC are the same as the parameters used in [10]. Convergence is considered as the termination condition for all algorithms. For CCLA-EC, Se is set to 2 for all test functions with the exception of F3 and set to 3 for function F3.

The results of comparisons are reported in Fig.3 trough Fig.9. For all functions, continuous CLA-EC has a better result than Standard CLA-EC and GAc. The results for functions F1, F2, F5 and F7 are given in log scale in order to see the difference. The obtained Results in Table2 show High accuracy our Proposed Method in Compare with Other Methods in functions Optimization. In total, reported Results indicating the superiority of the proposed algorithm over the Standard CLA-EC and GAc.

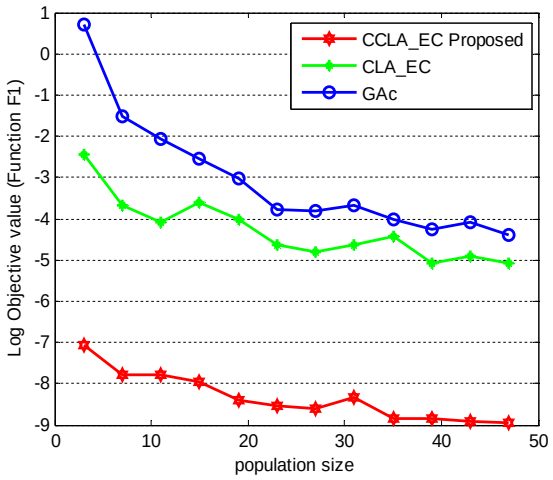

Figure3. Log of Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F1.

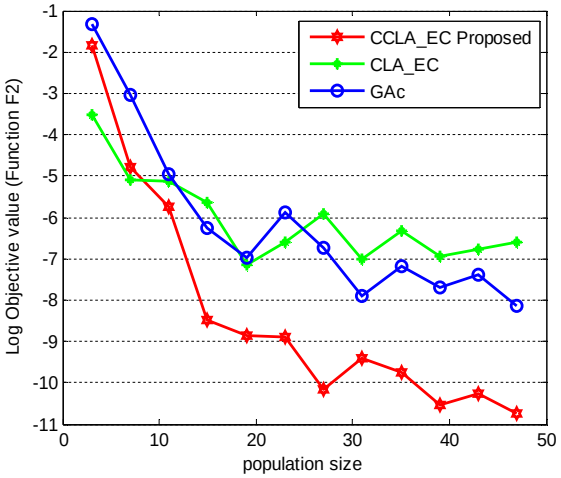

Figure4. Log of Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F2.

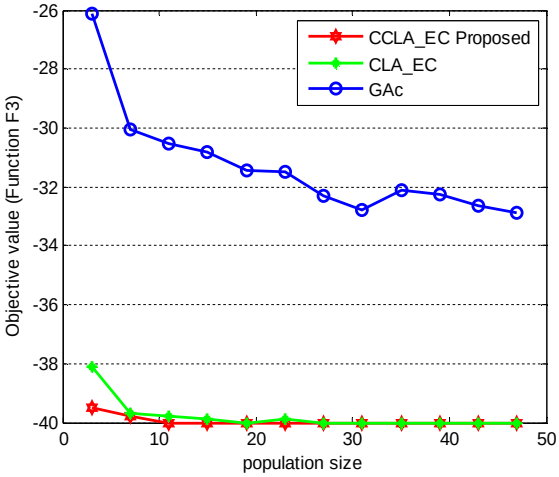

Figure5. Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F3.

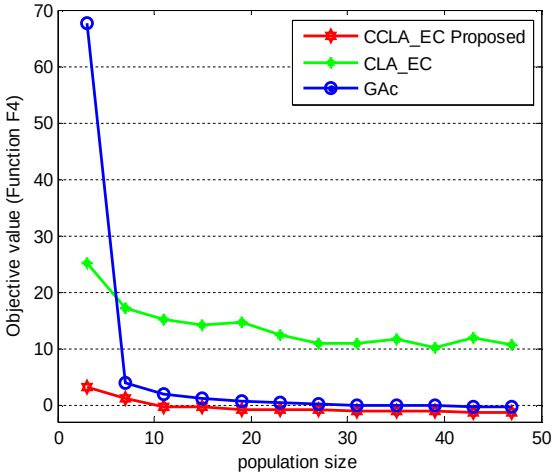

Figure6. Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F4.

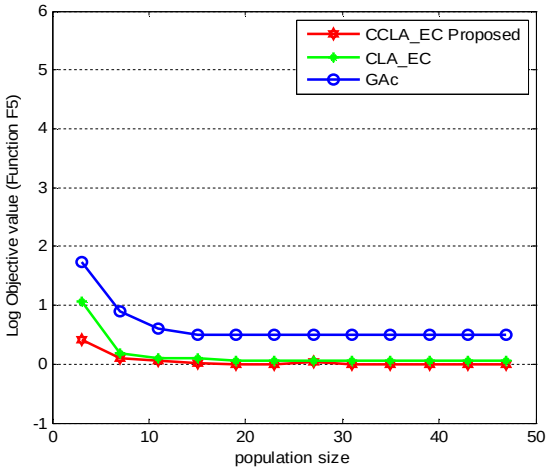

Figure7. Log of Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F5.

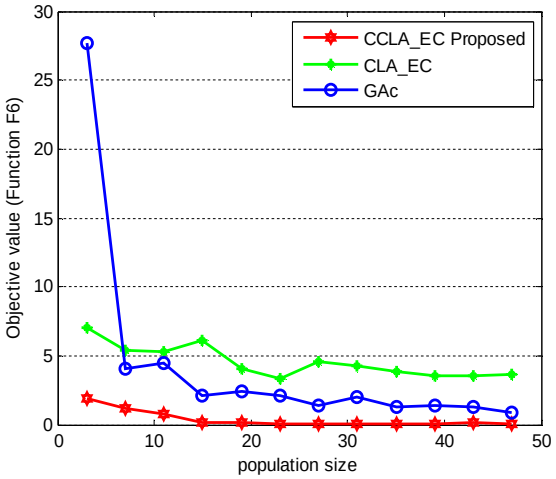

Figure8. Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F6.

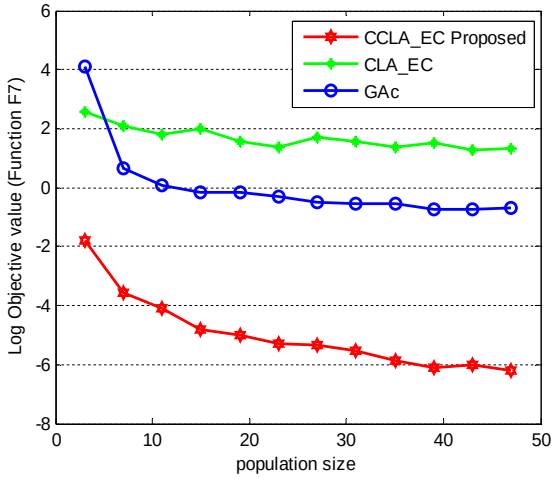

Figure9. Log of Objective value for proposed continuous CLA-EC, Standard CLA-EC and GAc for Function F7.

VI. CONCLUSION

In this paper, a new version of CLA-EC, called continuous CLA-EC obtained from standard CLA-EC in which the finite action set learning automaton in each cell is replaced by a continuous action set learning automaton. The results of experimentations have shown that the proposed CCLA-EC comparing to standard CLA-EC and GAc has both higher accuracy and speed of convergence and also continuous CLA-EC needs fewer numbers of learning automata than standard CLA-EC in almost all cases.

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TABLE I. TEST FUNCTIONS

Sphere model	$\mathbf{F_1(x) = \sum_{i=1}^{n} x_i^2}$	n=3 , -5.12≤ $\mathbf{x_i \leq 5.12}$
Rosenbrock function	$F_2(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + (1 - x_i)^2\right]$;	n=2 , $\mathbf{-2.048 \leq x_i \leq 2.048}$
Step function	$\boldsymbol{F_3(x) = \sum_{i=1}^{n} integer(x_i)}$	n=5 , $\mathbf{-7.12 \leq x_i \leq 7.12}$
Quartic function	$\boldsymbol{F_4}(x) = \sum_{i=1}^{n} ix_i^4 + Gauss(0,1)$	$\boldsymbol{n = 30}$, $\mathbf{-1.28 \leq x_i \leq 1.28}$
Shekel function	$\boldsymbol{F_5}(x) = \left(0.002 + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{n}(x_i - a_{ij})^6}\right)^{-1}$	n=2, $\mathbf{-65.536 \leq x_i \leq 65.536}$
Rastrigin function	$F_6(x) = \sum_{i=1}^{n}\left[\left(x_1 - x_i^2\right)^2 + (x_i - 1)^2\right]$	n=5, $\mathbf{-5.12 \leq x_i \leq 5.12}$
Griewangk function	$F_7 = 1 + \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right)$	n=10, $\mathbf{600 \leq x_i \leq 600}$

TABLE II. OBJECTIVE VALUE

	CCLA-EC Proposed	Standard CLA-EC	GAc
Test Function F1	**9.8606e-009**	0.00987	0.0122
Test Function F2	**3.0792e-009**	9.9565e-004	1.9370e-004
Test Function F3	**-40**	-40	-32.9030
Test Function F4	**-1.8206**	10.2014	-1.2790
Test Function F5	**8.7565e-004**	0.0345	1.2354
Test Function F6	**1.0040e-006**	3.2977	0.9017
Test Function F7	**1.8337e-006**	3.6357	0.04724