THE DESIGN OF NEW LEARNING AUTOMATA FOR PROBLEM GRAPH COLORING

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ABSTRACT. *Graph coloring issue, is one of satisfied existing constraints issues in the literature of artificial intelligence. Coloration apical includes assigning color to node graph so that any two adjacent vertices are isochromatic. The minimum number (colors numbers) that we assign to these graphs for coloring are called number of color. This issue is from the group of very difficult issue, NP – complete. Given the importance of graph coloring issue and its many uses, many algorithms suggested finding allowed coloration in graph. Among these can be noted in, exact algorithms, distributed algorithms, parallel algorithms, approximation algorithms and heuristic algorithms, ...The concept of learning Automata at first was introduced by Tsilyan. He was interested in modeling the behavior of biological systems, and definite automata worked in a random environment, introduced as a model for learning. The aim of this research is to present new algorithm on the basis of learning automata to color with accuracy and high speed and the ability to learn graph vertices. The proposed method also has transfer chart and individual performance and this method was examined on the graph with low vertices and high vertices and medium vertices, on the bottom, a number of works steps and total dyes used for coloring of specific graph with optimization algorithms were matched. Evaluation results show high accuracy, speed and its performance of the proposed method is superior to other optimization methods.*

Keywords: Learning Automata; Reward; Fine; Graph Coloring; Transfer Diagram.

Abbreviation: LA= Learning Automata; GCP= Graph Coloring Problem; GA= Genetic Algorithms; PGAs= Parallel Genetic Algorithms; MVCP= Minimum Vertex Cover Problem.

1. Introduction. In graph theory, coloration graph is one of the special cases, is the issue of labeling of graphs, its general procedures are to use analogous colors to vertices, which this coloration observed special restriction. In the simplest case, a coloration that is desired, in which any two vertices are adjacent (coloration of vertices) which in this case one answer is plausible and to reach to this aim there are various algorithms [1].

The mathematical definition of a graph in order pairs $G = (V, E)$ where V is total of vertices and $E = [v]$ is edge set of graph G which has n vertex and m edge, and we indicated maximum degree of vertices with Δ [5]. Minimum of number (numbers of colors) which we assign to this graph for coloring is called color number of edges and show with $\chi(G)$ [2].

The graph coloring problem can be equivalent to a map with the least number of dyes, as any two adjacent cities in the map are not being equal color. Since it can be considered map geography like an equivalent graph, in the special cases, it can be extended to existing methods in graph theory to it, yet many existing methods in artificial intelligence are used to solve this problem [3].

2. Prior Work. The practical applications of graph coloring problems include, but are not limited to:

1. Map coloring [4]
2. Scheduling [3]
3. Radio frequency assignment [5]
4. Register allocation [6]
5. Pattern matching
6. Sudoku

In related articles demonstrate the use of genetic algorithms in solving the graph-coloring problem while strictly adhering to the usage of no more than the number of colors equal to the chromatic index to color the various test graphs.

A great deal of research has been done to tackle the theoretical aspects of the graph coloring problem in terms of its generalization as a constraint satisfaction problem [7]. The problem's various applications and solutions have been discussed in detail in porumbel's paper [8].

Evolutionary computation and parameter control has been detailed in a number of papers including ones by Back, Hammel, and Schwefel [9] as well as work by Eiben, Hinterding and Michalewicz [10]. Srinivas and Patnaik examined crossover and mutation probabilities for optimizing genetic algorithm performance [11]. Genetic algorithms and evolutionary approaches have been used extensively in solutions for the graph coloring problem and its applications [9, 12].

The concept of utilizing a crowd of individuals for solving NP complete problems has also been the topic of various papers. Most notably the Wisdom of Crowds concept has been used in solving the traveling salesman problem as well as the minimum spanning tree problem [13, 10]. There are generally three approaches to solve the graph coloring problems (GCP) [7-8]:

The first one consists in directly minimizing the number of colors by working in the legal colors space of the problem. In the second approach, the number of colors is fixed and no conflict is allowed, thus, some vertices might not be colored. The objective here is to maximize the number of colored vertices [14, 15]. The third approach consists of first choosing a number of colors K , and then iteratively tries to minimize the number of conflicts for the candidate K .

Whenever a solution with zero conflicts has been found, K is decremented by one and the procedure continues until were each a K where the number of conflicts cannot be equal to zero. As a result, the last legal K will be returned as the best solution [5].

GAs is categorized as global search heuristics and is generally able to find good solutions in a reasonable amount of time.

Common application areas are: scheduling problems [2], graph coloring problems [5], traveling salesman problem, optimization problems [6], and network routing problems for circuit-switched networks, financial marketing, bio-informatics and genomics. GAs is easily parallelized algorithms. PGAs) are parallel implementations of GAs that can provide gain in terms of computational performance and scalability. There exist two major kinds of parallelism in genetic algorithms:

In the computation of the fitness functions of individual and in the application of genetic operators (selection, crossover and mutation). An overview of theoretical advances, computing issues, applications and future trends in parallel genetic algorithms can be found in [12, 15] A more detailed discussion of parallel genetic algorithms can be found in [8]. A general framework for studying and analyzing PGAs was proposed by Alba and Troya [10, 15]. Recently, GAs can be applied for supervised and unsupervised data mining sessions. For data mining purposes uses population, individuals as elements defined by attributes and values. These elements or individuals represent candidate production rules.

In order to solve the graph with the genetic algorithm need to follow the below steps:

Step1: turn it in to genetic software.

Step2: Then, consider gene for each chromosome with the graph head numbers.

Step3: for each gene specialize a random color.

In the algorithm [16], each vertex of the graph is equipped with a learning automatic that has two actions in the candidate or non-candidate of the corresponding vertex cover set. Due to characteristics of learning automata, algorithm [16] significantly reduces the number of covering vertices of the graph. The algorithm [16] based on learning automata iteratively minimize the candidate vertex cover through the update its action probability. As the algorithm [16] proceeds, a candidate solution nears to optimal solution of the

minimum vertex cover problem. MVCP is an NP-complete problem [17, 18] which has exponential time complexity. Several practical applications of this problem include communication networks, social network [20], computer network and Bioinformatics [21]. MVCP introduced by Gary and Johnson and proved by Karp as NP-complete problem in connected graph in 1972. Therefore it is almost impossible finding polynomial time complexity algorithm for solving it. Thus many researchers have attracted to solve minimum vertex cover problem [22, 23].

In general, proposed solutions for MVCP are classified in two categories as heuristic and approximation algorithms [20]. Although, exact solution as branch and bound technique has been for this problem, the time complexity is very high [24].

Heuristic algorithms for solving problem [16] have received many attractions for obtaining good approximate and near optimal results in reasonable time. For example, a greedy algorithm starts with an empty set, then, at each step, selects the best candidate with maximum degree and continues to reach the stop condition [25]. A popular approximation technique removes vertices of edges that have been chosen randomly from set. In algorithm [16], the obtained result is always lower than twice the optimum solution, although approximate method in [16] does not optimum solution but can be provided near optimal solution [26].

In recent years, several learning automata based algorithms are presented to solve graph problems and successful results have been reported in literatures such as shortest path problem [27], minimum spanning tree problem [28], minimum dominating set problem [29], maximum clique problem [17, 30] and graph coloring problem [31].

In paper [16], learning automata is applied to solve minimum vertex cover problem. In the algorithm [16], a network of learning automata is created corresponding given graph, the collaboration between learning automata and learning mechanism that exist for each automaton.

In article, this problem is solved by simulating the behavior of insect in wheat farms, namely Eurygaster. These insects attack to farms and when one farm is disrupted, they attack to other farms in a manner that all farms will be disrupted. On the other hand, graph coloring is a NP-Hard problem which by using some Heuristic method like Eurygaster can be solved. The evaluation results show that algorithm is suitable to solve graph coloring problem.

Eurygaster algorithm acts as follows:

First several Eurygasters based on the size of the problems partitions are generated and distributed in the space of the first part to find the solution of the problem. It should be mentioned that if the number of eurygasters is not enough to exhaustively cover all the space of the related partition, can search all the related space by redistributing them and changing their position so that they can cover all the space mentioned. Eurygaster integriceps is an insect pest that predominantly attacks grains, feeding on the leaves, stems and grains, reducing yield and injecting a toxin into the grains which adds a foul smell to the resulting flour, and substantially reduces the baking quality of the dough [32].

If Euragaster assure that for every pair of adjacent vertices different color can be have its suitability is set to 1. So the suitability of Eurygaster is 1 or ∞ . We show this suitability by $S(E)$.

In [33], four learning automata-based approximation algorithms are proposed for solving the minimum (vertex) coloring problem. It is shown that by a proper choice of the parameters of the algorithm, the probability of approximating the optimal solution is as close to unity as possible.

The last proposed algorithm is compared with CHECKCOL [13], GLS [9], ILS [5], TPA [6], AMACOL [1], some well-known coloring algorithms and the results show the efficiency of the algorithm [33] in terms of the color set size and running time of algorithm. Graph coloring problem is widely used in real life applications like computer register allocation, air traffic flow management, timetabling, scheduling, frequency assignment, and light wavelengths assignment in optical networks. The approximation approaches reported in the literatures can be classified as local search approaches, genetic algorithms, fuzzy-based optimizations, evolutionary algorithms, simulated annealing methods, ant colony-based approaches, Markov chain approaches, and neural network approaches.

Four intelligent approximation algorithms based on learning automata for coloring a given graph with the minimum expected number of colors (minimum coloring problem) as defined in [33].

In each algorithm, a network of learning automata isomorphic to the graph is initially formed by assigning a learning automaton to each vertex of the graph. Such a network of learning automata can be described by a duple $\langle A, \underline{\alpha} \rangle$ where $A = \{A_1, A_2, \dots, A_m\}$ denotes the set of learning automata and $\underline{\alpha} =$

$\{\alpha_1, \alpha_2, \dots, \alpha_m\}$ denotes the set of actions in which $\alpha_i = \{\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{iri}\}$ defines the set of actions can be taken by learning automaton A_i , for each $\alpha_i \in \underline{\alpha}$. The set of colors with which each vertex V_i can be colored form the set of actions can be taken by learning automaton A_i .

Each of the proposed algorithms contains of a number of stages, and at each stage, each learning automaton randomly selects one of its colors and assigns it to its corresponding vertex. Thus, a coloring is made at each stage. The set of colors to be selected at each stage is referred to as color-set. Then, the algorithm decides whether the coloring is a legal coloring or not (except algorithm 4).

At each stage k , the cardinality of the minimum color-set that has yet been found is denoted by dynamic threshold T_k . The cardinality of the color-set of a given legal coloring is then compared with dynamic threshold T_k . If it colors the graph with the smaller number of colors, then it is rewarded by the environment, and penalized otherwise. The various legal colorings are iteratively produced and the action probability vectors are updated until a near optimal solution is found to solve the minimum coloring problem with a probability close enough to unity.

In the first proposed algorithm in [33], which call algorithm 1, it is assumed that the number of colors can be assigned to each vertex V_i is equal to the number of vertices in the graph (i.e., n), and therefore the action set of each learning automaton A_i which is referred to as α_i , also contains the same number of actions. Another method is: Imperialist competitive algorithm (ICA) is a meta-heuristic optimization and stochastic search strategy which is inspired from socio-political phenomenon of imperialistic competition. Imperialist competitive algorithm (ICA) is a meta-heuristic optimization and stochastic search strategy which is inspired from socio-political phenomenon of imperialistic competition [34]. The ICA has excellent capabilities such as high convergence rate and better global optimum achievement. Which, a discrete version of ICA is proposed to deal with the solution of GCP? DICA can produce optimal and valid solutions for different GCP instances.

The GCP is one of the most important classical combinatorial optimization problems. So far, many researchers have been proposed different methods for solving the GCP. These methods fall into some broad categories such as polynomial-time approximation schemes, exact algorithms, greedy methods, parallel and distributed algorithms, decentralized algorithms, and heuristics [35].

One of the most well-known methods in approximation schemes is the successive augmentation [35]. This method assigns a partial coloring to a small number of vertices and this process is extended vertex by vertex until the whole of graph is colored.

Algorithms for finding optimal colorings are frequently based on implicit enumeration [35]. Brute-force search technique is one of the best well-known exact coloring methods. In these techniques all solutions are checked for finding a reliable and optimal coloring for a graph and have high runtime.

In the greedy algorithms, vertices of the graph are colored in a specific order. The two best examples of greedy algorithms are DSATUR and RLF¹.

NP complete problems can easily be solved by using distributed computing and parallelism. In the distributed algorithms, graph coloring problem is related to the symmetry breaking problem. Randomized algorithms are faster methods for large dimensional graphs. The fastest algorithm in the class of randomized algorithms is the method presented by Schneider et al.

Since graph coloring problem is an NP-hard problem, several artificial intelligence techniques have been applied on graph coloring problem including algorithms based on neural networks [36], DNA parallel approach (e.g. in [37]), learning automata (e.g. in [38]), evolutionary algorithms, hybrid methods (e.g. in [39] and [40]), scatter search [20], and local search algorithms (e.g. Tabu search [41] or simulated annealing [42]). And et al. presented an approach to the GCP using PSO algorithm that improves a simple deterministic greedy algorithm [43]. They proved that their proposed method is better than known heuristic algorithms. Lixia and Zhanli proposed a novel bi-objective genetic algorithm which employs an effective crossover and simple mutation as the genetic operators [44]. The authors claimed that their method is a promising approach to the GCP.

Authors in [45] presented a hybrid chaotic ant swarm approach for the GCP which is called CASCOL. This approach is based on a chaotic ant swarm² and a simple greedy sequential coloring, first-fit algorithm.

1- Recursive Largest First

2- CAS

In [46] present a hybrid technique that applies a genetic algorithm followed by wisdom of artificial crowds approach to solving the graph-coloring problem. The genetic algorithm described here utilizes more than one parent selection and mutation methods depending on the state of fitness of its best solution. This results in shifting the solution to the global optimum more quickly than using a single parent selection or mutation method.

Genetic algorithms share an overall structure and workflow yet they vary in the specific details according to the particular problem [47]. The algorithm consists of a parent selection method, a crossover method and a mutation method. The goal algorithm compare with previous algorithm is to improve the fitness of the population by mating its fittest individuals to produce superior offspring that offer a better solution to the problem.

3.Learning Automata. Interests in learning automata began with the outstanding work of Tsetlin in the early in 1960s in the soviet union. Eden brings the automaton theory used by Tsetlin in the field of learning. During last two decades, “Learning Automaton” term has been consistently used by researchers.

Two effective and important factors on automata efficacy are primary conditions and the possibility of fines set by the environment. Primary conditions can be the initial probability vector or condition. One Automata, entirely based on luck is an automata in which any action performed with equal probability. Therefore, an automata that is learning, should have better efficacy that this automata [2].

Learning is defined as changes in performance of a system based on past experiences. One of important features of learning system is the ability to improve their performance in the past. Mathematically, it can be stated that the purpose of a learning system is optimization of a task which is not entirely known [4]. Therefore, one procedure in this issue is reducing of purposes of learning system in an optimization issue that is defined on asset of parameters and its purpose is to find optimal set of parameters [2].

Automata, is a single system which is defined as quintuplet $[\phi, a, \beta, F(0.0), H(0.0)]$ where ϕ is total internal states. α is output set, β is input set, $F(0.0): \phi \times \beta \rightarrow \phi$ is Function by state and current input and $H(0.0): \phi \times \beta \rightarrow a$ is automata output function by state and current input.

If the output automata depend only on the current state, it is said to be output state automata. In this case function $H(0.0)$ is converted to $G(0): \phi \rightarrow a$ [2]. Figure 1 indicates general shape of learning automata and figure 2 is about feedback connection of automaton and Environment.

Figure-1: Indicates general shape of learning automata [5].

Figure-2: Feedback Connection of Automaton and Environment.

3.1. Definition. A learning automaton is an adaptive decision-making unit situated in a random environment that learns the optimal action through repeated interactions with its environment. The actions are chosen according to a specific probability distribution which is updated based on the environmental response the automaton obtains by performing a particular action.

Briefly, An automaton which selects on of actions related to its past experiences and rewards or punishments from the environment.

3.2. Learning. Ability of a system to improve its responses based on past experience.

3.3. Environment. The aggregate of all the external conditions and influences affecting the life and development of an organism. The environment can be defined by triple: $\{a, c, b\}$

$a = \{a_1, a_2, \dots, a_r\}$: Set of inputs

$b = \{b_1, b_2, \dots, b_r\}$: Set of outputs

$c = \{c_1, c_2, \dots, c_r\}$: Set of penalty probabilities

3.4. Environment Models. P-Model: The output can take only two values, 0 or 1

Q-Model: Finite output set with more than two values, between 0 and 1

S-Model: The output is a continuous random variable in the range $[0, 1]$

3.5. Applications.

- Network routing
- Priority assignment in queuing system
- Task scheduling
- Multiple-access networks
- Image compression
- Pattern classification

4. The proposed method. For the number of nodes in a graph. Received we have learning automata that are colored at the start of coloration by all nodes with one color, which this work is done randomly. So at first total color = 1 and during continuous process, adjacent vertices which have same color should change color the minimum of colors may be allocated to it. So in this regard we need to separate neighboring vertices of non – neighboring vertices.

During coloration, if a vertex has similar color to its neighboring vertices, vertex reviewed is fine, which this fine has 2 modes that in these cases, we fully express them.

5 times, change of colors takes place, and if it has also similar color, we should apply a new color, but if it has different color with its neighboring vertex, will reward and vertices color remains constant.

At the end of algorithm, to ensure, we check resulting coloration again, whether or not it has arrived to right answer.

That from auxiliary variable flag we have used to check, as long as acceptable coloration returns as result, algorithm trend is repeated and with color changes of nodes by increasing of colors (in the minimized mode) we attempt to consider vertex colors so that any neighboring vertices are iso chromatic.

As explained, an algorithm is composed of an infinite loop and as long as it is running that an acceptable coloration leads as results and results of each repeat namely, the number of colors allocated to graph keep in any step.

The input graph is defined as an array. The columns of this array indicate the number of vertices, so if we have n vertices, array should have n column of int.

This array is composed of 3 lines:

First line: includes number of colors is called color No.

Second line: includes automata memory is called memory No.

Third line: includes numbers of color with are colored wrong during coloration running and caused to fine is called wrong color.

4.1. Transfer chart. Recommended automata named $kh_{3,5}$ that transfer chart or its status change is as figure

Figure-3: Transfer chart kh_{3, 5}.

This linear automata has 5 mode which are numbered 1 0 5, and also we have 3 actions.

a_1 = constant color

a_2 = change color

a_3 = apply the new color

Similar to another automata we have 2 Rewards $\beta= 0$, $\beta= 1$ which are considered for Reward and penalty respectively. If a vertex has equal color with its neighboring vertex, it should be fine that is $\beta= 1$ and in contrast, if a vertex has different color with its neighboring vertex, it should get rewards, $\beta= 0$ for this vertex.

4.2. Reward Action.

This process composed of following steps:

Step (1) checks the adjacent vertices:

In this step at first it should be studied whether or not vertices are neighboring, which if it is true, we authorized to go to the next step.

Step (2) checks the color of adjacent vertices:

To study the color of vertices, first line of corresponding array to its vertices should be checked. If neighboring vertices have different color, checking vertex should rewarded otherwise, should be fined.

Step 3: Reward of neighboring vortices:

When 2 neighboring vertices have different color, should be rewarded and the color of that vertex should remain unchanged and memory no value (third line of array) vertex become equal to zero.

In summary in the chart of status change we came back to the first mode with receiving reward from each state and the color of vertices remain constant.

4.3. Punishments Action.

Penalty act in general occurred in 2 different times.

- 1) Memory number value lower or equal to 5 that the color of node with other vertices finds color change randomly, and added a unit to memory No value.
- 2) If memory No value become larger than 5, in fact, change of new color is allocated and memory no value changes to zero.

4.3.1. Change the color of the nodes. If Memory No value was ≤ 5 , we should add an unite to memory no value, and other vertices color except 2 reviewed vertices are considered for that vertex randomly and change of color is done.

4.3.2. Apply the new color.

In this step, we should do 2 sequential works as follow:

First step: The Memory No value of a node we make it zero.

Second step: In this step it should be allocated a new color to this vertex, that how to add new color is that at first we should get largest assigned color that is numerical value of last variable of Total color and then we add one unite to this value and resulting number is assigned as new color to the node.

5. **Simulated results.** The algorithms are implemented using MATLAB software; our test was run on desktop computer with following specifications.

CPU: Intel Core (TM) i3 CPU M350 @ 2.27GHz2.27GHz

RAM: 4.00 GB (3.23 GB usable)

OS: windows 7

Data used to test our approach are derived from the DIMACS benchmarking graph collection. DIMACS is the center for discrete mathematics and Theoretical Computer Science. It is part of Rutgers university (the state university of New Jersey Rutgers et al. 2011).The data are frequently used in challenges involving constraint satisfaction problems.

for evaluation algorithm Suppose have a set of colors $C=\{c_1, c_2, \dots, c_n\}$ and a set of vertices $V=\{v_1, v_2, \dots, v_n\}$ and a set of edges $E=\{e_1, e_2, \dots, e_n\}$.

According to partition, give c_1 to the first vertex so all of the vertices that are adjacent to first vertices can't take c_1 , but other vertices can have this color. After it, when want to color another vertex, if it is adjacent to first vertex it can't take c_1 ; otherwise it take c_1 to satisfy the minimalistic of used color to assign to vertices. According to this routine, Eurygaster is constituted in each partition.

To evaluate and compare of proposed algorithm with this algorithm, have chosen 5 files from DIMACS benchmarking graph collection. The number of vertices and edges in these files are different. Table1 shows the used color number and running time of proposed approach against genetic algorithm and Eurygaster algorithm.

Table 1.The evaluation result of proposed approach against genetic algorithm and Eurygaster algorithm

File name	Nodes	Edges	CN The number of used Color in proposed approach [33]	CN The number of used Color in genetic Algorithm	CN The number of used Color in proposed Approach	RT(sec) Running Time Of our approach [33] in second	RT(sec) Running Time Of Genetic algorithm in second	RT(sec) Running Time Of our approach in second
Myceil3.col	11	20	4	4	4	0.002	0.007	0.002
Myceil4.col	23	71	5	5	5	0.007	0.021	0.003
Queen6_6.col	25	290	7	8	6	2.120	14.043	0.217167
Huck.col	74	301	11	11	8	0.011	0.559	0.013689
David.col	87	406	11	11	9	0.128	0.540	0.021356

As you can see the number of color in proposed approach is optimal while in genetic algorithm and Eurygaster algorithm in some benchmark the number of color is not optimal. Also in proposed approach, running time is less than another algorithm. The reason for this is that in genetic algorithm after passing from some generation, some chromosome may be produced that existed in previous generations. This schema cause's genetic algorithm is rune slowly. The efficiency of the proposed method is compared algorithm [48] with GA on five well-known graph coloring benchmarks. These benchmarks are Dataset1, Dataset2, Myceil3.col, Myceil4.col and queen5_5.col these data sets cover examples of data of low, medium and large dimensions. Table 2 summarizes the characteristics of these benchmarks. Also Table 3 and 4 indicates the parameters set for DICA and GA in our implementations.

Dataset1 is a complete graph which has 15 vertices and 105 edges. The chromatic number of this graph is 15. Dataset2 is another complete graph which has 20 vertices and 190 edges and its chromatic number is 20. Myceil3.col has 11 vertices and 20 edges. Myceil4.col has 23 vertices and 71 edges. The chromatic number for Myceil3.col, Myceil4.col are 4, 5 respectively. Queen5_5.col has 25 vertices and 160 edges and the chromatic number for Queen5-5 is 5.

Another algorithm that compare with proposed algorithm:

Table5 shows the results (over 20 runs) obtained based on this measure. The results show the proposed method often works very well and finds the valid and optimal solution for different GCP instances.

Table 2. Characteristics of Data Sets considered

Graph	Number of Vertices	Number of Edges	Chromatic Number	Chromatic Number proposed algorithm
Dataset 1	15	105	15	6
Dataset 2	20	190	20	6
Myceil3.col	11	20	4	4
Myceil4.col	23	71	5	5
Queen5_5.col	25	160	5	4

Table 3. The DICA algorithm parameters setup

Parameter	Value
Population size	300
Number of Initial Imperialists	10 % of population size
Number of All Colonies	All population except imperialists
Number of Decades/ iteration count	100
Revolution Rate	0.25
Uniting Threshold	0.02
Assimilation Coefficient	1.50
Assimilation Angle Coefficient	0.50
Damp Ratio	0.90

Table 4. The GA algorithm parameters setup

Parameter	Value
Population size	300
Mutation rate	0.25
Selection probability	0.50
Number of Generation / Iteration count	100

Table 5. Results of DICA and GA algorithms against proposed algorithm on five data set, the quality of solutions is evaluated using efficiency metric. The table shows success

Graph	Number of vertices	Number of Edges	DICA Success	GA Success	Proposed Algorithm Success
Dataset 1	15	105	20	20	6
Dataset 2	20	190	19	18	10
Myceil3.col	11	20	20	20	5
Myceil4.col	23	71	20	18	8
Queen5_5.col	25	160	18	16	12

Also simulations show the size of population, the number of initial imperialist countries, the revolution rate, and also use an appropriate strategies for implementing the assimilation and revolution operators (in DICA) are effective to reach the optimal solutions.

As mentioned in above sections, like to the mutation in the GA technique we selected a low revolution rate. For graphs that have few vertices we can use an initial population with fewer individuals and for high dimensional graphs we use a large initial population and also we can increase the number of iterations. In GA method, among different selection methods, we used roulette wheel to choose individuals to create next population. Also 2-pt crossover is used in the recombination process. Selection and mutation rate are 0.5, 0.3 respectively. For DICA the revolution rate and uniting threshold are set to 0.25 and 0.02

respectively. As shown in Table 2, for Dataset1 the number of successful colorings of DICA and GA are same. For Dataset2 the number of successful iterations of DICA is greater than GA.

The number of successful iterations of DICA for Dataset2, Myciel4.col and queen5-5.col data sets is greater than GA. Simulation results indicate the runtime of DICA is lower than GA over on all data sets and this is due to the high convergence rate of the DICA method But As is observed, present method requires to less colors for coloration of graph and also proposed algorithm approaches to less repeat for optimum solution and has higher rate convergence.

7 files were chosen from the DIMACS collection. The graphs the files represent vary in vertex count, edge count and overall complexity. The vertex count ranges between 11 and 561 and the edge count ranges from 20 to 11654. The rationale behind the selection of these graphs other than the wide range of variation is that there is a known chromatic number for each of them, or at least a good approximation.

The following files were used in this approach:

(myciel3.col, myciel4.col, queen5_5.col, queen6_6.col, huck.col, jean.col, david.col).

Table 6 displays the following statistics for each file:

- The number of vertices $|V|$
- The number of edges $|E|$
- The expected chromatic number $\chi(G)$
- The minimum number of colors used by this algorithm k_{min}
- The minimum number of colors used by a comparative publication using a hybrid parallel genetic algorithm (HPGAGCP)
- Average time it took to find a solution as seen in the above table our proposed method in less time and with less color is the optimal solution.

Table 6.Results of running the Proposed algorithm on 7 .col files from the DIMACS collection

File	$ V $	$ E $	$\chi(G)$	K_{min}	HPGAGCP	CN Proposed algorithm	RT(sec) Algorithm [46]	RT(sec) Proposed algorithm
Myciel3.col	11	20	4	4	4	4	0.003	0.002256
Myciel4.col	23	71	5	5	5	5	0.006	0.003782
Queen5_5.col	23	160	5	5	5	5	0.031	0.077086
Queen6_6.col	25	290	7	7	8	6	6.100	0.217167
Huck.col	74	301	11	11	11	8	0.015	0.013689
Jean.col	80	254	10	10	10	7	0.015	0.016381
David.col	87	406	11	11	11	9	0.019	0.021346

6. Conclusion. In this article, for coloration of graph from new learning automata and with unique transfer chart and action is used. that the reason of proposed idea is improving of existing weak nesses in the past methods and reach to ultimate goal hence to gain minimum number of required color for coloration of graph vertices and also presents allowable coloration.

By analyzing the results, it can be stated certainly that these results from research simply and also with the best optimality results.

From the advantages of this method can be referred to above:

The ability to apply process for graph with small, medium and large dimensions, To obtain the most efficient possible state, The number of required colors for coloration of graph in each step, The total number of required colors for coloration of graph, high resolution, High rate of convergence and The ability to learn automata unlike other methods.

From disadvantages of this method it can be noted that:

Learning time of less number of nodes with the case of a large number of nodes does not matter.

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