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Review

A systematic study on meta-heuristic approaches for solving the graph coloring problem

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ABSTRACT

Typically, Graph Coloring Problem (GCP) is one of the key features for graph stamping in graph theory. The general approach is to paint at least edges, vertices, or the surface of the graph with some colors. In the simplest case, a kind of coloring is preferable in which two vertices are not adjacent to the same color. Similarly, the two edges in the same joint should not have the same color. In addition, the same goes for the surface color of the graph. This is one of the NP-hard issues well studied in graph theory. Therefore, many different meta-heuristic techniques are presented to solve the problem and provide high performance. Seemingly, regardless of the importance of the nature-stimulated meta-heuristic methods to solve the GCP, there is not any inclusive report and detailed review about overviewing and investigating the crucial problems of the field. As a result, the present study introduces a wide-ranging reporting of nature- stimulated meta-heuristic methods, which are used throughout the graph coloring. The literature review contains a classification of significant techniques. This study mainly aims at emphasizing the optimization algorithms to handle the GCP problems. Furthermore, the advantages and disadvantages of the meta-heuristic algorithms in solving the GCP and their key issues are examined to offer more advanced meta-heuristic techniques in the future.

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1. Introduction

Graph theory is a graph study where discrete structures are used to model relationships between pairs of objects. Graphs are key objects studied in discrete mathematics (Naz and Akram, 2019). They are of particular importance in modeling networks, computer science, biology, sociology, and many other disciplines (Barman et al., 2019). A graph in this field contains vertices, nodes/points associated with edges, arcs, or lines. The graph could be undirected, inferring that no refinement exists among the 2 vertices of each edge. Also, its edges may be directed, beginning with one vertex then onto the following (Prathik et al., 2016). They can be utilized to show many sorts of connections and procedures in physical, natural, social, and PC systems (Bhosale et al., 2013). Graphs can illustrate various practical issues. Graphs are usually applied to show numerous problems like the grids of communication, processing tools, flowing of processing, and data management in computer science. An architecture of a link from a webpage can be presented through a directed graph where vertices represent websites and directed edges to show a link starting with a page and then to the next one. A comparative view can be adopted for the problems of web-based social networking, tourism, science, PC chip framework, and many various areas (Grandjean, 2016). Improving the algorithm is an interesting issue in software engineering to cope withgraphs.

The emphasis of this study is on GCP as a key instance of graph labeling, which is the result of tags (colors) on the elements of a graph with specific constraints (Gamache et al., 2007; Shukla et al., 2019). Vertex, edge, and face coloring are three adaptations of the GCP (Mahmoudi and Lotfi, 2015; Zhou et al., 2014; Hatanaka et al., 2019). The reason for the importance of GCP is divided into two parts. First, there are numerous usages like arrangement (de Werra, 1985; Dowsland and Thompson, 2005), radio frequency allocation (Gamst, 1986), computer assignment (Chaitin et al., 1981; Chow and Hennessy, 1990), Printed Circuit Board (PCB) testing (Garey et al., 1976), and channel routing (Sen Sarma and Bandyopadhyay, 1989). More precisely, GCP is a well-known NP-hard problem (Cheeseman et al., 1991; Guo and Niedermeier, 2007). These two reasons provide careful consideration to solve this problem by meta-heuristic strategies . Also, most of the current methods for handling GCP have typically 2 categories: exact and approximate.

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Table 1
Abbreviation table.

Abbreviation	Definition	Abbreviation	Definition
GCP	Graph Coloring Problem	GA	Genetic Algorithm
MSCP	Minimum Sum Coloring Problem	MA	Memetic Algorithm
RGCP	Robust GCP	PSO	Particle Swarm Optimization
SLR	Systematic Literature Review	QA	Quantum Annealing
RQs	Research Questions	TS	Tabu Search
ACO	Ant Colony Optimization	SA	Simulated Annealing
ABC	Artificial Bee Colony	HA	Hybrid Algorithm
BA	Bat Algorithm	TSP	Traveling Salesman Problem
COA	Cuckoo Optimization Algorithm	QAP	Quadratic Assignment Problem
FA	Firefly Algorithm	PGCP	Partition GCP
APSO	An adaptive Particle Swarm Optimization	MMAS	Max-Mix Ant System
EBs	Employed Bees	HABC	Hybrid ABC
MFFA	Memetic FA	HEA	Hybrid Evolutionary Algorithm
EA	Evolutionary Algorithm	SAW	Stepwise Adaptation of Weights
DFPA	Discrete flower Pollination Algorithm	EA-SAW	Evolutionary Algorithm with SAW
ACS	Ant Colony System	GPX	Greedy Partitioning crossover
BPPC	Bin Packing Problem with Conflicts	MBO	Marriage in Honey Bees Optimization
GTCP	Graph T-Coloring Problem	CS	Cuckoo Search
HPGA	Hierarchical Parallel GA	CUDA	Compute Unified Device Architecture
MMA	Multilevel Memetic Algorithm	RL	Reinforcement Learning
DFA	Discrete Firefly Algorithm	HEAD	Hybrid Evolutionary Algorithm in Duet

Since exact algorithms can answer examples having a large number of vertices (up to 100), accordingly, bigger examples require heuristic techniques. Though the GCP is a discrete problem (Bendali, 1984), meta-heuristic strategies must give discrete capacities to tackle this problem. Along these lines, algorithm discretization is a vital issue. But, even with the importance of the meta-heuristic methods in the GCP, no overall and methodical investigation exists regarding this. Therefore, the main purpose of this study is to investigate the meta-heuristic algorithms and techniques in the GCP. Accordingly, the goal of this paper is to review the current meta-heuristic algorithms for GCP, compare differences between the above techniques, and specify the variety of important challenges and GCP problems in graph theory.

In brief, the main aims of this paper are as follows:

- Offering an outline of the current problems regarding the coloring of the graph
- Providing an outline of visions and execution of optimization methods in the graph coloring
- discussing the tendencies in usages of the meta-heuristic methods for GCP
- Highlighting the significance of meta-heuristic optimization algorithms and several advantages of them for tackling challenges of the graph coloring, and
- Organizing related open issues and a few insights to solve current problems of reviewed algorithms.

The architecture of the remainder is:

Section 2 reviews and examines the related works. Section 3 provides a systematic literature review and selected mechanisms. Section 4 discusses the review of selected meta-heuristic algorithms for GCP and categorizes them. Section 5 describes the results and comparison of reviewed mechanisms. Section 6 highlights some limitations. Section 7 maps out the same issues. Section 8 concludes the paper. Table 1 shows the commonly-used abbreviations in the paper.

2. Related work

In this section, we've reviewed the literature for the GCP and highlighted their weaknesses and strengths. Papers have been published between 2010 and 2018.

Jin et al. (2017) survey of approximation and applied answer methods planned for the Minimum Sum Coloring Problem (MSCP), has been developed over the last few years. The main current survey on the issue goes back to 2004. For the most part, it covers the historical background of MSCP and hypothetical advances on particular graphs. The reviews of papers written by 2016 provide the most illustrative and practical MSCP heuristic and meta-heuristic procedures divided into three large classes: Evolutionary Algorithms (EAs), greedy methods, and local search heuristics. In other words, a reason for this review is to give a far-reaching investigation of the latest and illustrative MSCP algorithms. Although good reviews have been done, they have not taken into account the effectiveness of the type of algorithms and the advantages and disadvantages of the studied articles.

Another study of graph coloring as a significant subfield of graph theory done by Formanowicz and Tanaś (2012), has described different coloring techniques and given a summary of the issues and inferences regarding them. Finally, they've turned their focus to cubic graphs, a very interesting set of graphs for investigating. In this case, an overview of graph coloring techniques (in Polish) a more comprehensive one (in a book) has been written by Furmanczyk and Kubale (2004). This paper has been reviewed in 2012.

Ansari (2013) has presented neural network algorithms to solve the GCP. In this paper, he has examined the most important progress in the field of algorithm and hardware related to GCP solving. In addition, a new neural network has been provided using the non-linear review in the usage of integration that can paint the graph more viably compared to current neural networks for that job. According to this paper, meta-heuristic algorithms have not been reviewed for the GCP, and the effects of future and open issues have not been well discussed. The main fault of this paper is that only one criterion has been implemented. The paper was published in 2013. But it has not been discussed in new papers yet.

Demange et al. (2015) have also studied a body of usages out of various areas of a specific GCP. Their work has been seen with many labels for specific designs. Its complicated quality has been considered for different categories of graphs. Demange et al. (2015) has started that systematic report. It has been proceeded by Demange et al. (2014). This paper has been reviewed in 2015, but it has not mentioned in the following years. Moreover, meta-heuristic techniques have not been regarded.

Chiarandini and Stützle (2010) have presented their computational experience on algorithms for coloring large general graphs.

They've considered 1260 graphs made by controlling a few structural parameters, so it was similar to picking up a superior insight into the relationship between algorithm implementation and graph features. They've examined graph size, edge density, sort of graph, and attributes of color classes. They've suggested that if described features were fully examined, the algorithm would be used on a graph with 1000 vertices. Although they've studied a good algorithm, they have not studied meta-heuristic algorithms and not compared them.

Zhou et al. (2016) has focused on building up a universally useful arrangement method for classifying issues, i.e. Reinforcement RLS, which joins Reinforcement Learning (RL) techniques with local exploration. The study has supplementary commitments: they've demonstrated that (1) RL can find valuable data from local optimum solutions; (2) a trained data can be positively applied to manage the inquiry calculation towards promising districts. It is an endeavor to introduce an official design that joins RL and local research to solve the grouping issues. The proposed approach has been checked on an outstanding illustrative-classifying issue (graph coloring). The categorization of reviewed mechanisms has not been properly presented in the paper. Moreover, the local search algorithm has been used, but other meta-heuristic algorithms have not been considered.

Kokosinski and Ochał (2015) have presented a new formulation of a robust graph coloring problem. Relative robustness is an adaptable measure for the representation of any strong framework shown by a graph. For trial confirmation, 2 predominant parallel meta-heuristics TS/PTS and SA/PSA have been utilized. They have investigated the number of colors on different graphs regardless of other criteria. They have not considered meta-heuristic algorithms but suggested that it would be better to review some meta-heuristic algorithms in future papers.

Finally, reviewing the GCP has been done by Malaguti and Toth (2010). The paper has overviewed the most vital algorithmic and computational outcomes on the vertex coloring issue and its conjectures. The first part of the article has discussed old designs for the GCP and tested how they could be used to calculate the precise heuristic methods for the issue. The next part of the paper was committed to a few conjectures on its issue, which were attained by considering extra essentials or an objective function with an exceptional structure. This paper was published in 2013. The paper has investigated the detailed algorithms, but not the meta-heuristic ones. There are no suggestions for further studies.

In spite of the importance of the meta-heuristic techniques in the graph coloring, there's no complete and methodical survey about their classification. Furthermore, future difficulties and the important role of meta-heuristic techniques in a graph coloring problem have not been specified properly. In brief, the reviewed papers have some limitations:

1 In many of them, only a few papers have been investigated.
2 The paper's choosing method has not been well defined.
3 The upcoming studies and unanswered issues have not been expressed properly.
4 Many high-quality papers have not been studied.
5 In a few papers, only traditional papers have been studied.
6 In a few papers, the selected papers could not be considered in the area of graph coloring.
7 In some cases, meta-heuristic techniques have not been regarded.
8 The classification of the studied procedures has not been presented properly.
9 The advantages and disadvantages of the selected papers have not been presented well.

Therefore, we've provided a few problems regarding the meta-heuristic techniques in GCP in the following section with a special goal of choosing the most significant studies to review meta-heuristic methodologies in GCP. Difficulties and future patterns have been underlined by proposing an explanation for each of these inquiries.

3. Organized review of the previous works

The present part has provided a Systematic Literature Review (SLR) with focusing on studies regarding the graph coloring to clarify the meta-heuristic methods in the GCP. According to Cook et al. (1997), SLR has been distinguished from an old study, if there's any duplicable, technical, and clear procedure. The goal of an SLR is presenting a thorough outline of present significant works (Aznoli and Navimipour, 2017; Pourghebleh and Jafari Navimipour, 2019; Shabestari et al., 2019). As a technique, it was stimulated by the discipline of medicine (Kitchenham, 2004; Ebrahimi et al., 2014; Rahim et al., 2013; Nesioonpour et al., 2014) which offered a look into technique and adequate points of interest repeated by different scientists (Cook et al., 1997; Charband and Navimipour, 2016). An initial phase of directing an organized overview is to play out a careful look at the previous works (Navimipour and Charband, 2016; Azhir et al., 2019; Souri et al., 2019). Previous studies have stated that applying such a strategy for literature analysis can confirm that systematic mistake is restricted, chance impacts are diminished, and the validity of data analysis is upgraded (Aznoli and Navimipour, 2017). The research methodology to direct the SLR depends on the rules proposed by Kitchenham et al. (2009), and Biolchini et al. (2005). The count of works on the GCP has been growing substantially, so, in this part, the required data has been obtained from 2010 onwards to implement complete research about the main procedures of the GCP. The SLR choosing method will be assessed and framed in the next sections.

3.1. Research questions

Study Queries are crucial in the investigation. They present a focal point, delineate the methodology, and direct all the phases of analysis, investigation, and writing. The present research aims to study the role of the meta-heuristic methods in GCP and the associated problems. The mining of the main characteristics of the meta-heuristic methods has been focused and described in particular. To do so, we have investigated the reviewed publications using a group of Study Queries mined from the aim to get a comprehensive summary of created answers (Akbar Neghabi et al., 2019).

The Study Queries of the investigation are:

- RQ1: What are the contributions and the challenges of the meta-heuristic methods in the GCP requested by the community yet?
  This inquiry manages the significance, difficulties, and a part of the meta-heuristic method (Hatef et al., 2018; Zhao et al., 2017) in the GCP and indicates the count of issued articles and their importance.
- RQ2: Which meta-heuristic methods and techniques are related to GCP? The aim is to indicate the role of meta-heuristic methods in GCP and its practical ones to obtain the best solution.
- RQ3: Which problems are determined concerning the progress of existing procedures for the upcoming tendencies in the area?

The questions will investigate the weaknesses of existing meta-heuristic solutions in the GCP and the paper will suggest some hints to solve these weaknesses.

3.2. Search query

Exploring articles is crucial for any research. In the time of electronic databases and burst of technical publications, keywords have a vital part in mining applicable published material. The keywords play as "keys" to open the wanted abstracts/full papers from a body of associated works (Saberi, 2009; Saberi, 2018). It is central to incorporate and choose related keywords, simply recognizing and exploring the significant references and examining through the extensive assemblage of the undesirable things (Sharma and Mediratta, 2002; Saberi and Ekhtiyari, 2019; Saberi et al., 2011).

Related keywords are: "vertex coloring", "exact algorithms approximate", "graph coloring", "workload coloring", "nature-inspired meta-heuristic", "combinatorial optimization", "planar graph coloring", and "meta-heuristic".

3.3. Paper selection process

Educational databases have been used in search of strings and prohibition criteria by depicting key terms, using Soltani and Navimipour (2016). We've concentrated on looking in e-databases like Google Scholar, IEEE Explore, ACM digital library, Science Direct, Emerald, Springer, and Wiley to direct the study. The paper choice method has 4 key steps:

A: Independent search based on the mentioned keywords
B: Omission based on the title
C: Omission based on the abstract and conclusion
D: Omission accorded to the full texts and abstracts

Stage 1 has discovered the relevant papers by searching for keywords. The consequence of the search was 984 sources from journals, books, conference papers, and chapters having the above keywords. This systematic literature review has 2 kinds of research articles - quantitative and qualitative, written in English from 2010 −2019. Stage 2 has chosen the papers, according to the titles regarding the graph coloring and its notions. The outcome was 446 papers. In Step Three, the abstracts and conclusions of the chosen papers have been studied, and 167 papers have been chosen. In Step Four, the selected papers have been studied, according to the full texts, although, some of them have been removed. Finally, 65 papers have been selected for more examination. Table 2 shows the selected meta-heuristic algorithms-based papers for graph GCP.

Exit criteria have been used at various stages, as shown in Fig. 1. Furthermore, the classification of the papers based on the year of publication (2010 – 2018) is shown in Fig. 4. The maximum number of articles have been published in 2011. Fig. 3 displays the classification of papers in five groups, where 35% of total papers of journals fit IEEE, 16% of papers with Springer; 21% of papers with other publishers; 26% of the papers with Science Direct, and 2% of papers with the ACM. Furthermore, Fig. 2 shows papers in each category based on their proposed algorithms where GA and PSO have the highest number of published papers among other meta-heuristic algorithms for GCP.

4. Review of the selected meta-heuristic algorithms for GCP

Here, we've reviewed the selected meta-heuristic algorithms for GCP. We surveyed meta-heuristic algorithms in 12 sets, including ACO, PSO, GA, ABC, FA, COA, BA, MA, QA, SA, TS, and HA. Next, we've analyzed the methods in terms of runtimes, convergence, performance evaluation, solution's space, global optima, graph size, number of iterations, and efficiency.

4.1. Ant colony optimization (ACO) technique

Ant colony optimization is an effective method stirred by the conduct of real ants (Milan et al., 2019). ACO has been principally applied to solve TSP (Brock et al., 1996), and then many hard issues like GCPs (Dorrigiv and Markib, 2012) and Quadratic Assignment Problem (QAP) (Abbasian et al., 2011). The fundamental point is that there is a local neighborhood correspondence between persons of the colony of ants (Asghari and Navimipour, 2019). They supply a material named pheromone on their way and shape a pheromone trail, which empowers them to discover the shortest ways among their home and sustenance sources. ACO is a population-oriented meta-heuristic that began by Dorigo (1992) in 1992. It is a useful method animated by the director of real ants (Navimipour and Asghari, 2017; Navimipour and Milani, 2016). ACO algorithm has principally applied to settle TSP (Brock et al., 1996) and after that effectively used for many troublesome issues such as routing in media transmission frameworks such as QAP (Abbasian et al., 2011) and GCPs (Dorrigiv and Markib, 2012). The essential idea is the indirect neighborhood correspondence between persons of a population of fake ants as they store pheromone on their way to create a pheromone trail and find the shortest ways between their home and nourishment sources.

Section 4.1.1 reviews the chosen procedures presenting the key characteristics of the selected papers. Section 4.1.2 presents the outcomes and juxtaposition of the papers.

4.1.1. Summary of the chosen mechanisms

Fidanova and Pop (2016) have suggested two strategies for solving the Partition GCP (PGCP), specifically a pure ACO algorithm and a hybrid ACO algorithm. Assuming an undirected graph $G = (V, E)$ whose nodes are divided into an assumed count of sets, the PGCP finds a subset of the graph nodes (that exactly contains one node of each cluster) and a color for that subset. A combined method has been achieved by running a local exploration method following the repetition of each ACO. The function of algorithms is based on a set of examples usually utilized as a benchmark. The computational results have shown that the integrated ACO algorithm is better than the advanced ones. The results were similar to those of the standard deviation. Algorithms have been highly comparable, however, both pure ACO algorithm and hybrid ACO algorithm ran a similar count of repetitions. The active time of the hybrid ACO is around 25% more than that of the pure ACO.

Yuan et al. (2014) has proposed a 0–1 integer programming design of BPPC and later changed it into the portrayal of the conflict graph architecture. Then, an ACO system has been introduced to solve the conflicting removal process of BPPC in light of a graph coloring heuristic. Therefore, periods of conflict removal and bin packing ought to be mixed together unifying algorithm outline. As a result, an enhanced ACO has been intended to actualize the conflict rejection process by vertex coloring on the conflict graph and a first-fit-decreasing heuristic method with bin shuffling operations. At that point, the execution of the algorithm has been contrasted with an avaricious based heuristic algorithm. The outcomes have demonstrated that the enhanced ACO calculation is reliable and can give an achievable and brilliant arrangement of BPPC effectively. However, the algorithm is not capable of solving large complex graphs. Moreover, they have not considered the runtime and the number of high iteration algorithms in their review.

Douiri and Elbernoussi (2013) have studied the MSCP, an NP-hard issue from the GCP. Its objective is to limit the total of colors applied as a part of the graph. They have proposed a strategy in light of ACO, which is applied to a few standard graphs. By contrasting the outcomes of the trial and those of the previous works, they have shown the viability of the proposed strategy. According to the results, the efficiency of the algorithm is high. Its runtime is low and upper bound to improve the MSCP. Several iterations have not been repeated, and the comparison has not been done among the algorithms. Therefore, it is suggested to combine the algorithm with another meta-heuristic one to reach higher performance than these results.

Table 2
Distribution of the meta-heuristic algorithms for graph coloring.

Meta-heuristic algorithm	Publisher	Year	Author	Title
Ant Colony Optimization (ACO)	Science Direct	2016	Fidanova and Pop (2016)	An improved hybrid ant-local search algorithm for the partition graph coloring problem
	IEEE	2014	Yuan et al. (2014)	An improved ACO algorithm for the bin packing problem with conflicts based on graph coloring model
	Springer	2013	Douiri and Elbernoussi (2013)	An Effective Ant Colony Optimization Algorithm for the Minimum Sum Coloring Problem
	Springer	2013	Douiri and Elbernoussi (2012)	A new ACO algorithm for the lower bound of the sum coloring problem
	IEEE	2011	Mohamed and Elbernoussi (2011)	Max-Min ant system for the sum coloring problem
	IEEE	2010	Aicha et al. (2010)	Two-hybrid ant algorithms for the general T-coloring problem
	Springer	2010	Plumettaz et al. (2010)	Ant local search and its efficient adaptation to graph coloring
	IJESC	2017	Scholar (2017)	Ant Colony System for Graph Coloring Problem
	Science Direct	2017	Mosa et al. (2017)	Graph Coloring and ACO based Summarization for Social Networks
Artificial Bee Colony (ABC)	IEEE	2015	Markid et al. (2015)	A new TabuCol embedded Artificial Bee Colony based algorithm for Graph Coloring
	IEEE	2013	Tomar et al. (2013)	A novel ABC optimization algorithm for Graph Coloring Problem
	IEEE	2013	Greenwood and Chopra (2013)	A modified artificial bee colony algorithm for solving large graph theory problems
	IEEE	2013	Fei et al. (2013)	Artificial Bee Colony Algorithm for the Minimum Load Coloring Problem
	Springer	2012	Fister et al. (2012)	A hybrid artificial bee colony algorithm for graph coloring
	International Journal of Contemporary Mathematical Sciences	2011	Faraji and Javadi (2011)	Proposing a new algorithm based on bees behavior for solving graph coloring
Bat Algorithm (BA)	Symposium on Complex Systems and Intelligent Computing (CompSIC)	2015	Djelloul and Chikhi (2015)	Combining bat algorithm with angle modulation for graph coloring problem
	IEEE	2014	Djelloul et al. (2014)	Binary bat algorithm for graph coloring problem
Cuckoo optimization algorithm (COA)	Science Direct	2015	Mahmoudi and Lotfi (2015)	Modified cuckoo optimization algorithm (MCOA) for solving graph coloring problem
	Inderscience	2015	Djelloul et al. (2015)	Quantum inspired cuckoo search algorithm for graph coloring problem
	Natural Science	2013	Zhou et al. (2013)	An improved cuckoo search algorithm for solving the planar graph coloring problem
	Springer	2017	Aranha et al., (2017)	Solving the graph coloring problem using cuckoo search
Firefly algorithm (FA)	IEEE	2016	Del Ser et al. (2016)	Community detection in graphs based on surprise maximization using Firefly heuristics
	Cornell University	2012	Fister et al. (2012)	Memetic firefly algorithm for combinatorial optimization
	IEEE	2017	Chen and Kanoh (2017)	A Discrete Firefly Algorithm Based on Similarity for Graph Coloring Problems
Genetic algorithm (GA)	Springer	2018	Marappan and Sethumadhavan (2018)	A solution to Graph Coloring Using Genetic and Tabu Search Procedures
	IEEE	2016	Marappan and Sethumadhavan (2016)	A solution to Graph Coloring Problem using Divide and Conquer based Genetic Method
	International Journal of Computer Applications	2015	Bhasin and Amini (2015)	The applicability of the Genetic Algorithm to Vertex cover
	Science Direct	2014	Douiri and Elbernoussi (2015)	Solving the graph coloring problem via hybrid genetic algorithms
	Springer	2014	Zhang et al. (2014)	The accelerating of a genetic algorithm for solving graph coloring problem based on CUDA architecture
	Springer	2013	Abbasian and Mouhoub (2013)	A hierarchical parallel genetic approach for the graph coloring problem
	IEEE	2013	Sethumadhavan and Marappan (2013)	A genetic algorithm for graph coloring using single parent conflict gene crossover and mutation with conflict gene removal procedure
	IEEE	2013	Marappan and Sethumadhavan (2013)	A new genetic algorithm for graph coloring
	University of Cincinnati Cincinnati, Ohio	2012	Hindi and Yampolskiy (2012)	Genetic Algorithm Applied to the Graph Coloring Problem
	International Journal of Contemporary Mathematical Sciences	2011	Douiri and Elbernoussi (2011)	A new algorithm for the sum coloring problem
	ACM	2011	Abbasian and Mouhoub (2011)	An efficient hierarchical parallel genetic algorithm for graph coloring problem
	International Journal of u-and e-Service, Science and Technology	2010	Maitra et al. (2010)	Hybridization of Genetic Algorithm with Bitstream Neurons for Graph Coloring
	IEEE	2010	Han and Han (2010)	A Novel Bi-objective Genetic Algorithm for the Graph Coloring Problem
Memetic algorithm (MA)	Springer	2018	Moalic and Gondran (2018)	Variations of memetic algorithms for graph coloring problems
	IEEE	2016	Zhuang et al. (2016)	A Memetic Algorithm Using Partial Solutions for Graph Coloring Problem
	Springer	2015	Moalic and Gondran (2015)	The New Memetic Algorithm HEAD for Graph Coloring: An Easy Way for Managing Diversity

(*continued on next page*)

Table 2 (*continued*)

Meta-heuristic algorithm	Publisher	Year	Author	Title
	Science Direct	2014	Jin et al. (2014)	A Memetic Algorithm for the Minimum Sum Coloring Problem
	IEEE	2011	Benlic and Hao (2011)	A multilevel memetic approach for improving graph k-partitions
	Science Direct	2010	Lü and Hao (2010)	A memetic algorithm for graph coloring
Paper swarm Optimization (PSO)	Science Direct	2016	Gong et al. (2016)	Discrete Particles Swarm optimization for high- order graph matching
	Science Direct	2015	Agrawal and Agrawal (2015)	Acceleration Based Particle Swarm Optimization for Graph Coloring Problem
	IEEE	2015	Aoki et al. (2015)	PSO algorithm with transition probability based on the hamming distance for graph coloring problem
	IEEE	2015	Bensouyad and Saidouni (2015)	A discrete flower pollination algorithm for graph coloring problem
	IEEE	2013	Consoli et al. (2013)	Swarm intelligence heuristics for graph coloring problem
	IEEE	2012	Dorrigiv and Markib (2012)	Algorithms for the graph coloring problem based on swarm intelligence
	Science Direct	2011	Hsu et al. (2011)	MTPSO algorithm for solving planar graph coloring problem
	Journal of computers, vol.6, no.6	2011	Qin et al. (2011)	Hybrid Discrete Particle Swarm Algorithm for Graph Coloring Problem
	IEEE	2011	Rebollo-Ruiz and Graña (2011)	Further results of gravitational swarm intelligence for graph coloring
	IEEE	2010	Anh et al. (2009)	A Novel Particle Swarm Optimization based Algorithm for the Graph Coloring Problem
Quantum Annealing (QA)	The public library of Science	2012	Titiloye and Crispin (2012)	Parameter tuning patterns for random graph coloring with quantum annealing
	Science Direct	2011	Titiloye and Crispin (2011)	Quantum annealing of the graph coloring problem
	Science direct	2011	Titiloye and Crispin (2011)	Graph coloring with a distributed hybrid quantum annealing algorithm
Tabu search (TS)	IEEE	2015	Kouider et al. (2015)	Mixed-integer linear programs and TS approach for solving mixed graph coloring for unit-time job shop scheduling
	Springer	2014	Barany and Tuza (2015)	Circular coloring of graphs via linear programming and tabu search
	Science Direct	2010	Bouziri and Jouini (2010)	A tabu search approach for the sum coloring problem
Simulated Annealing (SA)	Science Direct	2012	Pal et al. (2012)	Comparative Performance of Modified Simulated Annealing with Simple Simulated Annealing for Graph Coloring Problem
Hybrid Algorithms (HAs)	Science Direct	2015	Astuti (2015)	Graph Coloring Based on Evolutionary Algorithms for supporting Data Hiding Scheme on Medical Images
	Springer	2014	Bessedik et al. (2014)	A Cooperative approach using ants and bees for the graph coloring problem
	Inderscience	2011	Pahlavani and Eshghi (2011)	A hybrid algorithm of simulated annealing and tabu search for the graph coloring problem
	Science Direct	2012	Wu and Hao (2012)	An effective heuristic algorithm for sum coloring of graphs
	Science Direct	2017	Zhou et al. (2018)	Improving probability learning based local search for graph coloring
	IEEE	2018	Lim and Wang (2004)	Meta-heuristics for robust graph coloring problem

Douiri and Elbernoussi (2012) have been interested in an elaboration of an approximate solution for the MSCP. They have tried to give a lower bound for MSCP by searching for a disintegration of the graph, predicated on the meta-heuristic of ACO. They have tested diverse examples to verify the method and suggested the investigation of the lower bound of the MSCP. For this, they've emphasized the coloring of the complement graph. An ACO has also been applied to reach the decomposition of a clique of the primary graph. This clique disintegration offers an improved lower bound for MSCP over the other graph disintegrations. As a result, the advantages of the paper include high convergence and the improvement of lower bounds. However, several high iterations of algorithms and some unsuccessful performances are the main disadvantages of this paper.

Mohamed and Elbernoussi (2011) have examined the problem of the MSCP and answered it by linking a Max-Mix Ant System (MMAS) with a surrogate constraint heuristic. They have associated adjusted ACO calculation to this issue to acquire the decomposition of a clique of the first graph. This clique disintegration gives preferred lower bound to MSCP over other graph disintegrations. They have also contrasted their numerical outcomes and existing ones. The adequacy of this approach, in the case of the literature, is acceptable. The algorithm has also combined with other heuristics to improve its performances. As a result, this method has high convergence and low runtime. However, it suffers from a disability in solving complex graphs.

The ACO has been used in Graph T-Coloring Problem (GTCP) by Aicha et al. (2010). They have presented 2 advanced combined methods using an ACO (ACS1) and a TS (ACS2) for the GTCP. These procedures have been tested for typical and confined instances of the GTCP with various arrangements of the parameter. They've compared the results of two algorithms with those of the Hao algorithm (Dorne and Hao, 1999) published in 1999. Results are often better than those of the Hao algorithm. The productive technique seems the best for small graphs regarding expense and time. Sadly, no identical strategy exists to set GTCP. It is important to grow strategies like that or different ones as safe frameworks and bee's colony optimization later on. This algorithm is unsuccessful for large and complex graphs. It has not also improved cost efficiency. The strategy looks to be effective in the future for large charts in terms of cost and runtime.

Plumettaz et al. (2010) has proposed another typical optimization technique named ant local exploration that, conversely with other ant algorithms, utilizes every one of the ants as a local exploration pursuit method, and where every choice of every ant can be immediately figured. Moreover, approaches to diminish the computational effort related to each ant decision have been proposed. Another general ant procedure is then associated with the outstanding k- coloring issue, which is an NP-hard issue. Computational tests have been done to prove that their algorithms focus on the best coloring strategies. As a result, the advantages of this paper are high convergence, high efficiency, global solution, and

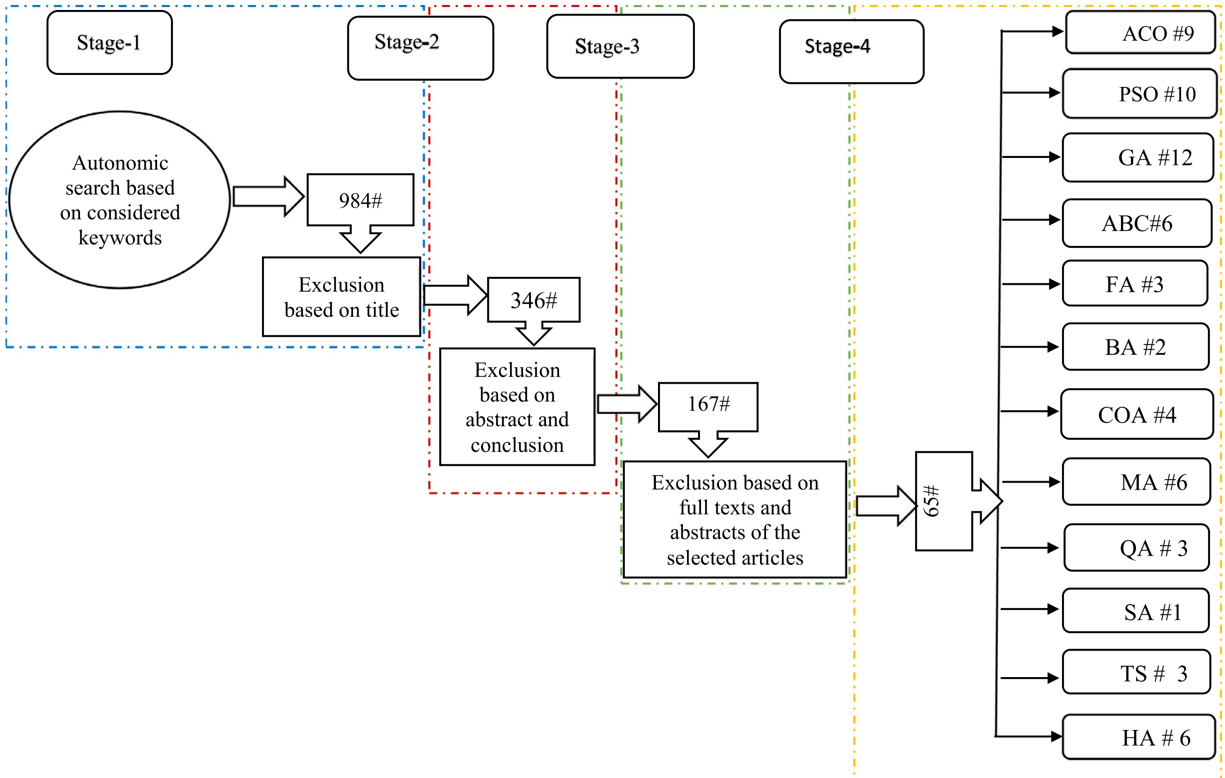

Fig. 1. The technique used for selecting the papers.

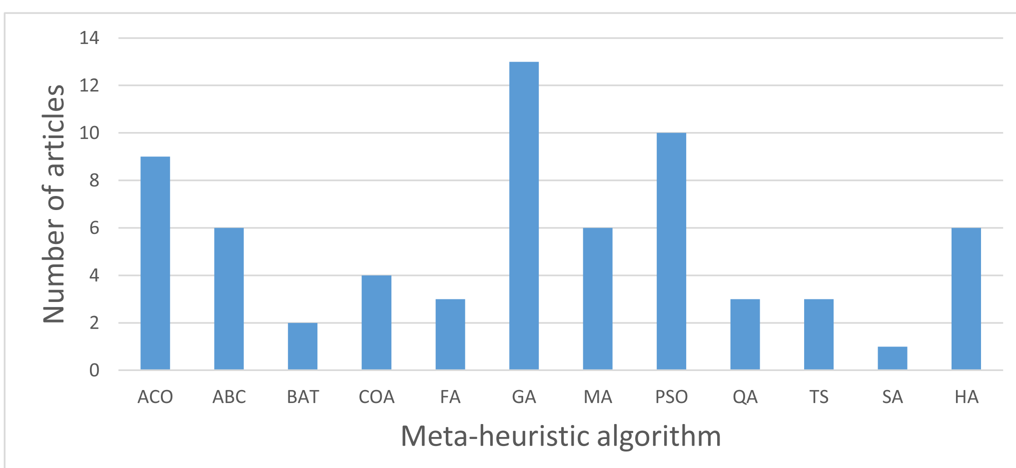

Fig. 2. Percentage of the reviewed meta-heuristic algorithms.

applying in large graphs. The disadvantages of the paper are unsuccessful performance and high runtime.

Scholar (2017) has designed an automated system for setting the timetable by staining the GCP with an ant algorithm. Using color graphics, it is suggested to create a typical mechanism that meets the growing needs of big instructive firms. It has an effective arrangement of programs and actions, in which sophisticated resource components have effectively been allocated to scheduling. The program is quick, able to change, easy to use, and high capability. This suite is efficient in optimization; a collaborative method for meeting the needs of the operator. This software is designed as a client-server software-manage server administrator. An administrator stores the input/teacher/checking information and other ones on the server; the server keeps information in the database by information; the Conflict generator produces a conflict graph and the graph Negative produced by the graph coloring unit. This unit applies an ant algorithm for graph coloring. An allocation unit allocates matching time lots for the abstract color; the final result is a color graph. The benefits of this scheduling system make it a good decision for the firms that eliminate their present request, limited or non-flexible to the altering needs of their arrangement. The mechanism uses a highly effective data architecture that can be erratically increased. It does not have a dimension limitation of actions. While more than one client is not running at a time, it can easily work with the multicast applications of this system as a centralized mechanism that does not support decentralized structure. The impermanent adjustment is restricted to the server, but it can continually be upgraded to the client module. This system has not been implemented on several monitors. Its results have not been included in the paper.

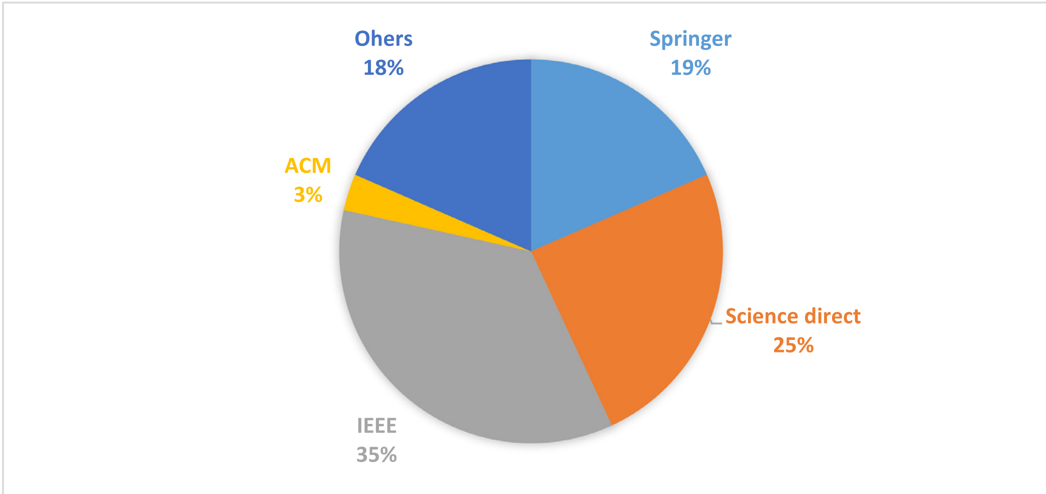

Fig. 3. A pie graph of the percentage of the meta-heuristic algorithm in graph coloring papers, according to various publishers.

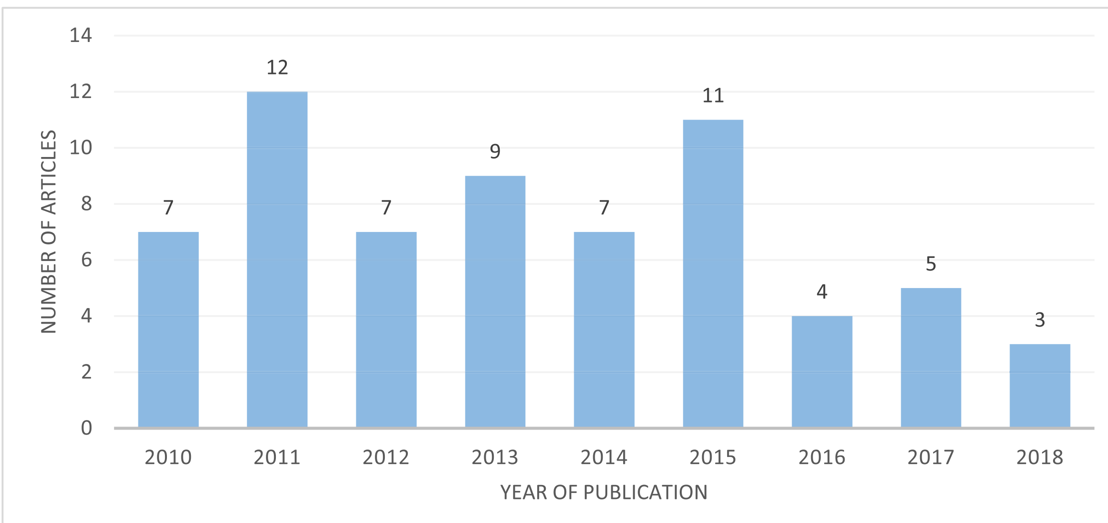

Fig. 4. Distribution of papers based on year of publication.

Mosa et al. (2017) has developed a new text abstraction field based on optimization of the colony of hybrid mice, which is presented with the ACO-LS-STS (ACO- Local Search- Short Text Summarization) local search mechanism for an ideal or near-ideal summary. The STS algorithm has been maintained by reflecting views of various fans though keeping the main concepts of high-quality text in the summary. STS was officially recognized as an optimization issue. Initially, the graph-coloring algorithm named GC-ISTS has been used to reduce the field of the ant's response to minor sets. Obviously, the key goal of applying the GC is to make the exploring procedure more comfortable and quicker; it stops ants from being optimally and locally optimized. First, different views have been assembled in the same color, while preserving the ratio of information as a basic list of views. Then, it activates the ACO-LS-STS, a new method for extracting common views out of each color in a parallel shape. At last, the finest summary of the best color has been selected. The issue has been recognized as an optimized issue using GC and ACO-LS to produce the ideal answer. The introduced method has been examined on a set of Facebook messages. In fact, it is clear that the introduced method is able to obtain an appropriate answer ensured to be close to ideal and significant functionality compared to old document summary methods. It is possible that in the future, this paper will be improved by specifying the type of operations.

4.1.2. Overview of the studied ACO-oriented methods

Since GCP is an NP-hard optimization issue, meta-heuristic methods like the ACO will be better to solve them. This algorithm offers better results than others do. This algorithm is suitable for discrete problems such as GCP, which cannot be used with gradients. Because of losing pheromones in paths, it prevents early convergence and ensures the convergence. The algorithm has a low initial dependency. Convergence rates may slow down despite the assurance of convergence. It may even lead to a local solution. The algorithm requires high memory because the whole clone information should be stored instead of the previous generation of data storage. In the last part, 7 ACO algorithms chosen for GCP have been studied along with their benefits and drawbacks. Table 3 demonstrates the strengths and weaknesses of each paper.

4.2. Bat algorithm (BA) optimization technique

BA is a meta-heuristic method for universal optimization. It was stimulated by the echolocation conduct of microbats with

Table 3
The juxtaposition of the main advantages and disadvantages of the ACO for graph coloring.

Paper	Advantage	Disadvantage
Fidanova and Pop (2016)	• Similar Standard deviations • Ensuring convergence • High comparability	• The high runtime of the ACO hybrid algorithm compared to ACO • Running on small or medium-scale graphs
Yuan et al. (2014)	• Decreasing heuristic algorithm • Introducing one of the applications of the GCP • High comparability	• Not suitable for complex problems • Improve the algorithm to improve the quality of the solution
Douiri and Elbernoussi (2013)	• High Efficiency • Development of upper bound • Low runtime	• Not met with other meta-heuristic algorithms • The need to combine with other meta-heuristic algorithms
Douiri and Elbernoussi (2012)	• Improving theoretical bounds • Better lower bound • High convergence	• Running on small-scale graphs • Some unsuccessful runs
Mohamed and Elbernoussi (2011)	• High convergence • Low runtime	• Not suitable for complex graph • Low performance
Aicha et al. (2010)	• Low runtime • Decreasing solutions • space	• Not suitable for complex problem • Not improving the cost efficiency
Plumettaz et al. (2010)	• High comparability • Global solution • High efficiency • Applying in large graphs	• Some unsuccessful runs • High runtime
Scholar (2017)	• Flexible system • The system has a very high capacity • Do not limit the size of the events • The system can be upgraded	• The paper is a descriptive paper. • Not comparable
Mosa et al. (2017)	• The search process is easier and faster • Solution guaranteeing • Comparable	• The type of operation is not clear • Not flexible

changing pulse rates of release and loudness (Seneviratne et al., 2009). The BA has been produced by Yang (2010) in 2010. With a particular purpose to care for complex problems, considerations gathered from characteristic components have been misused to create heuristics. A definitive objective is to create frameworks that can learn gradually to be useful to their condition and be tolerant of noise.

The BA is obtained from the echolocation conduct of bats. Echolocation is a propelled hearing-oriented direction-finding mechanism utilized by bats and some different animals to identify protests in their environments by producing a sound in nature. Whereas they are chasing targets or exploring, they deliver a sound wave that goes over the canyon and comes back to them as an echo. The sound waves go at a steady velocity where the atmospheric air pressure is indistinguishable. By considering the time delay of the returning sound, they can decide the exact separation to surrounding things. Also, comparative amplitudes of the sound waves got at any one‘s ears have been used to detect the form and heading of objects. The data collected regarding these lines of hearing is used and arranged inside the brain to delineate a mental image of their surroundings. When everything is done, echolocation calls have been described by three components; to be specific pulse emission, pulse frequency, rate and loudness (intensity). In the sky, bats radiate echolocation calls with differing frequencies (25 kHz-150 kHz) relying upon vicinity to the objective (Yang, 2010). Even though low recurrence sounds travel more remote compared to high-frequency ones, at last, they give bats unmistakable data about the surrounding items. Then, a beat rate compares with the count of heartbeats produced every second. It can likewise be balanced by bats as indicated by the separation from the goal. It is realized that bats increment the rate of a heartbeat to 200 for every second when moving toward an objective. Lastly, bats diminish the intensity of a pulse from 120 dB (loudest) to 50 dB (quietest) as they get nearer to their target. Yang (2010) has reproduced the echolocation conduct of bats and its related parameters in a numerical optimization algorithm.

4.2.1. Summary of the chosen methods

Djelloul and Chikhi (2015) have introduced a discrete binary form of the BA intended to the GCP called AMBCOL. Their primary contribution is the definition of a new binary modification for the GCP solution, using a binary representation of binary correction action to avoid an unacceptable solution, and using a modified Recursive Largest First algorithm (RLF) to produce the primary solution. This method has been fully evaluated with a variety of sample and size issues from the DIMACS criterion. The presented algorithm effectively diminishes the dimension of the population and the count of repetitions to optimize the answer. Nevertheless, there are many problems in developing the algorithm; the integration of a local exploration technique such as TS into the core of the algorithm to eliminate local solution. The disadvantage of this method is that it needs to be improved so that sometimes it can eliminate local solutions.

Djelloul et al. (2014) has introduced a distinct binary shape of the BA for the GCP named BBCOL. The fundamental commitment of their method is to characterize another binary change to explain the coloring of the graph and utilize the altered RLF to make an underlying arrangement. This approach is completely assessed with various sorts of tests and size problems of the DIMACS standard. The introduced algorithm has successfully decreased the dimension of the population and the count of echoes to enhance the arrangement. Although a few problems exist for enhancing the algorithm, this method is more accurate compared to coordinate local search techniques such as calculating tabu in the center of the algorithm. If this algorithm performs inappropriate conditions, sound control and parameters will be perfect. This algorithm will be a good alternative for the GCP. As a result, the advantages of this paper are low population size, global solution, and the low

Table 4
The juxtaposition of the main benefits and drawbacks of the BA for graph coloring.

Paper	Advantage	Disadvantage
Djelloul and Chikhi (2015)	• Low population size • The low number of iterations	• Local solution • Need for combining with TS algorithm
Djelloul et al. (2014)	• Low population size • Low memory requirement • Global solution	• Need for improving the algorithm to coordinate local search techniques • Not compared with other meta-heuristic algorithms

number of iterations in the algorithm. The need to improve the algorithm and lack of review's runtime of an algorithm are the drawbacks.

4.2.2. Overview of the studied BA-oriented methods

BA, like many other meta-heuristic algorithms, has simplicity and flexibility, and its implementation is simple for GCP. These three main reasons for the effectiveness of the BA can be summarized as follows: BA uses voice reflection and frequency regulation to solve the GCP problem. This feature can provide some of the functions that may be the same. Thus, BA has other advantages of group-based algorithms. BA has an automatic rising compared to other meta-heuristic algorithms. This ability leads to promising solutions. The action is carried out by automatic switching, ranging from exploratory moves to localized and centralized operations. Accordingly, BA has a fast convergence rate with minimal initial stages compared with other algorithms. Many of the meta-heuristic algorithms apply proven parameters using some pre-configured algorithms depending on the parameters. In comparison, BA controls the parameter that can change the parameter values in the upcoming repetitions. It provides an automatic switching method, from survey to application, when they approach an optimal solution. It is another BA advantage over meta-heuristic algorithms. In addition, the initial analysis shows that BA ensures the universality of features under accurate conditions and explains GCP large-scale issues efficiently. If the mentioned advantages have not been fulfilled under suitable conditions, the rate of rapidity may not be high. The algorithm cannot run on large-scale graphs. In the subdivision, two chosen BA algorithms and their benefits and drawbacks have been studied for GCP. The comparison of the results of each paper is presented in Table 4.

4.3. Artificial bee colony (ABC) optimization technique

The ABC algorithm is an optimization method in the light of enthusiastic rummaging behavior of bee congestion (Consoli et al., 2013; Karaboga, 2005; Hajimirzaei and Navimipour, 2018). The ABC algorithm is a nature-stimulated optimization method that impersonates the rummaging conduct of bee swarm (Karaboga and Basturk, 2007). It has been effectively used to look through an optimal answer for some improvement issues (Akbari et al., 2010). In the ABC, the state of fake bees has been separated into 3 gatherings: spectators, observers, and EBs. Half of the colony fills in as EBs, and another half fills in as spectators. The location of a sustenance source is related to a potential answer for an optimization issue, and the nectar measure of every nourishment source denotes their wellness of related solutions. The number of utilized bee's equivalents to the number of sustenance sources. At this point, when bees surrender a sustenance source, the relinquished utilized bee would turn into a scout. When the algorithm starts, it initializes with a distributed bee population at different food source positions and sends EBs, onlookers, and observers to work. In the remainder of the present part, a summary of particular systems has been provided for GCP, using the ABC and their key characteristics.

4.3.1. Summary of the chosen methods

Markid et al. (2015) has presented a method for handling the GCP; the integration of ABC and tabucol techniques. To apply the ABC for answering GCP as an integrational issue, they've applied a few alterations to the initial ABC. The initial change was the starting step, the next was embedding tabucol algorithms in the architecture of ABC. The third change was bringing a system for collecting information around the best answers throughout the procedure to apply them for producing novel food-sources. Actually, they've used 2 systems to prevent local goals. The primary system is tabu list applied for the architecture of the embedded tabucol method and the other is raising scout bee to discover novel food sources and alter them by over-searched one. The outcomes have shown some enhanced productions, and in a few instances, quicker convergence of the introduced method. It has been compared with other algorithms. The results have shown a low number of colors and a high runtime. Also, the algorithm has only performed on small-scale charts.

Tomar et al. (2013) has suggested an amended ABC optimization algorithm for GCP. GCP for coloring the nodes of each graph with the smallest probable count (confirming at two nearby nodes with different colors) and optimizing the new ABC algorithm for GCP. In the present article, the introduced method has been compared with three other methods: prioritization, instructions based on a large-scale, and degree order based on saturation. Furthermore, these results have shown the ABC has converged in several repetitions. Also, it can optimize colors to vertices of a graph. However, it has a high runtime, and it runs only on small-scale graphs.

Greenwood and Chopra (2013) have introduced an upgraded ABC to answer the NP-complete theoretical issue. Two NP-complete graph problems, known as the maximum independent set (MIS) and the maximum clique have been used to test the proposed method. Their modified algorithm replaces the updated operator used for the EB (counter) at the stage of operation with a variant of operator evolution. The ABC algorithm searches for an integer dimensional integer and its true value components converge to binary strings that can be a potential solution for a graph theory problem. They've also looked at the more bees to progress exploration in a very different fitness landscape. While the algorithm has been executed on small graphs, it has received an infeasible solution with the highest runtime.

Fei et al. (2013) has applied two algorithms ABC and SA to the minimum load coloring problem (a combinatorial optimization problem). The experimental results have shown that it can solve a combinatorial optimization problem. The comparison between the ABC and SA algorithms has indicated that ABC outperforms SA for most of the graphs. However, some performances were unsuccessful. Since the ABC algorithm has good solution quality on the minimum load coloring problem, they've suggested that the ABC algorithm can be used to solve the computational problems within the field of material science and bioinformatics. In this paper, algorithms have been implemented on large-scale graphs. The ABC has a relatively lower runtime than the SA. The ABC prevents early convergence. It needs to be improved to compete with other algorithms.

Table 5
The juxtaposition of the main benefits and drawbacks of the ABC for graph coloring.

Paper	Advantage	Disadvantage
Markid et al. (2015)	• Comparison with different algorithms • The low number of colors	• Local optima • High runtime • Running on small-scale graphs
Tomar et al. (2013)	• Better results on the medium-scale graphs • High convergence • High comparability	• Moderate-size graph • Running on small-scale graphs
Greenwood and Chopra (2013)	• Global optima • The low number of iterations	• Running on small-scale graphs • Infeasible solutions
Fei et al. (2013)	• Low runtime • Applying in large graphs • Avoiding premature convergence	• Not comparing with other algorithms
Fister et al. (2012)	• Achieving good success on small graphs • High convergence • High comparability	• Running on small-scale graphs
Faraji and Javadi (2011)	• A felicitous connection between precision and speed • Substantially improving the results • High comparability	• High runtime • Running on small-scale graphs

Fister et al. (2012) has suggested a Hybrid ABC (HABC) calculation for graph 3-coloring, which has an outstanding distinct optimization issue. Consequences of HABC are contrasted consequences of today's outstanding graph coloring methods: the tabucol and Hybrid Evolutionary Algorithm (HEA) and the conventional EA with the SAW technique (EA-SAW). Broad investigations have demonstrated that the HABC has coordinated the aggressive aftereffects of the ideal graph coloring methods and showed improvement over the conventional heuristics EA-SAW, explaining arbitrary produced medium-sized graphs. The algorithm has been executed on small graphs. It has not considered the number of iterations and runtime. The HABC could be moved forward for 3-GCP. Specifically, particular learning through local exploration heuristics could be directed to the method. The ultimate experiment for additional effort rests on the settling of a big graph (1000 vertices). These graphs could be effectively understood by utilizing the proposed HABC calculation.

Faraji and Javadi (2011) have provided a new method for graph-coloring, according to the bee's natural conduct (BEECOL). Finding a better conclusion in contrast to a current ACO is the fundamental objective of this view. The outcomes of DIMACS (trial examples) have demonstrated changes over a current ACO for the GCP. From this improvement, it is expected that the algorithm will run on large graphs and run down with a low number of iterations. This paper has considered other issues such as low implementation time of the algorithm, a right linking between precision and velocity of an algorithm, and the ability to compare the results of the algorithms. The high number of iterations, high runtime and running on small-scale graphs are the drawbacks of the paper.

4.3.2. Overview of the studied ABC-oriented methods

The ABC is a type of algorithm that acts as an exploration in a defined environment to find its solutions. This algorithm has no limit regarding the scientific field. It should be noted that this algorithm could be used for search at the professional level of the GCP and RGCP. This algorithm is very effective in finding the optimal response with low running time. The ABC examines any point in a discrete space consisting of possible responses as sources of food. Therefore, in the studied graph, it is dubious that the color of the rice will be colorless. The results of this algorithm have been compared with those of the meta-algorithms. The disadvantage of this algorithm is its implementation on small-scale graphs. It also has a high dependency on the parameters of the algorithm. By changing the parameters, different solutions have been obtained. In the preceding subdivision, 6 chosen ABC algorithm for GCP and its benefits and drawbacks have been studied. The comparison of the results of each paper is presented in Table 5.

4.4. Cuckoo optimization algorithm (COA) technique

The cuckoo is a naturally attractive bird, not due to its excellent sounds, but due to its reproduction tactic. Very few animal groups, for instance, Ani and Guira cuckoos lay their eggs in public nests, though they can expel others' eggs to build incubating possibility of their owns. A significant count of species involves in compelling brood parasitism by putting their eggs in the homes of other hosts (usually different species). 3 essential sorts of congenital parasitism are nest takeover, intraspecific congenital parasitism, and cooperative breeding. Some of these hosts can involve in a direct fight with invading cuckoos. If a host realizes the cuckoo's eggs, they will either toss them away or just leave the nest and make another one somewhere else.

Some of its types, for example, new world brood-parasitic Tapera, have developed with the end goal that female parasitic cuckoos are habitually expert in the imitation of the color and case of the eggs of a pair of particular host types. It diminishes the likelihood of their eggs surrendered and accordingly builds their conceptive. To answer an optimization issue, the cuckoo method initially begins with a primary reaction and, next, goes to neighboring zones in a reiterating loop. If the neighbor's solution outperforms the present one, the method places it as the present solution, otherwise, the algorithm accepts the current solution. This section gives an overview of selected mechanisms for graph coloring using the COA and presents their key characteristics.

4.4.1. Summary of the chosen methods

Mahmoudi and Lotfi (2015) have introduced a new methodology for solving GCP based on COA. COA has demonstrated its brilliant abilities like fast convergence rate and superior universal minimum accomplishment. Discretization on the most integrational issues, GCP had done outcomes on the scope of benchmark functions of this problem. They've looked at the proposed algorithms in this specific circumstance. Thus, movement administrator in view of the distance's theory should be re-imagined in the discrete space to use COA to separate exploration space, the normal operators like addition, subtraction, and multiplication in COA. As a result, the success rate is nearly 100% and an appropriate balance between variation and integrating is one of the advantages of the paper. Falling into an optimal local trap and high runtime are two of the disadvantages of this paper.

Table 6
The juxtaposition of the main benefits and drawbacks of the COA for graph coloring.

Paper	Advantage	Disadvantage
Mahmoudi and Lotfi (2015)	• The success rate is nearly 100% • A good balance between diversification and centralizing	• Trapping in local minimum • High runtime
Djelloul et al. (2015)	• Adapted algorithm • Reducing algorithm operations	• Running on the small-scale graphs
Zhou et al. (2013)	• The low number of colors • High Efficiency	• Moderate-size graphs • achieving local optimization
Aranha et al. (2017)	• Reducing the number of evaluations • Comparing changes linearly • Running without changing the parameters	• Failure to compare algorithms with other algorithms • Not ensuring convergence

Djelloul et al. (2015) has tried to solve the GCP by employing a different approach in view of the quantum motivated CS algorithm. It defines a fitting quantum picture in view of qubit portrayal to indicate the GCP answers. The other aim is suggesting a dissimilar measure operator in light of the adjacency matrix. The 3rd aim includes the suggestion of an adjusted hybrid-quantum- mutation operation. The fundamental roles of their method are the meaning of a quantum portrayal for the graph coloring solution, Usage of another measure operation in view of the adjacency matrix, and the utilization of a modified mutation operator. By improving the algorithm, it is expected to be able to run on complex and large graphs. Updating the algorithm and reducing its operation are the advantages of the paper. Running on small graphs and high runtime are the disadvantages of the paper.

Zhou et al. (2013) has presented an enhanced CS optimization algorithm to solve GCP. A grasping algorithm has been applied to the CS algorithm to develop the functionality of the CS method. Experimental results have shown that this algorithm significantly affects the problem of medium-sized graphs. Also, ICS is more effective and precise compared to the revised PSO suggested by Cai et al. (2009). But as the problem scale increases, nest repeats should be increased and got out of the best approximation. In general, large-scale nests need more evolution time, so a greater amount of the best solution. The computational complexity will significantly rise later. Therefore, they need to discover the coloring algorithm for a wider scale of coloring. It will be a case in future research. Running on medium-scale graphs and achieving local optimization are the disadvantages of the paper.

Aranha et al. (2017) has compared the Cuckoo Search (CS) to solve the three-color graph coloring (3-GCP). The complexity of this CS adaptation job is due to the alteration of a constant domain to a distinct one, Lévi Flight (LF) operator. But this method has not considered the distance of the answer, which is a key feature of the LF. The present article provides a novel CS agreement that preserves the concept of the LF response distance. Moreover, the operator simplifies CS motivation and reduces the number of required evaluations. It has compared a combination of introduced alterations by GA as a starting point. A series of 3-GCP problems have been generated randomly. Results have indicated the importance of excellent compatibility with the LF operator to raise the success rate and offer auto-compatibility with the CS. LF is also able to apply CS to (3-GCP) without setting parameters or combining with local search. The paper does not have a comparison of algorithms and does not check the convergence of the algorithm. They are the drawbacks of the paper.

4.4.2. Overview of the studied COA-oriented methods

COA is guaranteed to meet the requirements of global convergence and of GCP's global convergence characteristics. It means that for optimizing GCP, COA can frequently converge to a global optimum. In addition, the COA has 2 exploration abilities: local exploration and global exploration, which are managed by the possibility of substituting or discovering. Local exploration is so tight with about 1/4 search time, whereas global one is around 3/4 overall exploration times. This lets us explore exploration space on a more effective global scale. As a result, global optimization can be set up with a higher likelihood. Another advantage of the COA is that it uses the global Levy flight search for standard randomized steps. Since the Levy flight has an average unlimited variance, the COA can explore the search area more effectively. This benefit (ensuring universal convergence). is quite effective, coupled with two local exploration abilities. It has a success rate of nearly 100%, though with a high runtime. Sometimes, there are fewer successes with a lot of iteration. Furthermore, in some cases, they may be trapped by the local optimum. In the preceding part, the chosen COA algorithms for GCP and their benefits and drawbacks have been studied. The comparison of the results is presented in Table 6.

4.5. Firefly algorithm (FA)

The FA has been introduced by Yang (2009). It depends on the adored conduct of the flashing features of fireflies. He's classified these flashing features into 3 principles (Yang, 2009):

- Fireflies are unisex. It is a characteristic of all fireflies with the goal of pulling to different fireflies paying little heed to their sex.
- The fascination is relative to their brilliance, like this, for any two flashing fireflies, the less brilliant one will go to the more brilliant one, and they both decline as their interval increments. If no one is more brilliant, they move arbitrarily;
- Shine or light power of a firefly is influenced or controlled by a scene of the objective function needs to be optimized.

In this algorithm, all firefighters are integrated, so that a firefly is absorbed into other colors based on the light and regardless of their sex. So, for both lightning flashing, the brilliant one will go to the more brilliant one (Hoseinnejhad and Navimipour, 2017). An appeal is in respect to the brilliance. So, they will diminish as their separation expands. The shine of a firefly is dictated by the vision of the target function. For a maximization problem, the shine can necessarily be corresponding to the amount of the target function (Ellis and Petridis, 2009; Bramer and Petridis, 2012). The FA has been utilized similarly for tackling load adjusting and arranging the issue in which each firefly is an answer for the job assignment; the exploration space size is the count of jobs. In the following part, an outline of the chosen components and their principle highlights are given for graph coloring by the FA.

4.5.1. Summary of the chosen methods

Del Ser et al., 2016) has explained the absence of a community detection algorithm in light of maximizing the well-known

Table 7
A juxtaposition of the main benefits and drawbacks of the FA for graph coloring.

Paper	Advantage	Disadvantage
Del Ser et al. (2016)	• Achieving an optimal global solution	• Not comparing with other algorithms
Fister et al. (2012)	• The improved solution with a constant parameter • Discovery of overlooked solutions	• Running on small graphs • The algorithm needs an elite initial solution • Not ensuring convergence
Chen and Kanoh (2017)	• Running on the big-scale graphs	• High runtime • Slow convergence • Failure to carefully check the distance between the firefly

surprise metric prepared to implement globally in a focused manner when associated to graphs of extremely different topology. The heuristic plan depends on the search technique of FA, a meta-heuristic solver in view of the aggregate conduct, reciprocal fascination and arbitrary yet managed development of these bugs. The introduced procedure has copied this observed social behavior of fireflies in the genotype of the graph-classification issue as opposed to an encrypted illustration of its exploration space (phenotype). Nevertheless, a new commitment of the article depends on imitating the acquitted FA in the genotype of community detection problem instead of a phenotype or arithmetical portrayal of a graph separating. The proposed strategy adopts an alternate strategy by specifically planning the representation of uncertain search methods. This means that the advantage of the algorithm is a global optimization in most cases. Lack of proper review of the count of repetitions and the runtime is the paper's disadvantage.

Fister et al. (2012) has associated the FA, hybridized with local exploration heuristic, to integrational optimization issues in which they utilize graph 3-coloring issues as trial standards. After the assessment scheme of the FA, the heuristically local exploration attempts to enhance the present answer. This heuristic has been implemented to that point when changes are distinguishable. Consequences of proposed MFFA were thought about against aftereffects of the HEA, tabucol, and the EA with SAW strategy (EA-SAW) by coloring the set of medium-size arbitrary graphs (500 vertices), utilizing the Culberson accidental graph producer. Great outcomes have been obtained on average. Unfortunately, due to the change in the parameters of the algorithm, the recovery algorithm has not been observed in the response. The need for an algorithm as an elite initial response and lack of convergence are disadvantages of this paper. However, the discovery of neglected responses of other algorithms is another benefit of this algorithm.

Chen and Kanoh (2017) have proposed a distinct FA grounded on likeness and used it to answer 3-coloring issues. Though the FA, hybrid for GCP, has been introduced (Fister et al., 2012), the proposed approach with the discrete ABS, PSO has been compared to evaluate its performance. Original FA solves the problems of continuous optimization. To apply it to discrete issues, they have defined the original space again in discrete space and called it a discrete Firefly Algorithm (DFA). An experiment on 100 arbitrarily produced graphs shows that the introduced technique has a great achievement, though the graph is so big. Solving flattening problems improves the success rate of discrete PSO and ABC. In addition, because the proposed method fails to use the original FA algorithm directly from any other combination method, it is useful for big Combinatorial Optimization Issues (COP). However, the disadvantage of the proposed method is also clear. Before finding an optimal answer, it will spend more time with its rivals. Therefore, they have not claimed that the introduced technique is the ideal way of answering the graph-coloring issues. Three things will be done in the future. At first, the sluggish convergence will be investigated thoroughly. Next, hamming intervals and similarities will be applied to assess the variance among firefly creams. Other methods will test the distance and compare their performances. Finally, this method will be applied to other COPs, and its performance will be tested.

4.5.2. Overview of the studied FA-oriented methods

FA is based on congestion intelligence. Two main advantages of the FA are auto-segmentation and the ability to handle a multi-quality problem such as GCP. FA is based on absorption and brightness. This will automatically divide the entire population into subgroups with a mean interval, and each group can conquer around an optimal locale. Between all these optimizations, the best global optimum can be discovered. This division allows one to find the optimal one at a time. This feature is suitable for the FA, especially for GCP optimization issues. In addition, parameters in the FA can be set for random control over repeatability, so that convergence can also be speeded up by adjusting these parameters. These advantages make FA more able to deal with the GCP problem, diversity in solutions, and combined optimization by automatically dividing the entire population into subgroups. This algorithm has some disadvantages, such as low exploration capability of Firefly which is always in one direction, making it impossible at times to achieve optimal solutions. In the preceding part, two chosen FA methods and their benefits and drawbacks have been studied for GCP. Table 7 presents a juxtaposition of the results of each paper.

4.6. Genetic algorithm (GA)

GA is a meta-heuristic motivated by the procedure of normal choosing, which fits a bigger category of EA (Keshanchi et al., 2017; Panahi and Jafari Navimipour, 2019; Abreu et al., 2020; Folkestad et al., 2020). Generally, GAs are applied to create the best answers for optimization and exploration issues, depending on bio-stimulated operators, for example, choosing, crossover, and mutation (Goldberg, 1989; Hamian et al., 2018). GAs (Schorle et al., 1996; Goldberg and Holland, 1988) are EAs in natural possibility selection and evolution. GAs are effectively connected to a wide range (Navimipour and Rahmani, 2010; Jafari Navimipour et al., 2014). In GAs, there are populations of possible answers named individuals. The GA implements unmistakable genetic operations on the population when the assumed stopping factors have been met. A parallel genetic algorithm (PGA) is an augmentation of the GA. A notable benefit of PGA is its ability to encourage distinctive subpopulations to advance in diverse directions at the same time (Lim et al., 2007). It is demonstrated that PGAs accelerate the search procedure and may well create high-quality solutions for complex issues (Cui et al., 1993; Sena et al., 2001; Liu et al., 2004). Genetic methods have been quite effective in traditional optimization techniques for answering linear, convex, and other issues. But they are far effective to solve distinct and nonlinear issues. In fact, improved generations of better chromosomes are formed.

4.6.1. Summary of the chosen methods

Douiri and Elbernoussi (2015) have introduced another hybrid GA in view of a local exploration heuristic known as DBG to provide estimated amounts of χ (G) for GCP. This procedure happens as follows: they've begun from a primary count of colors equal to k; they've picked their individuals relating to a task of k colors to all vertices of the graph G. In case a substantial k-coloring has been discovered, the count of k has been updated. They've repeated the method for the same number of iterations that k-coloring has been accomplished without clash and at the same time, the maximum count of iterations has not been touched. For this, they've utilized the heuristic DBG to decide a maximal independent set approximation. The computational experiments done on an arrangement of 68 standard graphs have been transported as DIMACS collection between 12 main graphs by means of 900, 1000, 2000 and 4000 vertices. It has demonstrated that the outcomes have a competitive advantage rather than the current famous outcomes of six advanced works. The outcomes of this paper have been compared to those of the other six papers. The number of successes is high compared to those of the other six papers. Despite good results, it is necessary to improve the number of iterations of the method and the active time.

Bhasin and Amini (2015) have utilized GAs to deal with the GCP. Their algorithm has been executed and verified. The procedure is a development of the effort done earlier that can deal with graphs that couldn't be taken care of before (Guo and Niedermeier, 2007). Results have demonstrated that the procedure functions admirably for the vast majority of cases. Nevertheless, there are a few situations where the technique does not work. The cases where the graph is complete still need a better method. An extensive literature review has been carried out to understand the concept (Demange et al., 2014). Diploid genetic algorithms have already been applied to TSP (Chiarandini and Stützle, 2010; Zhou et al., 2016). The future extent of the present study is expected to relate diploid genetic methods to the issue to fuse strength into the introduced method. The need for the proposed robustness of the algorithm, running on small graphs, and the need for a better method for full graphs are disadvantages of the paper.

Zhang et al. (2014) has presented a novel PGA to solve the GCP in Computing Unified Device Architecture (CUDA). The GA beginning, crossover, mutation, and choosing operators have been modeled parallel in CUDA structure. The method has offered a parallel initialization population, choosing, crossover and mutation operators, which are the most critical procedures for GA. Additionally, the execution of their method has contrasted to that of the other graph coloring methods utilizing 36 DIMACS standard graphs. The comparison of the outcome has demonstrated that their algorithm is more aggressive regarding the algorithm time and graph case dimension. As a result, high **graph size** compared to that of the best algorithms and the best known upper bound on the chromatic number are the paper advantages. But, the algorithm has been implemented on small-scale graphs.

Hindi and Yampolskiy (2012) have presented a hybrid method that applies a GA in the light of artificial multitude of ways to comprehend the GCP. The GA portrayed here uses more than one-parent choosing and mutation techniques, relying on the condition of fitness of its ideal answer. The outcome moves the solution for the global optimum more rapidly than utilizing a solitary parent choosing or mutation technique. Algorithms depicted here can be used in different subgroups of the wide-ranging GCP. Specifically, Sudoku can profit by these methods in which a graph with 81 vertices required to be colored, utilizing about nine different colors (i.e. distinctive numbers). As an advantage, this algorithm has quickly become an optimal solution and demonstrated the success of the solution. However, this algorithm has a high cost of localization and runs on small-scale graphs.

Sethumadhavan and Marappan (2013) have exhibited a better genetic technique utilizing the single parent conflict-gene crossover and conflict-gene mutation operators alongside the conflict-gene elimination strategy to answer the GCP. These operators decrease exploration space by minimizing the count of genetic generations to acquire an ideal answer. A fitness function in light of various conflicting edges, whose vertices allocated with similar coloring, has been characterized for the primary and resulting generations of gene orders. The introduced genetic technique has been analyzed on a portion of standard graphs. The outcomes have been satisfactory. The approximation strategies decreasing the exploration space and furthermore incrementing the level of effective runs has been displayed. Significantly, computational complexity has been evaluated. This algorithm has poor performance in some cases, such as the average number of mutations, the average number of generations, and failure in some implementations.

Marappan and Sethumadhavan (2013) have presented a new GA for GCP. They've directed a few analyses with standard graphs to evaluate the processing difficulty of GCP. This paper has shown the robustness of GA to explain a GCP. The proposed GA has utilized a creative single conflict gene mutation and a conflict gene crossover as its operators. The exploratory results of the proposed algorithm have been contrasted; it is observed to be capable. As per this new GA, χ(G) coloring is gotten in a minimal count of generations. The introduced approximation GA diminishes the processing difficulty and constantly makes an ideal answer. New SPCGX crossover and conflict-gene mutation operators decrease the count of generations of the GA and diminish the exploration space meaningfully to accomplishing an ideal answer. However, it was expected to compare computational complexity with that of the other meta-heuristic algorithms.

Abbasian and Mouhoub (2011) have first talked about confinements for answering the GCP utilizing EAs. To address their objective, they've proposed various methods like the HPGA to answer the GCP with various coloring areas at the same time and to look in different ways of the exploration space. They've additionally introduced a new estimator to locate an upper bound for the graph's chromatic count. Moreover, they've introduced an expansion to the GAs, in particular, the Genetic Modification (GM) and the parental success crossover operators, particularly intended for tackling distinct optimization issues. Based on the idea of the proposed algorithm, a general estimator for GCP has not been designed. Different algorithms have not been embedded in the GM operator to solve the GCP. Moreover, Abbasian and Mouhoub (2013) have examined some broad problems in solving the GCP utilizing EAs, too. They have introduced a few distinctive methods like the HPGAGCP to answer the GCP with various coloring areas and to seek various directions of the exploration space. They have additionally introduced a new estimator to locate an upper bound for the graph's chromatic count. A modification to the GAs (in particular, GM) has mainly intended to solve optimization problems. Later, they've presented a new variable ordering method to work with the GM operator. In the investigations leading to different GCP samples, they've demonstrated that their introduced methods are exceptionally exact and quick in answering the GCP. The disadvantage is that the algorithm runs only on small-scale graphs.

Maitra et al. (2010) has shown a GA-based approach. However, the GAs have not been successful because of the symmetrical temperature of the solution space for the graph coloring. In fact, when combining two good solutions, the production of a suitable child is impossible. Therefore, GAs have often been considered inappropriate for issues such as coloring a graph with a very scary goal function. To deal with this degeneration, Bitstream neurons (Boltzmann machines) have been used in the GA answer. Unlike the traditional GA and ANN approaches, the proposed hybrid algorithm has guaranteed a 100% convergence rate for a valid solution with no parameter setup. The tests of the combined algorithm have been performed on the large DIMACS Challenge charts. Results are very competitive compared to those of the other algorithms. However, by running on large graphs, no results have been achieved. In addition, the runtime was high.

Douiri and Elbernoussi (2011) have displayed the problem of the sum coloring problem (MSCP). They've comprehended it by relating a GA to a surrogate constraint heuristic F. Glover algorithm)DBG(. The suggested algorithm has started with the development of a primary population of individuals using the DBG and setting a count of varieties (k). They've differentiated their numerical outcomes and existing ones. They've linked the presented algorithm with another heuristic to enhance its achievement. Their determination approach depends on the hybridization of a GA and a local heuristic in light of the changing the maximal autonomous group of algorithms assumed by Glover (2003).

Han and Han (2010) have introduced a two-goal GA (BGA) method for the GCP. In light of this new method, The BEA has been introduced, which utilizes new crossover and mutation operators as the genetic ones. The convergence to a globally ideal group of BGA has been demonstrated. Replication outcomes have shown that the novel method is practical. BEA can give some non-dominated answers for the decider just with a single run. For the over-constrained GCP, the BEA is more possible. Trial outcomes have shown that the method brings about the ideal solution for every redundancy with the low runtime. The disadvantages of this algorithm can be the implementation of the algorithm only on small-scale graphs.

Marappan and Sethumadhavan (2018) have presented 3 diverse genetic approaches by modifying Single Parent Conflict Gene Crossover (SPCGX) (Marappan and Sethumadhavan (2013) with a novel Advanced Local Guided Search (ALGS) operator to decrease the exploration area, by correcting exploration into a decreased exploration area. They have extended operators to perform 3 novel genetic and Tabu exploration tasks that use Single Parent Conflict Gene Extended Crossover (SPCGEX), Conflict Gene Mutation (CGM), Extended SPCGEX (ESPCGEX), Extended CGM (ECGM), Multipoint SPCGX (MSPCGX), and Multipoint CGM (MCGM). Experiments have done on small, medium, and big benchmark graphs. The proposed ALGS operator corrects the chosen gene succession before exploiting the crossover operation. It adjusts the crossover offspring before exploiting the mutation, too. The introduced ALGS operator is impressive in detection fine answers in a special area of the exploration area. ALGS with Tabu exploration provides a fine agreement between processing difficulty and the answer quality. 2 improved gene succession has been studied by fitness adequate, choosing to decrease the generations (g). A struggle has been made to formulate multipoint crossover and mutation operators to decrease the exploration area. The available genetic methods implement crossover operation on multiple parents, which needs more calculation. This work implements improved genetic operations on single parent, which are helped to reach quick stochastic convergence in achieving improved near-ideal answer in contrast with the current techniques. The outcomes of the introduced approaches are useful for a dissimilar set of graphs like arbitrary ones. Their approaches have decreased the bound for minimum colors gained up to now for specific families of graphs. Contrived operators have a key part in monotonically reducing the amounts of the fitness function and so minimizing generations (g) toward achieving the quick stochastic convergence. The graph density has an effect on output proficiency measurements of designed genetic processes, too. The trial outcomes have consummated that accidental convergence of the introduced genetic operators is symmetrical to the graph examples and its density to achieve an ideal answer. Less average crossovers and average mutations have been implemented for minor and medium graphs. But crossovers and mutations are institutes to be growing for big graphs. Failure to combine SPCGEX, CGM, ESPCGEX, ECGM, MSPCGX, and MCGM with other meta-activations for reducing the search space and the lack of implementation of the proposed operator with intelligent information for reducing other generations compared with a reduction of the manufacturer of the proposed operator are the disadvantages of the paper.

Marappan and Sethumadhavan (2016) have presented a novel genetic process via divide and conquer tactic on a few medium ($100 \leq n \leq 500$) and big standard graphs ($n \geq 500$) to achieve the near-ideal chromatic count. The discovery of the chromatic count is an NP-hard and integrational optimization issue. The divide & conquer tactic has been executed by separating the vertex group V (G) into some subgroups answered heuristically. SPCGEX & CGM genetic operators with Conflict Gene Removal (CGR) restrictions decrease the exploration area, the mean count of genetic generations, the mean crossovers, and mutations, to raise the count of effective runs regarding the percentages. The developed technique has been compared with a few current ones. The introduced method outperforms the others. The developed technique has significantly deceased the difficulty of reaching the near-ideal answer. The computational complexity has been reduced, not minimized. So, it's a disadvantage. The defect can be addressed by repairing the algorithm.

4.6.2. Overview of the studied GA-oriented methods

Being good or bad (GAs) is mainly related to the ability to run, i.e. it works well in some applications or weak in some others. The algorithm has many parameters that can be created by the correct setting of these parameters. The algorithm has very different results for GCP. It can improve some of the poor performances. In general, the advantages of these algorithms are in solving the GCP. These algorithms will always find a good solution. The algorithm can be stopped at any stage of the operation. In this case, there will be a solution as the work progresses. It is easy to run these algorithms in parallel on several graphs. This algorithm has some disadvantages. For example, although it has found a good solution, it's not optimal. It needs so much memory and processing. In two diverse implementations, different answers have been obtained. In the previous sub-section, 13 selected GA papers and their benefits and drawbacks have been studied for GCP. The comparison results of the papers are presented in Table 8.

4.7. Mimetic algorithm (MA) optimization technique

MA denotes a current developing field in EA. The term is well-known today as the cooperative energy of EA or any population-oriented method with particular individual learning or local change processes for issue exploration (Keshanchi and Navimipour, 2016). An MA is a population-oriented method in which the customary mutation operator is substituted by a regional exploration strategy (Jin et al., 2014; Amaya et al., 2015; Neri et al., 2012). MAs are some of the best standards for answering NP-hard integrational optimization issues. Specifically, they have effectively associated with GCP. (Lü and Hao, 2010; Galinier and Hao, 1999; Malaguti et al., 2008; Porumbel et al., 2010) These algorithms are divided into static, adaptive, and self-adaptive categories in terms of versatility.

4.7.1. Summary of the chosen methods

Moalic and Gondran (2015) have exhibited a successful MA called HEAD for the GCP, a variety of the algorithm (Galinier and Hao, 1999) with just two candidate solutions. HEAD creates great outcomes for an arrangement of testing DIMACS graphs. HEAD permits a simple path to deal with the diversity. They have centered their examination on the control of diversification in their MA,

Table 8
A Juxtaposition of the main benefits and drawbacks of the GA for graph coloring.

Paper	Advantage	Disadvantage
Douiri and Elbernoussi (2015)	• Highly competitive results • Comparing with the best algorithms. • The high number of success • Applying on large graphs	• High runtime
Bhasin and Amini (2015)	• Successful implementation of the algorithm for some NP-hard problems	• Needing a superior method for full graphs • Running on small graphs
Zhang et al. (2014)	• Comparable with algorithms • High graph instances size • The best known upper bound on the chromatic number	• Running on small graphs
Hindi and Yampolskiy (2012)	• Getting fast to the global optimum • High success in solving	• High cost for localization • Applying on small graphs
Sethumadhavan and Marappan (2013)	• Evaluation of the computational complexity • Reaching the smallest number of colors • Reducing the search space	• Weak performance in the average number of mutations • Low performance in the average number of generations
Marappan and Sethumadhavan (2013)	• Reducing the number of genetic generations • Reducing the search space • Increasing the percentage of successful runs	• Failure to compare computational complexity with other meta-heuristic algorithms
Abbasian and Mouhoub (2013)	• High convergence • Improving at each iteration • High comparability • low runtime	• Applying on small graphs
Abbasian and Mouhoub (2011)	• High accurate • Being fast • Reducing the search space • Generating near-optimal solutions.	• Not Designing A General Estimator for GCP Based on the Idea of the Proposed Algorithm Estimator • Lack of embedding of different algorithms in the GM operator to solve GCP
Maitra et al. (2010)	• 100% convergence rate on small graphs • High comparability	• High runtime on large graphs • Not getting a good solution to large graphs • Applying on simple graphs
Douiri and Elbernoussi (2011)	• Satisfactory effectiveness • High comparability	• Applying on medium graphs
Han and Han (2010)	• High convergence • Finding the best solution in each run • Low runtime	• Applying on simple graphs
Marappan and Sethumadhavan (2018)	• High convergence • Low runtime • Applying on large graphs • A good agreement between the complexity of the calculations and the quality of the solution • Decreasing the number of generations in genetics • Reducing the number of colors	• Failure to combine SPCGEX, CGM, ESPCGEX, ECGM, MSPCGX, and MCGM with other meta-activation to reduce the search space • the lack of implementation of the proposed operator with intelligent information to reduce other generations compared with the reduction of the manufacturer of the proposed operator
Marappan and Sethumadhavan (2016)	• Applying on large graphs • High convergence • Reducing the number of colors • Decreasing the number of generations	• Not minimizing computational complexity

which has been point by point for the DIMACS benchmark graphs, where HEAD enhances essentially the outcomes accomplished by the reference methods. They've demonstrated that Hamming interval among 2 individuals is firmly associated with the wellness motivation to individuals. With all benefits and efficiency, the proposed algorithm has been expected to be used in various applications for GCP. The disadvantage of the algorithm can be seen in its dependence on the success number on swapping frequency.

Jin et al. (2014) has introduced an MA for the Minimum Sum Coloring Problem (MASC) to manage the MSCP. The proposed algorithm has utilized a powerful TS method with a mix of two neighborhoods, a population-updating tool for equilibrium intensification and diversification and a multi-parent crossover operator. It even keeps running on graphs over 500 vertices. Analyses on an arrangement of 77 famous DIMACS and COLOR 2002–2004 standard occasions have demonstrated that the introduced method obtained exceedingly aggressive outcomes in an examination with five best class algorithms. Specifically, the proposed algorithm can enhance the best-known outcomes for 15 examples. The MASC algorithm remains quite competitive. This algorithm has many advantages such as achieving best-known results, being quite competitive, applying on large graphs, and having a low standard deviation. The disadvantage of this algorithm is its dependence on the initial population.

Benlic and Hao (2011) have introduced a powerful Multilevel MA (MMA) for the well-adjusted graph partitioning problem. Their MMA has utilized a unique backbone-oriented multi-parent crossover operator, a perturbation-oriented TS system as a local optimization engine, and a shared substitution procedure considering either the arrangement quality and the separation between solutions. The above operator of MMA attempts to protect the components, that ideally have a place with optimal partition while allowing restricted perturbations inside offspring solutions. They've concentrated on acquiring consummately well-adjusted or somewhat imbalanced partitions. It can be seen that permitting more imbalance partitions may prompt improved partitions. As a result, the benefits of this paper are high efficiency, high-quality solutions, and competitive advantage. The disadvantages of the paper are high runtime and the need for designing a dedicated method.

Table 9
The juxtaposition of the main benefits and drawbacks of the MA for graph coloring.

Paper	Advantage	Disadvantage
Moalic and Gondran (2018)	• Achieving accurate and high-quality results • Low runtime • Running the algorithm with only two population	• The low success rate in some samples • The dependence of the density of the graphs on the number of vertices of the graph
Zhuang et al. (2016)	• Applying large graphs • High success rate • Capacity to escape from the local optimum	• High runtime
Moalic and Gondran (2015)	• Decreasing the number of needed colors • Low run time • Running on large graphs • Improving efficiency • High Success	• The dependence of the number of successes on the exchange frequency
Jin et al. (2014)	• Being quite competitive • Achieving the best results for the tested instances • Applying on large graphs • Low standard deviation • Low runtime	• The dependence of the algorithm on the initial population
Benlic and Hao (2011)	• High efficiency • High-quality solutions • Highly competitive	• Local optimization (Sometimes) • High runtime • The need for designing a dedicated algorithm
Lü and Hao (2010)	• Highly competitive • Being quite effective • High Success	• The need for robust and effective heuristic algorithms

A memetic method (MACOL) has been exhibited by Lü and Hao (2010) as a hybrid meta-heuristic algorithm incorporating a TS strategy using an evolutionary method for answering the GCP. The proposed algorithm has coordinated various original features. In the first place, they have proposed a versatile multi-parent crossover operator. Next, in view of the meaning of interval among two k-colorings, they've presented an interval among a k-coloring and a population. Then, they've introduced another integrity score function in view of either answer quality and an assorted variety of individuals. These methodologies equip the method with a decent interchange amongst intensification and divergence. They've demonstrated that the above method has acquired profoundly better outcomes on an extensive count of DIMACS challenge standard graphs. Following this way, they've wanted to outline even more powerful and efficient heuristic methods to solve GCP and other optimization problems. Requirements for robust and effective heuristic algorithms are the disadvantages of this paper.

Moalic and Gondran (2018) have introduced a novel method for the graph coloring, named Hybrid Evolutionary Algorithm in Duet (HEAD). This one integrates the local exploration method TabuCol as an intensification operator with a crossover operator with the Greedy Partition Crossover (GPX) as a method to pass the local minima. Its novelty is that it has a sample population of just 2 individuals. The introduced method has new management of divergence grounded on the best answers to avoid early convergence. According to the processing trials performed on a series of complicated DIMACS graphs, it has some advantages: HEAD results are accurate and of high quality using a large number of processors. It can be said that the algorithm has been successfully applied to other problems. The proposed method has implemented with only two people, integrating the tabu exploration method with an evolutionary method for the k coloring. It has dramatically improved results in terms of computing quality and time. A low success rate in some samples and dependence of graph density on the count of vertices are the disadvantages of this work.

A hybrid heuristic algorithm has been provided by Zhuang et al. (2016), according to the genetic and tabu exploration method called the memetic method with partial answers introduced to answer the graph coloring. For the assumed integer count of color k, according to the answer area, for k independent group and a group of remained vertices, we've introduced the interval and the fitness function based on the interval, and create the genetic method with mining appropriate independent groups as crossovers. The experiment on benchmark graphs has indicated that the method can answer typical graphs and find the ideal answer for a smooth sequence that many evolutionary heuristic methods can't answer. This shows that the continuous method with partial answers is quite stable. The algorithm is capable of dealing with a graph with a high success rank and the count of colors that represent the most optimal color from most of the criteria. It has an excellent capacity to escape from the local optimum for large and complex graphs. However, high runtime is the disadvantage of this paper.

4.7.2. Overview of the studied MA-oriented methods

The MA is a population-based algorithm used for complex and large-scale optimization problems such as GCP. The key principle of the method is using a local search method for the structure of the GA to improve the efficiency of the resonance process throughout the search. Therefore, the algorithm can improve the weaknesses in an evolutionary process. It can improve the convergence of a solution with the lowest color. It improves the efficiency of the algorithm. Given a high degree of equilibrium reality, the MA provides an impressive search procedure using enormous resources that only include a small population in a short time. Therefore, its disadvantages are early convergence, lack of attribution utilization of information, and lack of some vertices color from the graph. In the preceding part, four chosen MA methods and their benefits and drawbacks have been studied for GCP. The comparison results are presented in Table 9.

4.8. Particle swarm optimization (PSO)

PSO is a processing strategy enhancing an issue by frequently attempting to enhance a nominated answer regarding an assumed measure of value (Ghadimi et al., 2014; Ghadimi et al., 2013; Mir et al., 2018; Marichelvam et al., 2019). It answers an issue by candidate populations named Particles and shifting them around in exploration area over their location and speed (Manafi et al., 2013; Ebadi and Jafari Navimipour, 2019; Naseri and Navimipour, 2018). Every Particle's shifting has been affected by its ideal local location, however, in the meantime, it has directed to the identified locations (updated as better locations discovered by different Particles) (Dordaie and Navimipour, 2017; Sheikholeslami and Navimipour, 2017). PSO was at first accredited to Shi and Eberhart (1999), Zhenya et al. (1998) and expected to simulate social conduct (Kennedy, 1997). It has been simplified and seen to implement optimization. Eberhart et al. (2001) has portrayed numerous philosophical parts of PSO and swarm intelligence. A broad overview of PSO usage has been done by Poli (2008, 2007). Bonyadi et al. (2014) has published an exhaustive survey of theoretical experimental works on PSO.

4.8.1. Summary of the chosen methods

Gong et al. (2016) has suggested a distinct PSO to handle the high-order graphing matching issues, named DPSOHM. In DPSOHM, a Particle's speed, position, and its updating formula are re-characterized. In the present article, a distinct Particle optimization method has been provided to solve a top-level matching problem that includes several defined operations, an initial determination method for answering a problem based on heuristic information, and a local search method. The implementation of DPSOHM has been assessed on either artificial and practical datasets. Trial outcomes have shown that their suggested technique can reach capable execution in the above problem. They've also found that the best initial estimate could not guarantee the exact result. They will endeavor to use the most prominent thinkers in their future research to enhance the current strategy. For other parts, bigger processing difficulty is EAs' disadvantage compared to the conventional optimization methods. Their strategy has a reasonably bigger difficulty than the tested designs. Despite that, their strategy has generally brought lower complexity contrasted with different EAs because of the high simplicity of PSO. As a result, the benefits of this paper are the lower complexity and promising performance. However, the algorithm has not guaranteed an exact result. It needs to improve the current method.

Agrawal and Agrawal (2015) have tried an adjustment of PSO to solve the GCP. They've proposed an acceleration-based PSO strategy to address the GCP; to accomplish an exact optimal result, the troubleshooting in the PSO system, earlier convergence, and loss of diversity. Initiating powerful adjustment or development in the PSO process must reasonably handle the above issues. Henceforth, to achieve a further exact result and avoid the PSO defects, as opposed to settling the amount of an acceleration coefficient, they've presented an increasing acceleration-oriented PSO system where the coefficient amounts have been updated in view of the assessment function. Then, the introduced method has been used to answer the GCP. It has used on 10 DIMACS standard tests even though constraining the count of practical colors to the normal ideal count. They've compared APSO and typical PSO and indicated that the suggested method is predominant with regards to solving the example dataset and even against typical PSO, with a least count of colors and a least count of stages. Local optimum, the need for high memory, and high runtime are the paper disadvantages.

Aoki et al. (2015) has proposed a PSO algorithm with a probability of transferring based on humming distance to solve flat GCPs. At first, PSO has been considered to solve specifically constant optimization issues. The typical computing operators of the PSO are required to redefine the distinct area and see a cross-section of its parameters for using PSO in discrete issues. The trial outcomes have indicated that the presented method can achieve greater success rates and repeat lesser meanings from the GA and the typical PSO. In the future, they will investigate why a contradictory point arises and tries to apply its own way to a real-world program such as problem planning. It has also reduced the dependency of the algorithm on the parameters. The need for real programming, high dependency on the parameters, and achievements of an opposite point are the disadvantages of the paper.

Bensouyad and Saidouni (2015) have presented a Discrete Flower Pollination Algorithm (DFPA) to answer the combinatorial GCP. As shown, their proposed approach has converted continuous values digitally using a round function. Then, the algorithm has improved, using the strategy of exchange. A tactic like that is useful to guarantee variety and avoid the probable inactivity throughout the exploration procedure. The execution of the method has been assessed on the standard instances. The processing outcomes have demonstrated useful outcomes often with the most precise answers. For each occasion, they've mimicked 15 repetitions, a maximal count of repetitions was 10,000, and the pollinators 20. It has achieved similar results with lower complexity compared to other mathematic techniques. Generally, the low complexity of the algorithm, the high efficiency of the algorithm, and the achievement of similar results are the advantages of this algorithm. The emergence of a cross point, the high number of iterations, and applying on small graphs are the paper's disadvantages.

Consoli, Collera has exhibited two novel swarm heuristics construct separately with respect to ants and bees' simulated colonies, known as AS-GCP and ABC-GCP. The first has been constructed in combination with Greedy Partitioning Crossover (GPX) and a local search method that has a relationship with the pheromone trails framework. The last has rather qualities of three evolutionary operators (for example, a mutation operator), an enhanced adaptation of GPX, and a temperature instrument. At first, the report has been directed to fix the best parameters tuning, and examine the running time for two algorithms. After that, both swarm heuristics have been compared with 15 algorithms, utilizing the traditional DIMACS benchmark. By reviewing every one of the examinations, it is conceivable to state that AS-GCP and ABC-GCP are extremely competitive with all compared algorithms. Thus, it has shown the appropriateness of the variants and novelty of the design. At last, ABC-GCP has generally appeared to be more focused than AS-GCP as a normal of the best color has been found. However, the disadvantage of this algorithm is small-scale graphs.

Dorrigiv and Markib (2012) have suggested the ABC-GCP algorithm to solve the GCP in light of the ABC. They've partitioned the coloring problem into 2 separate phases: sequence production via the ABC and coloring depending on an adjusted RLF named SB-RLF. They've likewise presented 3 approaches to find improved answers about sustenance sources by the worker and spectator bees and watched the improvements via the ideal one (strategy 3). Although better results have been observed, the current method needs to be improved to provide an accuracy guarantee.

Hsu et al. (2011) has presented a Modified Turbulent PSO (MTPSO) to solve planar GCP in light of PSO. The presented model includes turbulent strategy, assessment scheme, and walking one strategy. It can solve planar GCP more effectively and precisely utilizing 4 colors. Contrasted with outcomes that appeared in Cui et al. (2008), the trial outcomes of the introduced design can get smaller average repetitions and acquire greater adjustment coloring rank when the count of points goes beyond thirty. Finally, we can say that the algorithm has been implemented on small graphs with a high runtime.

Qin et al. (2011) has endeavored for an adjustment of PSO for GCP. For speculation of PSO for a discrete issue, they've presented the concept of interval in excess of any distinct answer area. An interval has been characterized as the minimum count of successive uses of an operator in the answer area. It is a universal notion when a certain group of answers, and an operator on the answer is specified. By considering the interval, they've reclassified benchmark PSO operators in view of the essential principle of PSO. After revising the configuration of the speed of a particle, they've proposed a structure of PSO for any distinct issue. For solving

Table 10
The juxtaposition of the main benefits and drawbacks of the PSO for graph coloring.

Paper	Advantage	Disadvantage
Gong et al. (2016)	• Lower complexity • Achieving a promising performance	• The need for improving the current method • Not guaranteeing an accurate result
Agrawal and Agrawal (2015)	• Achieving a promising performance • A simple and powerful technique	• Having some limitations • Getting caught up in the local optimum • The need for high memory • High runtime
Aoki et al. (2015)	• Running on randomly-generated graphs • Efficient production solutions	• The need for real planning to resolve the point of conflict • The dependency of the algorithm on the parameters
Bensouyad and Saidouni (2015)	• Lower complexity • Similar results • Low runtime • Effective algorithm	• The emergence of a cross point • Applying on small graphs
Consoli et al. (2013)	• Competitive with all tested algorithms • Low runtime • Improving the performances • Able to find the best colors	• Applying on simple graphs • Having some limitations
Dorrigiv and Markib (2012)	• The superiority of the proposed algorithm • Low runtime • High comparability	• The need for improving the current method to ensure accurate work
Hsu et al. (2011)	• Low iterations • Higher correct coloring rate	• Not checking the runtime in the results • Applying on simple graphs
Qin et al. (2011)	• The number of high success • Competitive with other well-known algorithms • Improving the solution quality	• High runtime • Applying medium graphs
Rebollo-Ruiz and Graña (2011)	• The relatively high average success rate • Effective solutions	• Not ensuring convergence
Anh et al. (2009)	• The better result than known heuristic algorithms	• Applying on medium graphs

GCP by discrete PSO algorithm, an algorithm has been proposed to execute the key PSO operator variance of 2 locations (answers) that are outlined. At that point, a hybrid distinct PSO for GCP has been introduced by integrating a local exploration. Observational investigation of the introduced HA has been done in view of the other DIMACS difficulty standards. The trial outcomes are aggressive with those supplementary confidently famous algorithms. By improving the algorithm, it can run on large-scale graphs with low runtime. Therefore, it can be said that the implementation of the algorithm on small-scale graphs with high runtime is a disadvantage of this algorithm.

Rebollo-Ruiz and Graña (2011) have proposed another algorithm for the GCP utilizing swarm intelligence. They've demonstrated the issue as a set of factors endeavoring to achieve a few objectives. Objectives have shown the node colorings. The factors have denoted the graph's points. The color aims have applied a sort of gravitational fascination over the virtual world. Considering the presumptions, they've tackled the GCP utilizing a parallel development of the factors in the area. They've contended the merging of the framework and shown exactly that it gives successful answers as well as accuracy and computational time. They've kept on testing their algorithm on a broad body of graphs and compared its outcomes with those of the advanced heuristic methods. They've worked on an official convergence confirmation of the dynamics of the method. Above all, the runtime and the number of repetitions have not been considered. Most importantly, the convergence of the algorithm has not been guaranteed.

Anh et al. (2009) has proposed a new PSO for graph coloring. This algorithm has been implemented in five steps (Particle introduction, Particle correction, starting with a primitive population with corrected Particles, the fitness of Particles as a function, and stopping with a condition). They've utilized the PSO developmental advance to enhance a straightforward deterministic greedy method. The novel method can outperform the known heuristic algorithms (Largest Degree Ordering (LDO), First-Fit (FF) algorithm, Saturation Degree Ordering (SDO)), as confirmed by a broad simulation study. It has also evaluated the processing difficulty of the method. By some improvements, the algorithm can run on a large-scale graph with low runtime. Of course, the runtime has not been considered in this paper.

4.8.2. Overview of the studied PSO-oriented methods

The PSO is a new evolutionary technique recognized to be used for discrete optimization problems. In this method, moving to the optimal point is based on two categories of data. One of them is the best point obtained by each factor in the primary population. The other is the best point found by neighboring points. The second group facilitates the work of the PSO algorithm on GCP problems. Implementing PSO on GCP issues has some advantages: fewer setup parameters, easy-to-implement, and simple concepts. Moreover, the performance of the algorithm will not be diminished by increasing the size of the graph and by using Particle participation to increase the convergence speed. However, the algorithm needs a lot of memory. Mostly, the algorithm runs on small-scale graphs. It has a relatively high execution time. In the preceding part, 10 chosen PSO methods and their benefits and drawbacks have been studied for GCP. The comparison of the results of each paper is presented in Table 10.

4.9. Quantum annealing (QA) technique

QA is a meta-heuristic to determine the least universal amount of an assumed objective function in excess of an assumed arrangement of nominated answers (states), by a procedure utilizing quantum oscillations. QA has been utilized mostly for issues in which the exploration area is distinct (integrational optimization issues) with numerous local minima (for example, obtaining the ground state of a spin glass) (Ray et al., 1989). Kadowaki and Nishimori (1998) have proposed it.

Another strategy to minimize multidimensional functions is QA. It begins from a quantum-mechanical superposition of every single conceivable state (candidate states) with equal weights. At that point, the framework advances resulting in time-reliant Schrödinger equation, a characteristic quantum-mechanical development of physical frameworks. Amplitudes of all applicant answers continue altering, understanding quantum parallelism, as indicated by the time-subordinate quality of the crosswise area, which leads to quantum burrowing amongst answers. In case the rate of progress of the crosswise area is sufficiently moderate, the framework remains local to the ground condition of immediate Hamiltonian; the adiabatic quantum algorithm (Farhi et al., 2001). On the off chance that the rate of progress of the crosswise area is quickened, the framework may pass the ground state briefly yet deliver a bigger probability of deducing on the ground condition of last issue Hamiltonian; the diabetic quantum algorithm (Crosson et al., 2014; Muthukrishnan et al., 2015). At last, the crosswise area is turned off. The framework is relied upon it to achieve the ground condition of the traditional design compared to a solution of the original optimization problem. A test has shown the success of QA for arbitrary magnets after the initial theoretical proposal (Brooke et al., 1999). The advantage of the quantum algorithm is that the problems can be solved within a little time.

4.9.1. Summary of the chosen methods

Titiloye and Crispin (2012) have demonstrated that a rotation design for the k-coloring of large dense arbitrary graphs can be modified thus its approval ratio will deviating throughout the Monte Carlo QA till achieving a ground answer. Besides, they've found that recreations displaying a deviating acceptance ratio like that are better than the ones adjusted to the older scheme of a diminishing and additionally decaying one. This perception encourages the revelation of solutions for a few understood benchmark-coloring cases, some of which have been open for about two decades. Successful simulation with the continuous acceptance ratio is increasing. Although the number of achievements is very high, the algorithm only runs on small graphs with a high runtime. So, the algorithm needs improvement.

Titiloye and Crispin (2011) have acquainted three improvements with essential QA for graph coloring: settling Gamma, hybridization with evolutionary systems, and an explanation of an exceedingly scalable dispersed form of the method. Each of the changes has been appeared to be effective, bringing about preferred solutions over any great method for 2 deeply-investigated DIMACS standard graphs. It is possible that the above improvements would be movable to other optimization issues. Rather than utilizing just the essential QA to plan algorithms for different issues, they've prescribed that researchers endeavor to fuse the three upgrades. It is necessary to use them in parallel in the proposed algorithm. By combining them, the algorithm has been improved to provide a complete algorithm. Therefore, it can be considered highly competitive. This algorithm is comparable with other algorithms. Its success rate is higher than that of the other ones. Therefore, the need for incorporating the three enhancements, lack of reviewing the number of iterations, and high runtime are disadvantages of the paper.

Titiloye and Crispin (2011) have depicted QA-COL, a first GCP in view of the Path-Integral Monte Carlo (PIMC-QA) which is a population-oriented augmentation to SA roused by quantum mechanics. By considering the domain-specific knowledge, an important association among singular imitations has been characterized as kinetic energy. QA-col can outflank the classical SA and even discover colorings of similar quality to the ideal algorithm for some DIMACS graphs. QA is probably going to have more extensive pertinence to other integrational optimization issues. The present article has demonstrated running an algorithm on large-scale graphs is a good area for future researches. Similar quality and low runtime are the advantages of the algorithm. Applying the algorithm on medium graphs and the dependency of the algorithm on parameters are the disadvantages of the paper.

4.9.2. Overview of the studied QA-oriented techniques

QA is one of the well-known meta-exploratory algorithms for artificial intelligence algorithms. It is based on local search. So, designing appropriate local search methods is very important for it to give conditions and limitations of the simulated problems in this algorithm. Using GXP can be the advantage of this algorithm. There is very little memory to solve GCP issues. Its implementation is relatively simpler than that of the other algorithms of its own because of focusing on local searches and commonly found solutions. Owing to the existence of a randomized driven process (low probability of acceptance for non-optimal responses), it can pass through local optima. There are also some weaknesses. The above algorithm depends on the initial value of parameters. If you select an inappropriate value for the initial temperature parameter, it will likely hit local optimum. Choosing the initial value for parameters is impossible without a benchmark. In the earlier part, 3 chosen QA algorithms for GCP and their benefits and drawbacks have been studied. The comparison of the results of each paper is presented in Table 11.

4.10. Tabu search (TS) algorithm technique

"Tabu" originates from Tongan, a dialect of Polynesia, utilized by natives of Tonga to demonstrate things that can't be impressed because they are sacrosanct. TS is a meta-heuristic algorithm used to solve combinatorial optimization (issues where an optimal ordering and determination of alternatives are fancied). TS, made in 1986 by Glover (1986) and officialized in 1989, (Glover, 1990) is a meta-heuristic exploration technique utilizing local exploration strategies utilized for optimization. TS improves the execution of local search by unwinding its fundamental run show. To begin with, at each progression, the worsening move can be acknowledged if no enhancing movement is accessible (like when the search is stuck at a strict local minimum). Also, prohibitions (hereafter the term tabu) are acquainted with demoralizing the search from returning to previously-visited solutions. Execution of tabu hunt utilizes the memory structures that encountered solutions or user-provided collections of principles (Glover, 1989).

4.10.1. Summary of the chosen methods

Kouider et al. (2015) has shown 2 Mixed Integer Linear Programs (MILP1 and MILP2) and a TS method to the color of a particular set of combined graphs. This set has been prepared out of a combination of best groups and routes, and its coloring speaks to decreasing job shop programming issues with unit-time operations. Processing analyses on altered standards have demonstrated that MILP2 is superior to MILP1 regarding various ideal solutions and the number of hubs navigated in pursuit of tree and the hub where the ideal arrangement is. Processing trials on revised standards have indicated that MILP2 outperforms the MILP1 regarding the count of ideal answers, the count of points navigated in the exploration tree, and the point in which the ideal answer is. Similarly, the TS algorithm is proficient regarding the count of ideal answers, the best comparative divergence between the best blended chromatic count and lower bound. Moreover, designs have been utilized to demonstrate the productivity of the TS when a few standards settled ideally by the TS having a unique goal in relation to lower bound. The maximal relative deviation, the efficiency,

Table 11
The juxtaposition of the main benefits and drawbacks of the QA for graph coloring.

Paper	Advantage	Disadvantage
Titiloye and Crispin (2012)	• Successful simulation with a continuously rising acceptance ratio • Numerous achievements	• Applying on medium graphs • High runtime
Titiloye and Crispin (2011)	• Highly scalable • The high success rate at high density • Highly competitive	• The need for incorporating the three enhancements in the algorithm • Applying on simple graphs
Titiloye and Crispin (2011)	• Discovering colorings of similar quality • Comparable quality to the best algorithms • Low runtime	• The dependency of the algorithm on the parameters • Applying on medium graphs

Table 12
The juxtaposition of the main benefits and drawbacks of the TS for graph coloring.

Paper	Advantage	Disadvantage
Kouider et al. (2015)	• The maximum relative deviation between the best chromatic mixed colors and the lower boundary • The high number of success	• High runtime • Applying on medium graphs
Barany and Tuza (2015)	• Using rich linear programming tools • Understanding the benefits of parallel architecture • Using GCP in open store marketing	• Low success rate • Not ensuring the convergence
Bouziri and Jouini (2010)	• Starting the algorithm with an impractical solution (random) • High performance • Better results	• The experiment of the algorithm with a fewer number of graphs • Applying the algorithm on medium graphs

and the high number of successes are the advantages of the paper. High runtime and applying only on medium graphs are the disadvantages.

Barany and Tuza (2015) have proposed a method to figure the circular chromatic number of a graph. Their proposed technique can always benefit from rich devices of linear programming and upsides of parallel models. It is additionally exceptionally adaptable; the TS part is effectively flexible: for example, it is conceivable to apply diverse sub-problem selection rules. The present paper has quickly reviewed an extraordinary class of open shop scheduling that can be solved via circular coloring. Low successes rate and not ensuring the convergence are disadvantages of the algorithm.

Bouziri and Jouini (2010) have used TS to solve the MSCP. It is a variation of vertex coloring issue where the goal is to decrease the number of colors utilized as a part of coloring vertices. Initial solutions have been produced indiscriminately. The adjacency assumed in the present paper is to pass a clashing point from a color set to the other. At last, the trials have been done on samples separated from the second DIMACS issue. The outcomes have demonstrated major progress on some chromatic sum bonds. The proposed TS method works on the answers (can be possible or not) and shakes aimlessly on the exploration area. This infers that joining extra data to the search procedure may upgrade the outcomes. Also, combining their method with greedy ones can prompt productive search methods. Starting the algorithm with an unfeasible solution (random), high performance, and highly-competitive results are the advantages of the paper. Applying with a few numbers of examples and applying on medium graphs are the drawbacks of our paper.

4.10.2. Overview of the studied TS-oriented methods

TS is a well-known algorithm for optimizing problems such as GCP. TS explicitly uses search history to avoid local optimization and implements an exploration strategy. Using a simplified TS, the local search implements the best improvement as a basic component and utilizes short-term memory to get away local optimization and avoid cycles. Usage of the forbidden search prevents a return to recent solutions after endless cycles are prevented. The search is forced to only improve movement and get the smallest count of colors. Nevertheless, it may have a higher runtime. The number of successes is less than that of the other algorithms. In the earlier part, the 3 chosen TS and their benefits and drawbacks have been studied algorithms for GCP. The comparison of the results of each paper is presented in Table 12.

4.11. Simulated annealing (SA) algorithm technique

SA is a random-search and general-purpose scheme for discovering the universal least amount of an assumed function. SA has been first defined by Glover and Tabu search—part (1989) in 1979 and by Khachaturyan et al. (1981) in 1981 as a method achieving a reduction of a function of a high count of variables to statistical mechanics of equilibration (annealing). They've utilized PC replication imitating annealing and cooling of a framework like that to locate its global minimum. Specifically, SA can be considered as a meta-heuristic to estimate universal optimization in a big exploration area. It has regularly utilized when the exploration area is distinct (e.g., all travelers that see an assumed group of urban areas) for issues in which discovering an estimated universal ideal is more vital than an exact local one in an established measure of time. SA might be desirable over other choices like gradient descent. Unlike usual search methods, this method, in addition to moving to a better answer, accepts answers with a value of the objective function as well as non-zero probability.

4.11.1. Summary of the chosen methods

Pal et al. (2012) has considered "GCP" as a standout amongst the most essential issues in graph theory. They've improved and associated a hybrid meta-heuristic in view of an integration of SA and TS. Besides, another heuristic method has been produced to find the primary answers. Components of local exploration methods are the fundamental pattern of the algorithm. Neighborhood architecture of an assumed arrangement has been distinguished as a well-organized pair, where the main component is a vertex directory, and the next component is the color set of the vertex. Local

Table 13
The juxtaposition of the main benefits and drawbacks of the SA for graph coloring.

Paper	Advantage	Disadvantage
Pal et al. (2012)	• Considerable solution quality • Low runtime • Finding unexpected better solutions • High speed in search	• High dependency on parameters. • Not applicable on complex graphs

exploration operators choose a neighborhood answer as for its systems. Because of the arbitrary nature of SA, it can be obstructed in a few states when the produced solutions won't be acknowledged or enhanced amid a couple of counts of repetitions. Hence, they've introduced a blending procedure to pass the condition. Their recommendation is using a TS where SA can't enhance the answer. Accordingly, the impressive performance, the solution quality, low runtime, finding unexpected better solutions, and high speed in search are the advantages of the paper. High dependency on parameters and not applying to complex graphs are the drawbacks of the paper.

4.11.2. Overview of the studied SA-oriented methods

Methods of SA for GCP accelerate computations and prevent additional computing. In this way, sensitivity algorithms coincide with a usually simulated refraction algorithm in less time with the same precision. Success with the acceptance ratio is constantly rising. Outcomes of the method have been compared with those of the different ones. In some cases, the algorithm is running high. Most algorithms have been executed on the Kuchi graphs and are unable to solve complex and large graphs. In some cases, several algorithms have advanced on a GCP problem; they've needed to be combined to achieve a signature algorithm. In the earlier part, one selected SA algorithm and its benefits and drawbacks have been studied for GCP. The comparison results of each paper are presented in Table 13.

4.12. Hybridization of meta-heuristic algorithms technique

The combination of elements from various algorithms is right now a standout amongst the best trends in optimization; the hybridization of meta-heuristics, for example, ACO, EA, variable neighborhood search methods from operations research and artificial intelligence, assumes an essential part. The subsequent HAs have usually been marked as the hybrid meta-heuristics. The ascending of this new research field was because the concentration of research in optimization has moved from an algorithm-oriented perspective to an issue-oriented one.

In this short study on hybrid meta-heuristics, they've given an overview of probably the most intriguing and representative advancements. The interested reader can discover different surveys on hybrid meta-heuristics in Andrea et al. (2008), Cotta-Porras (1998), Dunker et al. (2005, 2006). The proper function of combined algorithms is to provide a reasonable response at a reasonable time.

4.12.1. Summary of the chosen methods

Astuti (2015) has provided an execution examination with a data hiding scheme in light of GCP utilizing two EAs (GA and PSO). Both of them as developmental algorithms can be utilized to answer GCP on the introduced conspire. They've specified around the same execution in concealing limit in data hiding pattern plan. In light of investigating the test, it can be reasoned that GCP with an EA can bolster a data hiding scheme on the medical image. Regarding computational time, the GA plot always gives preferred execution over PSO conspire, which is utilized by a unique plan (Yue et al., 2013). In this way, they've prescribed the GA utilization in the data hiding plotted to be executed on cell phones. In the subsequent investigation, they've supplied an execution examination with data hiding scheme in light of GCP, utilizing two EAs (GA and PSO). The application of the proposed algorithm in real work (mobile use) and low runtimes are the advantages of the paper. However, the algorithm should be improved and should not be implemented for small-scale graphs.

Bessedik et al. (2014) has keened on parallel participation between ACS and MBO for the determination of the GCP. They've displayed 2 novel techniques for ACS to answer the GCP. The development procedure has not applied helpful strategies in the self-adjustment stage. For example, RLF and DSATUR were quicker compared to ACS-R and ACS-D introduced in Abbass (2002). An experimental investigation has accomplished for every technique. They've actualized the popular methods (Ant framework and a method of ACS) for the GCP to test their algorithms. Parallel usage of ACS has essentially decreased the execution period and guessed rapidly the ideal elements (pheromone trails). They've demonstrated that collaboration between ACS and MBO has enhanced the outcomes acquired independently by every method. Surely, adding up to the participation has enabled the ACS2 to achieve the ideal and BeesCol to enhance its average expense. Then again, in the halfway of collaboration, ACS1 has helped BeesCol and ACS2 to handle the local ideal. As a result, gaining the smallest number of colors, reduced runtime significantly, computing the best parameters quickly, improving solutions, improving its average cost are the advantages of the paper. Applying on medium graphs is a disadvantage of the paper.

Wu and Hao (2012) have proposed a hybrid self-adaptive developmental system for graph coloring that is hybridized with the accompanying new components: heuristic genotype-phenotype mapping, a swap local exploration method, and an impartial survivor's choosing operator. This method has been contrasted to the SAW strategy of Eiben and Smith (2003), the bucolic system of Hertz and de Werra (1987), and the HEA of Galinier and Hao (1999). The exhibitions of the systems have been tried on a set comprising of arbitrarily created 3-colorable graphs of different architectural characteristics, for example, graph dimension, sort, edge density, and fluctuation in coloring sizes sets. Implementing inadequately (all of them) on flat graphs has indicated that this type of graphs is truly the most difficult one to color. Enhancing the best-known upper bounds and verifying (good) exhibitions of essential extraction technique are the advantages of the paper. This algorithm has neglected to achieve the best-known values just in two cases.

Pahlavani and Eshghi (2011) have considered "GCP" as a standout amongst the most critical issues in graph theory. They've established and associated a hybrid meta-heuristic in light of the integration of SA and TS. Moreover, another heuristic has additionally been created to produce primary answers. Systems of local exploration systems are principle paradigms of the algorithm. The neighborhood structure of a given solution has been recognized as a requested pair where the primary component is a vertex directory, and the next one is the color set of the vertex. Local exploration operators have chosen a neighborhood for their systems. The proposed algorithm empowers issue solvers to select a fitting combination of SA and TS relying upon necessity issues and gives an adaptable structure in consolidating benefits of SA and TS. At last, another hybrid architecture can likewise be prescribed utilizing SA and TS, where TS is the center, and SA is the help in tabu list development. Using SA to get unexpected solutions, an adaptable system in joining points of interest of SA and TS, and efficiency are the advantages of the paper. High dependency on parameters and the need for a better solution started are the disadvantages of the paper.

Zhou et al. (2018) has presented well-known graph-based learning based on advanced learning for a well-known graphic coloring problem, that improves the relative Reinforcement Learning-based Local Search (RLS) method (Zhou et al., 2016). The algorithm has been repeated through three distinct steps: Staging process based on a possible matrix, a stage of exploration staining, and a possible learning-oriented update step. The initial improvement enhances the probabilistic learning program of the novel RLS by a set matching approach to discover an intergroup and group relationship among the start answer and its upgraded one. This approach addresses the problems of conventional GCP solutions. The second progression is based on the taboo search algorithm, which is stronger compared to the landing system of RLS and consistent with more complicated ones. In addition, with regard to the optimization step as a black box, they have accepted the prevalent hurricane method for staining enhancement step. They have shown extensive computational results for known DIMACS criteria and comparison with more advanced coloring algorithms. An empirical assessment of the famous charts of famous DIMACS challenges has shown that PLSCOL (Probability Learning-based local Search algorithm) is competing with all local locale localization algorithms. Finally, enhancement learning techniques (Busoniu et al., 2010; Sutton and Barto, 1998; Szepesvári, 2010; Wang et al., 2009; Xu et al., 2014) can be combined with exploratory search ones. In general, learning enhancement can assist the exploration method to make the correct decisions. Compared to more advanced developmental methods (with more complicated designs), PLSCOL is better despite the simplicity of the underground painting algorithm. The limitations of this paper are: Initially, the PLSCOL optimization element is a black box. Similarly, it is motivating to examine whether the use of a stronger algorithm than the TabuCol results in improved outcomes. Second, PLSCOL, by matching group method, prevents the problem of symmetric answers of grouping issues with substitutable ones. It is motivating to adopt this method for other similar grouping issues. Third, this indicates that learning methods can assist coloring systems to discover improved answers. Therefore, further researches should have more creativity.

Lim and Wang (2004) have introduced a few meta-heuristics for answering RGCP, a fascinating expansion of traditional graph coloring. Local exploration, the replicated annealing, and 2 tabu exploration approaches have been introduced and examined by different dimensions of data regarding the exactness and implementing period. The trial outcomes on different dimensions of the input graph have shown the functionality of the above methods regarding the exactness and implementing period. The superiority of meta-heuristic algorithm SA in large-scale charts does not have the advantage of this paper. Failure to provide an excellent algorithm for graph coloring is one of the main disadvantages of this work. The high implementation time is another disadvantage.

4.12.2. Summary of the reviewed hybridization of meta-heuristic algorithm-based techniques

The purpose of combining the meta-heuristic algorithms is to improve the algorithm and apply it to achieve the optimal solutions and fix some of the disadvantages of previous meta-heuristic algorithms. With the implementation of combination algorithms on the GCP problem, most of the disadvantages have been resolved. Inadequate accuracy is a disadvantage of meta-heuristic algorithms. In the earlier part, 6 HA algorithms and their benefits and drawbacks have been studied for GCP. Table 14 shows the comparison of the results.

Table 14
The juxtaposition of the main benefits and drawbacks of the hybridization of meta-heuristic algorithms for graph coloring.

Paper	Advantage	Disadvantage
Astuti (2015)	• Better performance than PSO • Nearly the Similar performance in data hiding • Low runtime	• Applying on medium graphs • The need for improving the current way to use on mobile (applied issues)
Bessedik et al. (2014)	• Best results and Being quite fast • The best results of the coloring • Reducing the runtime (significantly) • Computing the best parameters (quickly) • Improving its average cost	• Applying on medium graphs
Wu and Hao (2012)	• Improving the best-known upper bounds • Verifying the (good) performance of the basic extraction method	• Not applicable to some known graphs.
Pahlavani and Eshghi (2011)	• Use SA to get unexpected solutions • The flexible framework in combining the advantages of SA and TS • Low runtime • considerable performance regarding the solution quality	• High dependency on parameters • Needing a better solution to get started
Zhou et al. (2018)	• Combining learning algorithm with search methods • Matching group methods to avoid difficulties solutions	• Incompatible approach with some group methods • Needing a stronger coloring algorithm than the TabuCol to achieve better solutions
Lim and Wang (2004)	• Applying on large graphs • The better performance than the introduced Meta-heuristic algorithms	• Failure to provide a new algorithm for RGCP • High runtime

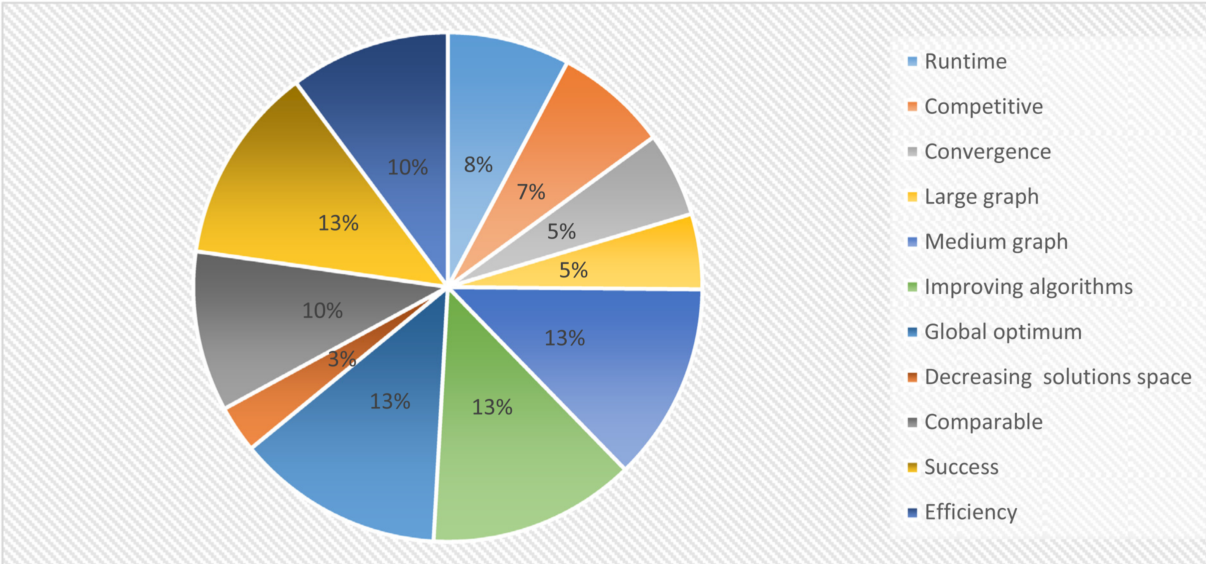

Fig. 5. Percentage of graph coloring criteria in the reviewed techniques.

5. Outcomes and comparisons

In the earlier subsection, the chosen meta-heuristic techniques for the GCP have been reviewed and analyzed. Researchers have focused on famous GCPs by studying meta-heuristic algorithms. Based on the studied works, scholars can resolve graph coloring issues: the improvement of the current method, runtime, efficiency, competitiveness, best coloring, dependency on parameters, and success rate. They can also decrease the solution's space in graph coloring. However, the hybridization of meta-heuristic algorithms for GCP and the improvement of the algorithms have to be answered in the upcoming years. Meta-heuristic methods can enhance the iteration number, runtime, competitiveness, and applying size graphs. However, many papers have not thoroughly investigated the standard deviations and the improvement of the cost-efficiency. Fig. 5 shows a study of the meta-heuristic approach for the GCP. Also, scholars have documented the factors affecting the meta-heuristic system. Table 15 shows a discussed outline of meta-heuristic procedures and their key features like improving the current method, runtime, iteration number, efficiency, competitiveness, best coloring, dependency on parameters, success rate, and decreasing solutions space. The comparison outcomes have shown that runtime, iteration number, and global optimum comparatively are vital in meta-heuristic systems for GCP. However, standard deviations and the improvement of the cost-efficiency meaningfully affects the GCP, which has not been investigated in a few papers. Based on Table 15, the highest and the lowest scores of each system in all the papers are clear. The least score is for 'decreasing solution's space' and the top score is for "Makes span" and "resource consumption". Table 16 shows the percentage of the used criteria in each of the investigated papers.

6. Restrictions

The present paper has been designed to lead an organized study as thoroughly as it can be; however, Of course, some restrictions exist:

6.1. The study space

GCP has been considered in numerous sources like scientific printed works, editorial notes, reports, and websites. In particular, scholars have removed national papers. Furthermore, they've eliminated papers, which were not about GCP. So, one can consider that the present study has investigated the main available worldwide works.

6.2. Research and publication

scholars have chosen Google scholar as a reliable database grounded on the present statistics. This e-database would offer the best works. But, it could not be ensured that every choice is relevant. it is possible that a few applied works have not been considered during the paper selection in Section 3. Some applicable papers may go unnoticed due to various causes, from the limitation of incorrect keywords to the data mining.

6.3. Method scopes

the scholars have chosen meta-heuristic methods as a restriction as actual optimization issues are frequently extremely difficult to answer. Also, numerous usages are needed to manage NP-hard issues. The optimization tools must be utilized to handle such issues, however, there is no guarantee that an optimal solution is reachable. The meta-heuristic optimization methods are high-level procedures that guide search agents to logically enhance the overall solution. The solution has consequently been advanced by checking over some random components and possibilities, in expectation of finding a superior quality solution, while the candidate solution would be acquired starting with one stochastic iteration then onto the next. They've created an adequately great solution, most of the time inside a sensible measure of time (Yang and Press, 2010). In such cases, it may be captured in a locally optimal solution. Perhaps, because of different reasons such as execution time, the number of replays, optimal local response, and optimal global response, some other basic issues may have been ignored.

7. Open issues

The present part provides the key GCP technique's concerns that have not been considered extensively and comprehensively as study guides in the future. Considering meta-heuristic techniques in the GCP and criteria mentioned in this paper (such

Table 15
An overview of the discussed meta-heuristic techniques for graph coloring and their main features.

Algorithm	Reference	Iteration number	Runtime	Competitive	Convergence	Large graph	Medium graph	Improving algorithms	Global optimum	Decreasing solutions space	Comparable	Success	Efficiency
ACO	Fidanova and Pop (2016)	✗	√	√	✗	✗	✗	√	✗	✗	✗	✗	✗
	Yuan et al. (2014)	✗	✗	✗	✗	✗	√	✗	√	√	√	✗	✗
	Douiri and Elbernoussi (2013)	✗	√	✗	✗	✗	✗	✗	✗	✗	✗	✗	√
	Douiri and Elbernoussi (2012)	✗	✗	✗	√	✗	✗	√	✗	✗	✗	✗	✗
	Mohamed and Elbernoussi (2011)	✗	√	✗	√	✗	√	√	✗	✗	✗	✗	✗
	Aicha et al. (2010)	✗	√	✗	✗	✗	√	✗	✗	√	✗	✗	✗
	Plumettaz et al., (2010)	✗	✗	✗	✗	√	√	✗	√	✗	√	✗	√
BA	Djelloul and Chikhi (2015)	√	✗	✗	✗	✗	✗	✗	✗	✗	√	√	✗
	Djelloul et al. (2014)	√	✗	√	✗	✗	✗	✗	✗	✗	√	√	✗
ABC	Markid et al. (2015)	✗	✗	✗	✗	√	✗	✗	√	✗	✗	✗	✗
	Tomar et al. (2013)	✗	✗	√	✗	✗	✗	✗	√	✗	√	✗	✗
	Greenwood and Chopra (2013)	√	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	✗
	Fei, Bo (Fei et al., 2013)	✗	√	✗	√	√	✗	✗	✗	✗	✗	√	✗
	Fister et al. (2012)	✗	✗	✗	√	✗	✗	√	✗	✗	✗	✗	✗
	Faraji and Javadi (2011)	✗	✗	✗	✗	✗	✗	√	✗	✗	√	√	✗
COA	Mahmoudi and Lotfi (2015)	✗	✗	✗	✗	✗	✗	√	√	✗	✗	√	✗
	Djelloul et al. (2015)	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	✗	✗
	Zhou et al. (2013)	✗	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	√
FA	Del Ser et al. (2016)	✗	✗	✗	✗	✗	√	✗	√	✗	✗	✗	✗
	Fister et al. (2012)	✗	✗	✗	✗	✗	√	✗	✗	✗	✗	✗	√
SA	Pal et al. (2012)	✗	√	✗	✗	✗	✗	√	√	✗	✗	✗	✗
GA	Douiri and Elbernoussi (2015)	✗	✗	√	✗	√	✗	✗	✗	✗	√	√	✗
	Bhasin and Amini (2015)	√	✗	✗	✗	✗	√	✗	✗	✗	✗	√	√
	Zhang et al. (2014)	√	√	✗	✗	✗	✗	√	✗	✗	√	✗	✗
	Hindi and Yampolskiy (2012)	✗	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	✗
	Sethumadhavan and Marappan (2013)	✗	✗	✗	✗	✗	✗	✗	√	√	✗	✗	√
	Marappan and Sethumadhavan (2013)	✗	✗	✗	√	✗	✗	✗	✗	√	✗	✗	✗
	Abbasian and Mouhoub (2013)	✗	√	✗	√	✗	√	√	✗	✗	√	√	✗
	Abbasian and Mouhoub (2011)	✗	✗	✗	✗	✗	√	✗	√	√	✗	✗	✗
	Maitra et al. (2010)	✗	✗	✗	√	✗	√	✗	✗	✗	√	✗	✗
	Douiri and Elbernoussi (2011)	✗	✗	✗	✗	✗	√	✗	✗	✗	√	✗	√
	Han and Han (2010)	√	√	✗	√	✗	√	✗	√	✗	✗	√	√

(*continued on next page*)

Table 15 (*continued*)

Algorithm	Reference	Iteration number	Runtime	Competitive	Convergence	Large graph	Medium graph	Improving algorithms	Global optimum	Decreasing solutions space	Comparable	Success	Efficiency
MA	Moalic and Gondran (2015)	✗	√	✗	✗	√	✗	✗	✗	✗	✗	√	√
	Jin et al. (2014)	✗	√	√	✗	√	✗	✗	√	✗	✗	√	✗
	Benlic and Hao (2011)	✗	✗	√	✗	✗	✗	✗	√	✗	✗	✗	√
	Lü and Hao (2010)	✗	✗	✗	✗	✗	✗	✗	✗	√	√	√	√
QA	Titiloye and Crispin (2012)	✗	✗	✗	✗	✗	√	✗	√	✗	✗	√	✗
	Titiloye and Crispin (2011)	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	√	✗
	Titiloye and Crispin, 2011)	✗	✗	✗	✗	✗	√	✗	✗	✗	√	√	✗
PSO	Gong et al. (2016)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	√	√
	Agrawal and Agrawal (2015)	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	✗	√
	Aoki et al. (2015)	✗	✗	✗	✗	✗	✗	✗	√	✗	✗	✗	✗
	Bensouyad and Saidouni (2015)	✗	✗	✗	✗	✗	✗	√	√	✗	✗	✗	√
	Consoli et al. (2013)	✗	√	√	✗	✗	√	√	√	✗	✗	✗	✗
	Lee et al. (2012)	✗	√	✗	✗	✗	✗	✗	√	✗	✗	✗	√
	Dorrigiv and Markib (2012)	✗	✗	✗	✗	✗	✗	✗	✗	✗	√	√	✗
	Hsu et al. (2011)	√	√	✗	✗	✗	✗	✗	√	✗	✗	✗	✗
	Qin et al. (2011)	✗	✗	√	✗	✗	√	√	✗	✗	✗	√	✗
	Rebollo-Ruiz and Graña (2011)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	√	√
	Anh et al. (2009)	✗	✗	✗	✗	✗	√	√	✗	✗	✗	✗	✗
TS	Kouider et al. (2015)	✗	✗	✗	√	✗	✗	✗	✗	✗	✗	✗	√
	Barany and Tuza (2015)	✗	✗	√	✗	✗	✗	√	✗	✗	✗	✗	✗
	Bouziri and Jouini (2010)	✗	✗	√	✗	✗	√	√	✗	✗	✗	✗	✗
Hybrid algorithms	Astuti (2015)	✗	√	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Bessedik et al. (2014)	✗	√	√	✗	✗	√	✗	✗	✗	√	✗	✗
	Wu and Hao (2012)	✗	✗	√	✗	✗	✗	√	√	✗	√	✗	✗
	Pahlavani and Eshghi (2011)	✗	√	✗	✗	✗	✗	√	✗	✗	√	✗	✗

Table 16
Percentage of main criteria in the reviewed meta-heuristic algorithms.

	ACO	BA	ABC	COA	FA	GA	MA	QA	PSO	TS	Hybrid algorithms
low runtime	57	0	17	0	50	27	50	0	27	0	75
High convergence	29	0	33	0	0	36	0	0	0	33	50
global optimum	29	0	17	0	0	36	50	33	36	0	0
High number of success	29	29	33	67	50	36	75	100	36	0	50
Applying on a large-scale graph	14	0	33	33	0	10	50	0	0	0	0

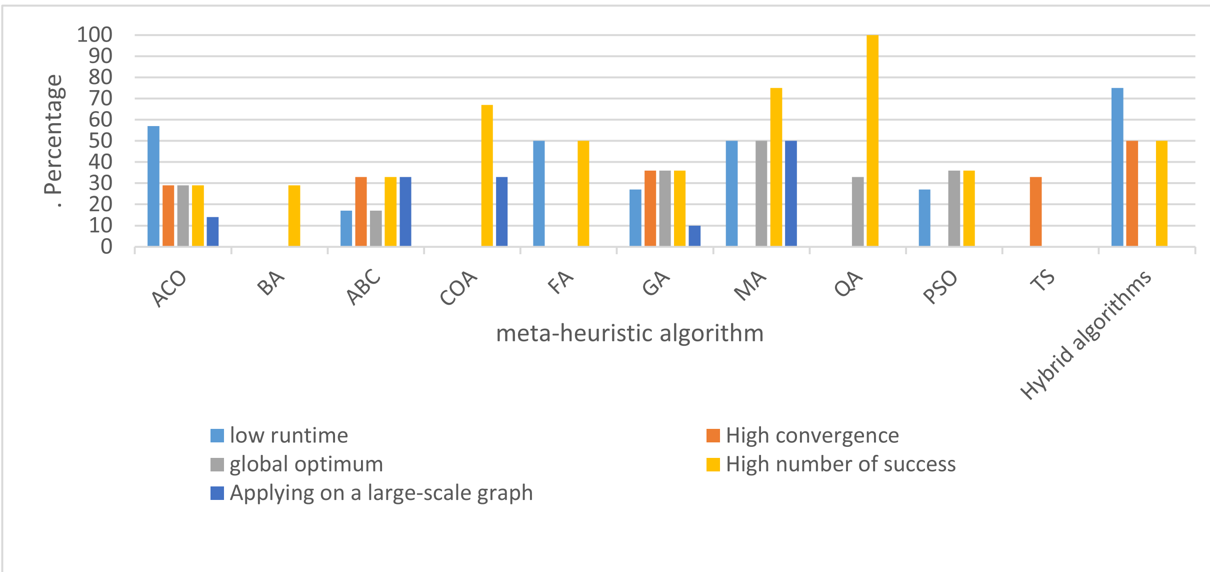

Fig. 6. Percentage of graph coloring criteria in the reviewed meta-heuristic algorithms.

as convergence, runtime, and improving algorithm), it is obvious that some criteria have been considered by some methods, while some of them have completely been ignored. For example, Yuan et al. (2014) has considered convergence, iteration number, runtime, and improving algorithms. Additionally, some techniques have considered competitive, comparable, success, whereas others have totally ignored them. For instance, Gong et al. (2016) has considered a competitive algorithm, comparability of algorithm results, and a number of successes in a series of repetitions. So, proposing a method considering all of the important metrics is crucial.

Another striking point for upcoming studies could be solving the problem of coloring a large-scale graph by meta-heuristic algorithms. In addition, we have suggested consideration of some meta-heuristic algorithms that are more efficient on these issues. The more the size of GCPs, the more the runtime and the count of iterations. To avoid these difficulties, meta-heuristic algorithms should be designed somehow to eliminate such difficulties. Furthermore, the efficiency of meta-heuristic algorithms for solving GCPs and large-scale ones is an important factor. Therefore, the efficiency of the algorithm for global optimal solutions, the number of successes and the convergence are good and interesting criteria for future studies. Fig. 6

Also, many new meta-heuristic algorithms such as SA optimization, artificial fish optimization algorithm, harmony search (Jalili and Ghadimi, 2016), imperialist competitive algorithm (Razmjooy et al., 2017, Habibi and Navimipour, 2016), two-stage algorithm (Maleksaeedi et al., 2015), and world cup optimization algorithm (Razmjooy et al., 2018) by balancing aim have not been applied to this problem, especially in the famous valid journals. Moreover, some factors have not been considered well, such as large-scale graphs, the dependency of algorithms on parameters, decreasing solution's space, starting with random nonfeasible solutions, global best position, and standard deviations. Moreover, the article has fully studied the usage of the meta-heuristic algorithms in GCP. By reviewing the papers, we have seen that the results of combined meta-heuristic algorithms are better than those of the innovative ones. So, a few novel hybrid methods are required later on.

8. Conclusion

In the present article, scholars have done a thorough study of the meta-heuristic algorithms for GCP. Based on determining the SLR from 201-2018, the count of published works has been low in 2016, but high in 2011. But, the highest counts of works have been printed in low-cited magazines. Between publishers, Science direct and IEEE have published most of the works in the magazines and seminars with 25% and 35%, correspondingly. Works have been categorized into twelve important groups (ACO, PSO, GA, ABC, FA, COA, BA, MA, QA, SA, TS, and Has). For each one, scholars have studied and compared a few features with respect to meta-heuristic methods. In the present article, scholars have also studied a few methods broadly while linking and stressing on a few exciting lines for upcoming works.

The overall result is that some algorithms have usually been trapped in local optima (not suitable for the GCP problem). According to the conducted studies, combined patterns had fewer challenges compared to simple ones. Therefore, new hybrid algorithms have been expected to be used in the future to meet the challenges.

According to obtained results, ACO, GA, ABC, and COA are the most popular algorithms that improve GCP solving. The upcoming works can work on them and achieve an exact method to meet all the above problems. Meta-heuristic algorithms in the GCP have been used to improve the iteration number, the runtime, the convergence to an optimal solution, the efficiency, and the improvement of the performance. Altogether, collected data on this survey will help the recognized investigators in the GCP. Especially, responses to specified questions condensate the graph coloring's main goal, existing challenges, open issues, and methods and techniques in the meta-heuristic. Finally, we honestly hope that the consequences of our study will result in the improvement of techniques in the GCP.

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