Archives of Computational Methods in Engineering (2023) 30:2181–2209
https://doi.org/10.1007/s11831-022-09859-9

REVIEW ARTICLE

# A Review on Constraint Handling Techniques for Population-based Algorithms: from single-objective to multi-objective optimization

Iman Rahimi[1] · Amir H. Gandomi[1,2] · Fang Chen[1] · Efrén Mezura-Montes[3]

Received: 21 August 2022 / Accepted: 19 November 2022 / Published online: 9 December 2022


**Abstract**
Most real-world problems involve some type of optimization problems that are often constrained. Numerous researchers have investigated several techniques to deal with constrained single-objective and multi-objective evolutionary optimization in many fields, including theory and application. This presented study provides a novel analysis of scholarly literature on constraint-handling techniques for single-objective and multi-objective population-based algorithms according to the most relevant journals and articles. As a contribution to this study, the paper reviews the main ideas of the most state-of-the-art constraint handling techniques in population-based optimization, and then the study addresses the bibliometric analysis, with a focus on multi-objective, in the field. The extracted papers include research articles, reviews, book/book chapters, and conference papers published between 2000 and 2021 for analysis. The results indicate that the constraint-handling techniques for multi-objective optimization have received much less attention compared with single-objective optimization. The most promising algorithms for such optimization were determined to be genetic algorithms, differential evolutionary algorithms, and particle swarm intelligence. Additionally, "Engineering," "Computer Science," and " Mathematics" were identified as the top three research fields in which future research work is anticipated to increase.

## 1 Introduction

Real-world problems involve some optimization problems that are often constrained, and most of these problems are considered multi-objective optimization problems (MOOPs). No single solution exists for a MOOP; instead, different solutions generate trade-offs for different objectives. Furthermore, MOOPs arise naturally in most fields, and solving them has been a challenging problem for researchers [1–3]. Evolutionary computation (EC) methods have been identified as more effective methods to tackle the challenges that arise from the MOOPs, for which the form of the Pareto-optimal front (discontinuity, nonconvexity, etc.) is not important [4, 5]. Moreover, most multi-objective evolutionary algorithms (MOEAs) use the dominance concept [6–11].

To solve the constrained optimization of all real-world problems, constrained evolutionary algorithm optimization (CEAO) implements an evolutionary algorithm (EA) combined with a constraint-handling technique (CHT). In work by [12], an infeasible individual will be divided into different categories based on their distances to the feasible region, and ranking will be conducted according to the classes. The authors of [13] introduced an approach that assigns high and low priorities to constraints and objective functions, respectively. The authors of [14] proposed a CHT that only considers the inequality constraints, wherein the algorithm uses tournament selection that has better convergence properties in comparison to the proportionate selection operator [15]. However, the latter algorithm employs niche count for all populations, which may increase the complexity of the computation.

✉ Amir H. Gandomi
Gandomi@uts.edu.au

Iman Rahimi
iman83@gmail.com

Fang Chen
fang.chen@uts.edu.au

Efrén Mezura-Montes
emezura@uv.mx

1 Data Science Institute, Faculty of Engineering & Information Technology, University of Technology Sydney, Sydney, Australia

2 University Research and Innovation Center (EKIK), Óbuda University, 1034 Budapest, Hungary

3 Artificial Intelligence Research Institute, University of Veracruz, Veracruz, Mexico

The authors of [16] introduced a novel approach that ignores any solution that violates any of the assigned constraints. The authors of [17] first proposed the use of a genetic algorithm (GA) population-based approach plus a controlled mutation operator to keep diversity among feasible solutions. The work of [18] proposed a CHT where three different non-dominated rankings of the population are performed using objective function values, different constraints, and a combination of all objective functions and values. Although the technique can handle infeasible solutions carefully and maintain diversity in the population, the algorithm performs poorly in choosing parameter values and is computationally expensive. The authors of [19] developed an EA based on the nondominated sorting concept that uses the min–max formulation for constraint handling.

The authors of [20] ran the simulation of the non-dominated sorting genetic algorithm II (NSGA-II) on a seven-constrained nonlinear problem, which exhibited better performance than Ray-Tai-Seow's algorithm. The authors of [21] conducted an overview and analysis of the most popular CHTs using EAs along with pros and cons. The authors of [22] combined a penalty function and multi-objective optimization technique, in which the ranking scheme is borrowed from the latter technique. The authors of [23] suggested two approaches, namely Objective Exchange Genetic Algorithm and Objective Switching Genetic Algorithm, for solving constrained MOOPs. A new partial order relation from the constraint MOOPs was proposed by [24], under which the Pareto optimum set satisfies the constraints. The authors of [25] introduced the Blended Space EA, which uses a rank obtained by blending an individual's rank in the objective space to check dominance.

The authors of [26] introduced a two-phase algorithm, which separates the objective function and constraints. The authors of [27] introduced a MOO-based EA (Cai and Wang method), abbreviated as CW, in addition to three other models for constrained optimization. In the proposed approach, the simplex crossover was used to enrich the exploitation and exploration abilities. The authors of [28] proposed an EA based on an evolutionary strategy for constrained MOOPs. The method uses a min–max formulation for constraint handling in which feasible individuals and infeasible individuals evolve toward Pareto optimality and feasibility, respectively. The authors of [29] suggested Pareto Descent Repair (PDR) to search for feasible solutions. The authors of [30] proposed an adaptive tradeoff model for constrained evolutionary optimization to address three main issues: evaluating an infeasible solution in case the population contains only infeasible solutions,achieving a balance between feasible and infeasible individuals when the population contains both solutions; and selecting the feasible solution in case the population possesses only feasible solutions.

The authors of [31] suggested a heuristic hybrid of particle swarm optimization (PSO) and ant colony optimization for the optimum design of trusses, which showed to handle the problem-specific constraints using a fly-back mechanism. The work of [32] suggested an infeasibility-driven EA (IDEA), which can retain a proportion of infeasible solutions among the population members and preserve diversity compared to NSGAII. The authors of [33] investigated an EA solution for approximate Karush–Kuhn–Tucker (KKT) conditions of smooth problems. The results of some test problems indicate that EA's operators lead the search process to a point close to the KKT point. The authors of [34] discussed the most critical techniques, many of which were previously proposed [21, 35]. The previous work also addressed some state-of-the-art constrained handling techniques, including feasibility rules based on GA [17], epsilon-constrained method [36], penalty functions [37, 38], and ensemble of constraint-handling methods [39, 40]. The authors of [41] introduced an evolutionary scheme for handling boundary constraints, combined it with differential evolution (DE) and compared the proposed method with other boundary constraints handling techniques. The results indicated the proposed approach is much better than the existing methods.

The authors of [42] developed a water cycle algorithm, inspired by observations of the water cycle process that could be applied to a number of constraint optimization problems. The authors of [43] introduced a population-based algorithm based on the mine blast explosion concept and then applied the proposed approach to some constraint optimization problems in comparison to other well-known optimizers. The authors of [44] used a constraint consensus method that helps an infeasible individual to move towards the feasible region and then combined the method with a memetic algorithm. The research conducted by [45] developed a feasible-guiding strategy to guide the evolution of individuals, in which a revised objective function technique with a feasible guiding strategy based on NSGA-II is introduced to handle constrained MOOPs. The study proposed by [46] proposed a class of constraint handling strategies in which infeasible individuals are repaired when they are considered in the search space and explicitly preserve the feasibility of the solutions.

The authors of [47] used a hybrid of PSO and GA to improve the balance between exploration and exploitation by using genetic operators, namely crossover and mutation in PSO. A few years later, the authors of [48] extended the parameter-less CHT so as to provide a balance between the feasible and infeasible solutions in a GA population. The authors of [49] proposed a new approach, known as the boundary update (BU) technique, which is able to handle constraints implicitly by updating variable bounds. The BU approach was tested on several constrained optimization problems and found to be very efficient. The method proposed by [49] possesses the potential to couple with MOEA.

It is noteworthy to mention that the majority of the mentioned studies focused on CHTs for single-objective optimization with little attention to multi-objective optimization. This is attributed to the fact that most constraint handling methods developed for single-objective optimization could also be modified for multi-objective optimization[34]. The main contribution of this work is reviewing the most state-of-the-art constraint handling techniques in population-based optimization for single- and multi-objective optimization problems, and then the study addresses the bibliometric analysis, with a focus on multi-objective, in the field.

To attain a better understanding of the research field and to provide new insights from relevant publications, this work aimed to answer the following questions:

- RQ1: What are CHTs, and how are they important?
- RQ2: What are the disadvantages of the different CHTs?
- RQ3: What are the key subjects and keywords regarding constraint handling techniques?
- RQ4: Could we extract the most active journals, researchers, and countries in the field?
- RQ5: What are the basic statistics of constraint handling techniques for multi-objective population-bassed algorithms?
- RQ6: What are the most active countries and affiliations in the field?
- RQ7: What are the gaps found in literature and future trajectory in the area?

The reminder of the study is as follows. Section 2 describes the research methodology. Section 3 presents the CHTs in EAs. Section 4 describes the other approaches. Section 5 addresses the benchmark test problems. Section 6 discusses the scientometric analysis. Section 7 provides a summary of the study along with recommendations for future research. Concluding remarks are offered in the last section.

## 2 Research Methodology

The research methodology in this work was divided into several stages (Fig. 1). First of all, documents from databases were gathered from databases, namely, Scopus and Web of Science (WOS). For this aim, the authors used special keywords, namely (TITLE-ABS-KEY (constrained AND multi AND objective AND evolutionary AND optimization) OR TITLE-ABS-KEY (constraint AND handling AND multi AND objective AND evolutionary AND optimization) OR TITLE-ABS-KEY (constrained AND multi AND objective AND swarm AND optimization) OR TITLE-ABS-KEY (constraint AND handling AND multi AND objective AND swarm AND optimization) to find the related articles published as of May 4, 2021. Supplementary A and B present the data extracted from Scopus and WOS, respectively. Since some of the articles were duplicates, they were identified and removed from the library in the next stage using Mendeley as a powerful reference manager. Also, some research questions for this study were designed. An overview, along with a general illustration of CHTs is provided in the next stage. A social network analysis, including co-occurrence, co-authorship, citation, and citation network analyses, is then conducted using VOSviewer [50, 51] and RStudio. Also, some interesting analytical features, such as

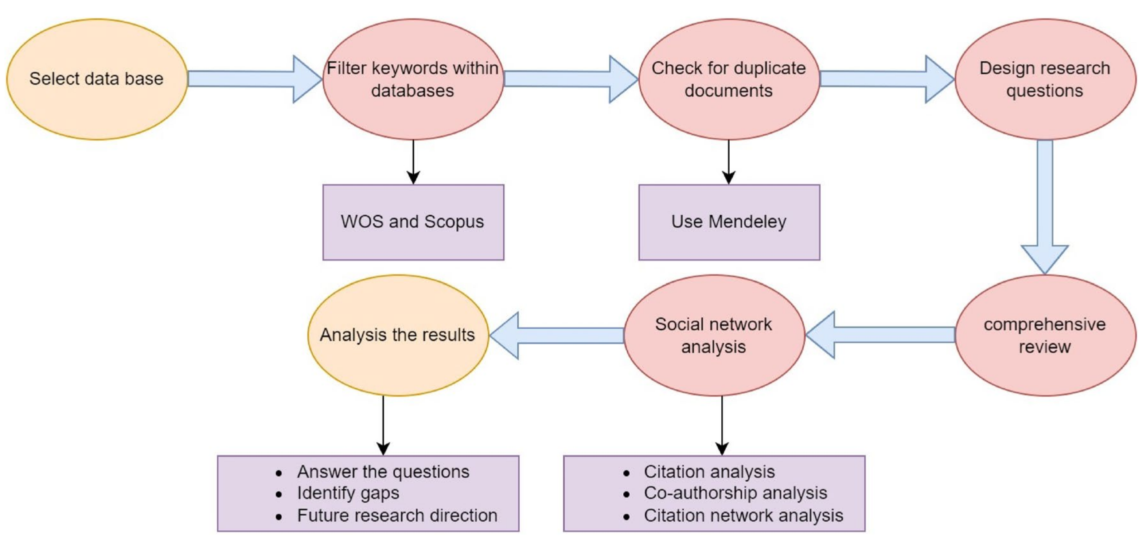


**Fig. 1** Research Procedure

number of pages and authors per article, were conducted in this stage. The last section required preparing the findings, identifying important gaps, and determining future research directions.

## 3 Constraint Handling Methods in Evolutionary Algorithms (RQ1)

Almost all real-world problems are considered constraint problems. A general form of a constrained multi-objective optimization problem (CMOOP) is described as follows (Eqs. 1, 2, 3):

$$\text{Maximize (Minimize) } \mathrm{F(x)} = \left(f_1(x), \ldots, f_t(x)\right) \tag{1}$$

s.t.

$$h_i(x) = 0 i = 1, \ldots, n \tag{2}$$

$$g_j(x) \le 0 j = 1, \ldots, m \tag{3}$$

where F(x) is the objective vector; and t, n, and m are the number of objective function, equality, and inequality constraints, respectively. There is no single solution for a MOOP that simultaneously optimizes each objective, instead, there exists a number of Pareto optimal solutions. A Pareto front of possible solutions is called optimal or nondominated if improving anyone's objective further would lead to a decrease in other objectives. According to previous surveys [21, 35], a simple taxonomy of the constraint handling methods in nature-inspired optimization algorithms is as follows:

- Penalty functions methods
- Decoderss
- Special operators
- Separation techniquess

The first and fourth techniques are discussed in detail later in the paper. As an example of decoders, [52] proposed a homomorphous mapping (HM) method between an n-dimensional cube and feasible space. The feasible region can be mapped onto a sample space where a population-based algorithm could run a comparative performance [52–55]. However, this method requires high computational costs. A special operator is used to preserve the feasibility of a solution or move within a special region [56–58]. Nevertheless, this method is hindered by the initialization of feasible solutions in the initial population, which is challenging with highly-constrained optimization problems. In addition, The authors of [59] presented a taxonomy of CHTs in MOEA as follows (Fig. 2):

- Penalty functions
- Separation method
- Retaining the infeasible solutions

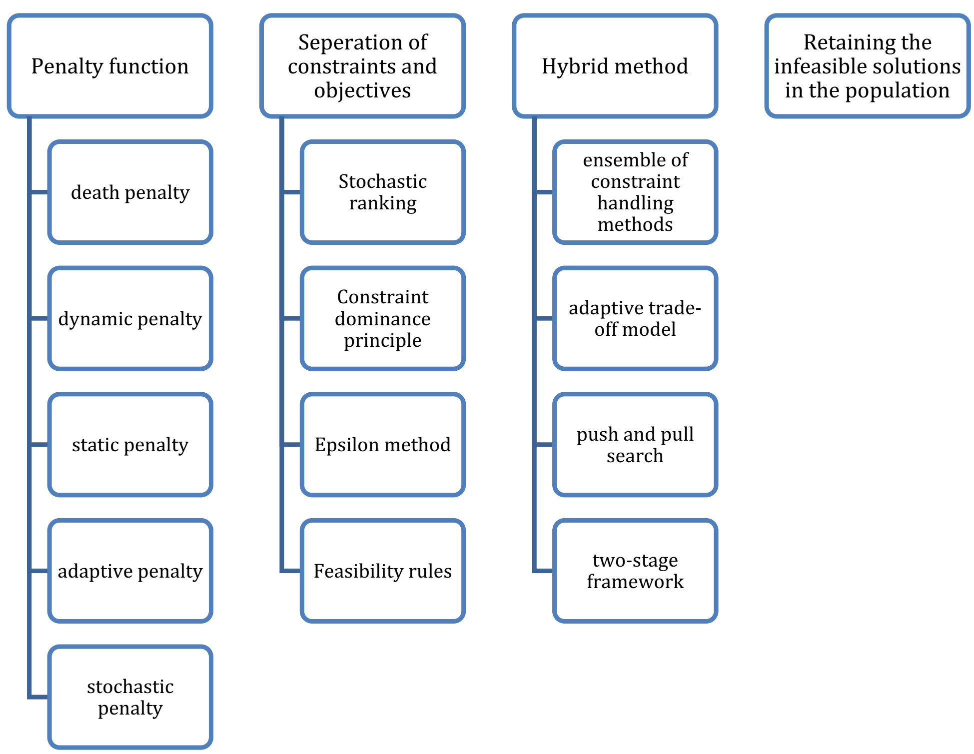


**Fig. 2** Taxonomy of different constraint handling methods in MOEA

- Hybrid methods

Generally, penalty function techniques are one of the most simple CHTs. There are several types of penalty functions used with EAs, the most important ones include [60]:

- Death penalty
- Dynamic penalty
- Static penalty
- Adaptive penalty
- Stochastic ranking

Details regarding the penalty function methods will be discussed in the next section.

## 3.1 Penalty Function Approach

The penalty function method is one of the easiest and most common ways to handle constraints in multi-objective evolutionary algorithms.

From a mathematical point of view, two types of penalty functions could be considered as follows:

Interior methods
Exterior methods

In the first type of penalty function, interior methods, the penalty factor is selected such that the value will be small away from the constraint boundaries and need an initial feasible solution [59], whereas exterior methossds do not need an initial feasible solution [4]. Also, it should be noted that some of the infeasible solutions should be retained in the populations so that they are able to converge to a solution, which lies in the boundary between the feasible and infeasible regions [61].

The penalty function method ignores any infeasible solution [62]. First, all constraints should be normalized, and for each solution, the constraint violations are calculated as follows (Eq. 4):

$$w_j(x^i) = \begin{cases} \left|\overline{g}(x^i)\right|, & if\ \overline{g}(x^i) < 0 \\ 0, & otherwise \end{cases}, \tag{4}$$

where $\overline{g}(x^i)$ refer to the normalized values for a given constraint $\overline{g}_j(x^i) \geq 0, j = 1, \ldots, J$. Once the violations for the constraints are calculated, the values are added to determine the overall violation as follows (Equation. 5):

$$\Omega(x^i) = j = \sum_{j=1}^{J} w_j(x^i) \tag{5}$$

Also, a penalty parameter is multiplied by the sum of constraint violations and then added to the objective function values. If a proper penalty parameter is selected, MOEAs will work well; otherwise, a set of infeasible solutions or poor solutions distribution is possible.

### 3.1.1 Static Penalty Functions

In the static penalty proposed by [63], the penalty coefficient increases as a higher level of violation is reached. In fact, penalty functions do not change, a static penalty function is suggested, and several levels of violation are introduced in which the static penalty parameter is changed in case higher levels of violation are achieved [64]. In the static penalty function, the expanded objective function is (Equation 6):

$$\varphi(\mathrm{x}) = \mathrm{f}(\mathrm{x}) + \sum_{\mathrm{j}=1}^{\mathrm{p}} \mathrm{C}_{\mathrm{kj}}\mathrm{G}_{\mathrm{j}} \tag{6}$$

where $G_j = max\{0, g_j(x)\}^{\beta}$; and k = 1,…,l where l presents the number of violation levels.

### 3.1.2 Dynamic Penalty Functions

In this category, functions are changed based on the iteration number. The authors of [65] proposed the following dynamic penalty function, in which the penalty increases when the iteration number increases.

Dynamic multi-objective optimization problems (DMOOPs) involve the simultaneous optimization of different objectives subject to a number of given constraints, where the objective functions, constraints, and/or dimensions of the objective space could change over time. EAs have acquired great attention among researchers for solving the above-mentioned problems.s

### 3.1.3 Adaptive Penalty Functions

In this category, infeasible individuals are penalized according to the feedback taken from the search process. The authors of [66, 67] proposed a CHT based on the adaptive penalty function and distance measure, which both change as the objective function value and constraint violations of an individual varies.

Penalty-based constraint handing for multi-objective optimization is similar to single-objective problems in which a penalty factor is added to all the objectives. The authors of [67] proposed a self-adaptive penalty function suitable for solving constraint multi-objective optimization problems using evolutionary algorithms. In the self-adaptive penalty function method, the amount of penalty added to infeasible individuals are identified by tracking the number of feasible individuals. Also, the method uses improved objective values instead of the original objective function values [68].

#### 3.1.4 Annealing-Based Penalty Functions

The authors of [69] introduced a multiplicative penalty function based on simulated annealing. In this type of penalty function, the temperature is decreased when the iteration number increases, which leads to an increased penalty.

#### 3.1.5 Co-Evolutionary-Based Penalty Functions

The authors of [21] proposed a co-evolutionary approach in which the population is partitioned into two subpopulations. The first population evolves solutions, and the second population evolves penalty factors. In this approach, the penalty function considers information taken from the amount of constraint violations and a number of violations.

There are other types of penalty function methods, and Table 1 presents a summary and critique of the techniques for constraint handling.

### 3.2 Separation of Objective Function and Constraints

Unlike the penalty function technique, another approach exists that separates the values of objective functions and constraints in the nature-inspired algorithms (NIAs) [70], which is known as the separation of objective function and constraints. The authors of [71] initially proposed the idea of dividing the search space into two phases. In the first phase, feasible solutions are found, and optimizing the objective function is considered in the second phase.

Representative methods of this type of CHT are as follows:

- Constraint dominance principle (CDP)
- Epsilon CHT
- Feasibility rules

**Table 1** The important CHTs (penalty function)-*RQ2*

| Method | Criticism | Consequences |
|---|---|---|
| Death Penalty [16] | •No information is used from infeasible points<br>•It may require the initialization of the population and lack of diversity | •Consumes many evaluations<br>•Low success rate |
| Static Penalty [63] | •It is required to set up a high number of penalty parameters<br>•It is also problem-dependent | •Time-consuming |
| Dynamic Penalty [65] | •It is hard to drive good dynamic penalty functions in real cases<br>•In some cases, this method converges to either an infeasible or feasible solution that is far from the global optimum [181], [218] | •Premature convergence or even an infeasible solution in some cases |
| Adaptive Penalty [66] | •Setting the parameters is difficult, such as determining the appropriate generational gap<br>•It requires the definitions of additional parameters [219] | •Time-consuming |
| Annealing Penalties [220] | •The main disadvantage is its sensitivity to the values of its factors<br>•To handle linear constraints, the user should provide an initial feasible point to the algorithm | •The performance of the algorithms is not good |
| Self-adaptive Penalty [221, 222] | •It defines four additional parameters that may affect the fitness function evaluations | •Time-consuming & weak or strong penalty during evolution |
| Segregated genetic algorithm (SGA) [223] | •The main difficulty is selecting the penalties for each of the two sub-populations | •Time-consuming |
| Penalty function based on feasibility [17] | •The main issue is maintaining diversity in the population, and in some cases, the use of a niching method combined with higher-than-usual mutation rates is essential | •Premature convergence |

The next section provides further details about this type of constraint handling method.

#### 3.2.1 Constraint Dominance Principle

Three feasibility rules are applied to compare the two solutions in the constraint dominance principle (CDP). If $x^1$ is feasible and $x^2$ is infeasible, then $x^1$ would be better than $x^2$. If both solutions are infeasible, then the solution with a smaller constraint violation is better. If both are feasible, then the one dominating the other is better. The authors of [20] adopted CDP to handle constraints in NSGAII (NSGAII-CDP), in which the population is divided into feasible and infeasible sub-populations. NSGAII-CDP first selects offspring from the feasible solutions and then selects solutions from the infeasible solutions. The authors of [72] also adopted CDP to handle constraints in the MOEA/D framework.

#### 3.2.2 ε-Constrained (EC) Method

The basic principle of the ε-constrained method, first introduced by [73], is similar to the superiority of feasible solution (SF) proposed by [74] (Equations. 12–13). The epsilon value is updated until the parameter k reaches the control generations $T_c$. The authors of [75] embedded the epsilon CHT in MOEA/to set the epsilon value adaptively to r comparison. Also, the violation threshold is based on the constraint type, the feasible space size, and the search outcome. In the method proposed by [75], the infeasible solutions with violations less than threshold are identified (Eqs. 7–8).

$$\varepsilon(0) = V\left(x_\theta\right) \tag{7}$$

$$\varepsilon(k) = \begin{cases} \varepsilon(0)\left(1 - \frac{k}{T_c}\right)^{cp}, & 0 < k < T_c \\ 0, & k > T_c \end{cases} \tag{8}$$

where $x_\theta$ presents the top $\theta$ th individual at initialization; and the cp parameter is selected between [2,10, 68].

#### 3.2.3 Feasibility Rules

The popularity of this method depends on its ability to be coupled to a range of algorithms without announcing new parameters (factors) [34].

The feasibility rules proposed by [17] are simple, could be integrated into a variety of algorithms without adding new parameters, and thus, are largely used in the research field. The authors of [76, 77] developed feasibility rules for the selection process, which have been adopted by different evolutionary algorithms such as DE, PSO, and GA. According to the number of feasible solutions, the search space could be divided into three phases as follows [68]:

- No feasible solution is found.
- There exists at least one feasible solution.
- Integrating the parent–offspring population has more feasible solutions than the size of the next generation population.

The feasibility rules used in multi-objective optimization, also known as the superiority of feasible solution (SF), are addressed as follows [68] (Equation 9):

$$fitness_m(x) = \begin{cases} f_m(x) & if\ x\ is\ feasible \\ f^m_{worst} + v(x) & otherwise \end{cases} \tag{9}$$

where $f^m_{worst}$ and v(x) show the m$^{th}$ objective value of the worst feasible solution and the overall constraint violation, respectively.

**3.2.3.1 Feasibility Rules in Differential Evolution (DE)** Although the feasibility rules introduced by [17] have also been widely used by other researchers in DE [78], [79] [77, 80–83], [84] [30], they have been rarely used in multi-objective differential evolution. Particularly, [85] used Pareto dominance in constrained space instead of the sum of constraint violations. Later, the authors of [79] adopted the Pareto dominance in Generalized Differential Evolution (GDE), but encountered difficulties when there exist more than three constraints and/or objective functions.

The authors of [78] proposed a scheme for partitioning the objective space using the conflict information for multi-objective optimization. The authors of [86] introduced an operational efficient model based on Data Envelopment Analysis (DEA) and introduced DE along with the feasibility rules to optimize the mentioned model. The authors of [87] proposed a combined constraint handling framework, known as CCHF, for solving constrained optimization problems, in which the features of two well-known CHTs (i.e. feasibility rules and multi-objective optimization) were addressed in three different situations (feasible situation, infeasible situation, and semi-feasible situation).

**3.2.3.2 Feasibility Rules in PSO** The authors of [88] employed feasibility rules as a constraint handling technique to recognize the most competitive PSO variant when solving constrained numerical optimization problems (CNOPs). In the research by [88], local-best was identified to be better than global best PSO. The authors of [89, 90] adapted an artificial bee colony algorithm (ABC) to solve CNOPs by using feasibility rules by modifying the probability assignment for the roulette wheel selection. The authors of [91] compared different GA variants using the feasibility rules as the constraint handling method. In the work of [92], a hybrid version of PSO to solve constrained optimization problems was introduced and the authors found that the swarm at each generation is split into several sub-swarms. Also, the hybrid version applied the feasibility rules to compare particles in the swarm.

**3.2.3.3 Feasibility Rules in GA** The authors of [93] proposed a GA with a new multi-parent crossover for solving constraint optimization problems, in which the feasibility rules were added to handle the constraints. The latter authors also solved constraint numerical optimization problems by using different GA variants along with feasibility rules and found that all GAs perform equally. In the work of [26] a two-phase framework for solving constraint optimization problems was introduced. Specifically, the first phase ignores the objective function and the genetic algorithm minimizes the violation of the solutions, while the second phase optimizes bi-objective functions, including the original objective function and constraints satisfaction. Moreover, feasibility rules is applied to assign fitness values to the individuals.

**3.2.3.4 Feasibility Rules in Other Population-Based Algorithms** Feasibility rules have been adapted to other population-based algorithms, such as artificial immune systems [94–99], organizational evolutionary algorithm [100, 101], biogeography-based optimization [102], and bacterial foraging optimization [103].

### 3.3 Retaining Infeasible Solutions in the Population

Another CHT is used to retain the infeasible individuals in the population. In other words, a constraint multi-objective optimization problem with m objective is transformed to an optimization problem with m + 1 objectives, which could save the infeasible solution during the evolution process [32, 104, 105] proposed a constraint handling technique so that individuals with low Pareto rank and low constraint violation will be chosen.

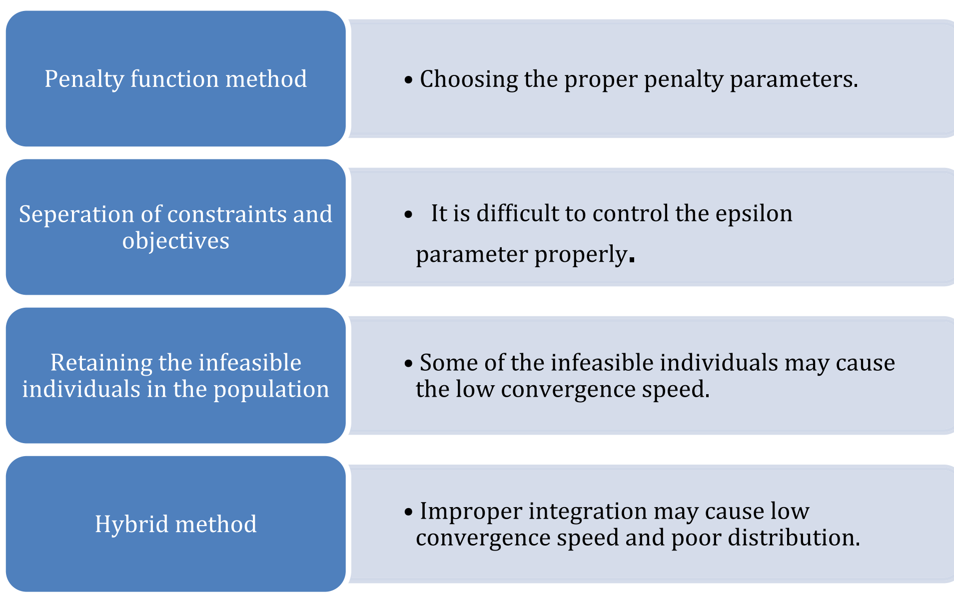


**Fig. 3** The main disadvantages of CHTs in MOEA- RQ2

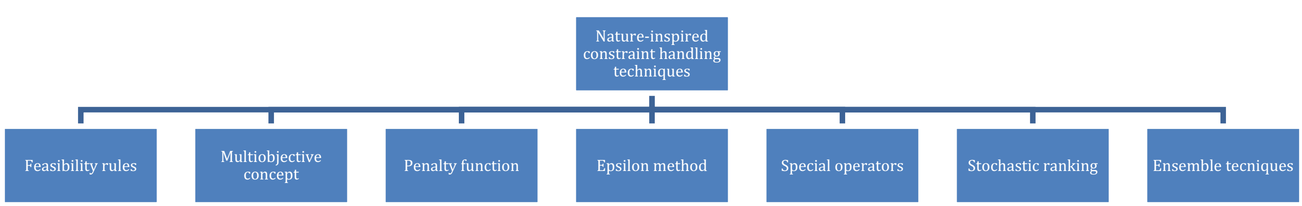


**Fig. 4** State-of-the-art CHTs [34]

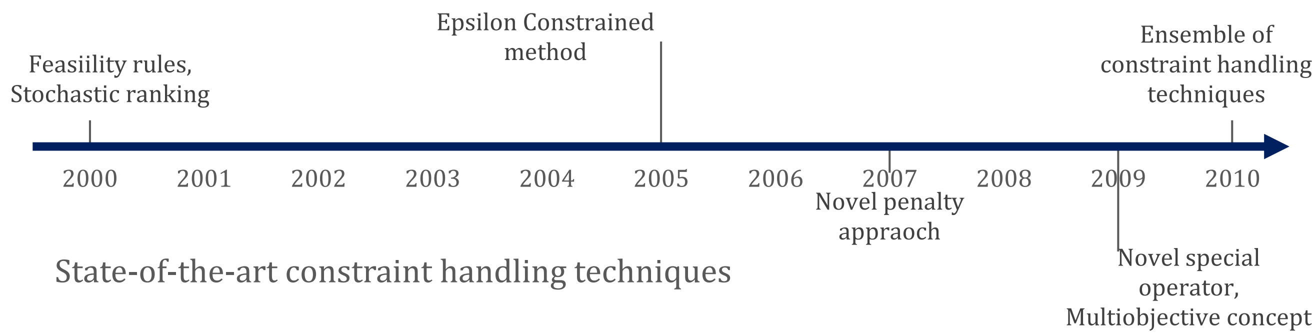


**Fig. 5** Timeline of different state-of-the-art CHTs

### 3.4 Hybrid Methods

Hybrid methods combine several CHTs to handle constraints. The authors of [106] addressed four different hybrid methods in their work: (1) the ensemble of constraint-handling method [68] separates the population into three subpopulations; (2) the adaptive trade-off model [107, 108] contains two different CHTs, (3) in the push and pull search [109], the population is pushed to the unconstrained Pareto front (push) then the population is pulled back to the Pareto front (pull), (4) the two-phase framework (ToP) [110] solves a constraint multi-objective optimization problem by first converting the objective functions into a single objective function via the weighting method then, in the second phase, a constrained MOEA is adopted to attain the Pareto feasible solutions. The disadvantages for each category are summarized in Fig. 3.

The authors of [34] presented a state-of-the-art taxonomy of CHTs, which is illustrated in Figs. 4 and 5 presents the different state-of-the-art CHTs that have been used since 2000. As mentioned, the authors of [17] first applied feasibility rules to the genetic algorithm. The authors of [111] introduced stochastic ranking, which employs a user-defined parameter instead of using penalty factors and is able to control the infeasible solutions based on the sum of constraint violation and objective function values. In a study of [38], the epsilon-constraint method was proposed to transform the constraint optimization problem into an unconstrained one. The authors of [38] addressed a multi-constrained optimization problem based on the KS function. The authors of [112] proposed a boundary search approach inspired by the ant colony metaphor based on conducting a boundary search between a feasible and infeasible solution. The authors of [32] proposed an additional objective to solve a bi-objective optimization problem, where the first objective is the original problem and the second objective is the constraint violation measure. In the work of [39], a combination of four CHTs, namely feasibility rules, stochastic ranking, self-adaptive penalty function, and the epsilon-constraint method to solve constraint numerical optimization problems, was addressed.

### 3.5 Stochastic Ranking

The authors of [111] proposed the stochastic ranking (SR) approach to balance between the objective and penalty functions stochastically. The method was tested using a strategy evolution on several benchmarks, and the results showed that the method is able to improve the search performance with a user-defined parameter without introducing complicated variation operators. SR has also been coupled with other population-based algorithms, such as ant colony optimization (ACO) [113, 114], differential evolutionary (DE) [115–117], and evolutionary programming (EP) [118].

### 3.6 Ensemble Techniques

Ensemble CHTs provide a new research platform to tackle constrained multi-objective optimization problems. Combining several CHTs could improve the capability of an approach compared with a single CHTs [34, 119]. For instance, [120] proposed a combination of four CHTs, namely nondominated sorting, constrained-domination principle, multiple constraint ranking, and dynamic penalty function, and incorporated the proposed technique into an MOEA based on NSGAII. Some other ensemble CHTs have been reported [39, 121, 122]. Although the ensemble CHT has a competitive performance, it suffers from being parameter-dependent.

### 3.7 Multi-Objective Concept

Based on the multi-objective optimization concept, a constraint single-objective optimization problem is transferred to an unconstrained multi-objective optimization problem [4]. The multi-objective version of the optimization problem possesses an extra objective function, which presents the sum of constraint violation [32, 123–125].

The authors of [126] presented a taxonomy for constraint handling strategies in multi-objective GA, which include:

- Penalty function methods
- Separation method
- Special operators
- Repair methods

Among these strategies, the penalty function method is not straightforward in multi-objective GA since the fitness assignment is based on the non-dominance rank of a solution rather than its objective function values [127]. Yet, the penalty function method is one of the most popular CHTs in constraint multi-objective optimization. Whenever the multi-objective function and constraint violation for each constraint are assessed, the sum of violations is added to each objective function value considering the multiplication of the penalty parameter [128, 129].The authors of [23] proposed two approaches, namely OEGADO and OSGADO. The OEGADO runs several GAs in parallel so that each GA optimizes one objective, whereas The OSGADO runs each objective sequentially with a common population for all objectives.

### 3.8 Repair Approaches

There are several techniques used as repair algorithms, in which the search space is reduced (since only feasible individuals are considered):

- In the permutation encodings method, each solution of an EA population is simply signified as an ordered list [130, 131].
- Repair procedures in binary representations, which could be shown as fixing the number of 1 s in binary representations and Hopfield networks [132, 133].
- Repair methods in graphs are represented as spanning trees and repairing graphs [134, 135].
- Repair methods in grouping GAs, are proper for scenarios where a number of items should be assigned to a set of groups [136, 137].

Pure EAs do not perform well in complex combinatorial problems with a high number of constraints [138, 139]. Single-solution-based algorithms (e.g. local search, simulated annealing) have good performance in exploitation, while population-based algorithms (e.g. swarm intelligence, EA are exploration-oriented. In these problems, the hybridization of population-based algorithms with single-based algorithms can improve the power of both exploration and exploitation [139–141]. A memetic algorithm is a hybridization of an EA and a local search (LS) approach that LS is applied to improve the quality of the fitness function. On the other hand, LS could be used as a CHT [139], i.e. the local repair algorithm only consider feasible individuals leading to reducing the search space. Repair methods could be applied to EAs in several ways, such as in permutation encodings [142], [131], in binary representation [143], and in graphs and trees [134–144]. Although repair algorithms have numerous advantages, some disadvantages do exist. For instance, repair algorithms are problem-specific and must be designed for a specific problem [145]. Table 2 shows a summary of the disadvantages of the state-of-art CHTs.

## 4 Other Approaches

Table 3 provides a summary of novel approaches proposed between 2020 and 2021 to tackle constrained multi-objective optimization problems. Based on Table 3, there are signs of a renewed interest in constrained multi-objective optimization, even the clear superior amount of research in constrained single-objective optimization.

As a general, a taxonomy of CHTs in MOEAs could be summarized in Fig. 6. The CHTs presented in Fig. 6 have been explained in details in previous sections. As it

**Table 2** A summary of disadvantages of the state-of-art CHTs- RQ2

| Method | Disadvantages |
|---|---|
| Ensemble method | Although the ensemble CHT has a competitive performance, the method is parameter-dependent |
| Repair method | Repair algorithms are problem-specific and, thus, must be designed for a specific problem |
| Feasibility rules | The method is likely to lead to premature convergence |
| Stochastic ranking | Although the method has been employed in several nature-inspired algorithms, it is not often used for the multi-objective version of the algorithms |
| Epsilon-constraint method | In some cases, premature convergence has been reported, while other works report that the method relies on gradient-based mutation |
| Multi-objective concept | It may require gradient calculation [34] |

**Table 3** Novel approaches for constrained multi-objective optimization problems between 2020 and 2021

| Source | Method |
|---|---|
| KKT points for constrained multi-objective optimization | [224, 225] |
| IoT and cloud computing | [226] |
| Indicator-based constrained handling technique | [227] |
| Decomposition-based algorithm | [228, 106] |
| Push and pull search embedded | [166] |
| Multi-stage evolutionary algorithm | [229, 230] |
| Partition selection | [161] |
| Surrogate-assisted evolutionary algorithm | [150] |
| Purpose-directed two-phase multi-objective differential evolution | [231] |
| Directed Weight Vectors | [232] |
| Gradient-based repair method | [233] |
| Detect and scape strategy | [234] |
| Reference points-based method | [235] |
| multi-objective wireless network optimization using the genetic algorithm | [236] |

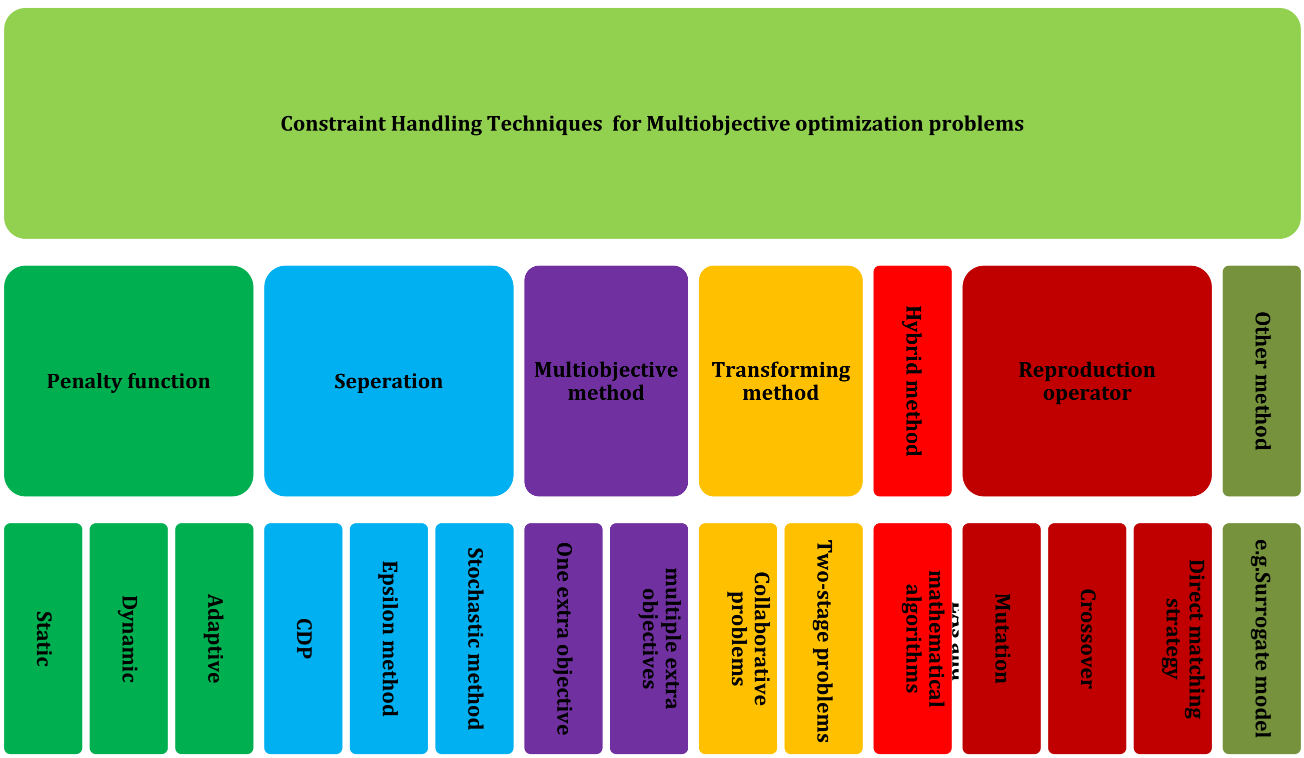


**Fig. 6** A generalized taxonomy of CHTS for multi-objective optimization problems

is mentioned earlier, most constraint handling techniques developed for single-objective optimization problems can be applied to MOOPs. It is worthy to note that among them, stochastic ranking [72] [146]–150], penalty function [23, 67], multi-objective method [32] [151] [127] [152], Epsilon constrained method [153–160], transforming method [106, 161, 100, 101, 162–166], feasibility rules (with a modification) [167, 168], hybrid methods [169–173], and repair operators [148, 149, 174–178] have been addressed to multi-objective optimization problems.

## 5 Benchmark Test Problems

Many benchmark or test problems have been suggested to measure the evolutionary algorithms' performance. On the other hand, benchmark problems help researchers better understand an algorithm's strengths and weaknesses [179]. These test problems are classified as single-objective such as Rosenbrock [180], G01-G09 [181], Himmelblau's problem [182], Welded Beam [183], Pressure Vessel [184], Speed Reducer [185], Corrugated bulkheads design [186], Heater exchanger [187], Multiple disk clutch brake [188],

Rolling element bearing [189], Car side design [190], Stepped beam design problem [191], multi-objective including BNH [192], OSY [193],, ZDT [194], BT [107, 108], Truss2D [195], and many-objective optimization problems, for example, C-DTLZ [196], WFG[197], DTLZ [198]. Among the above-mentioned test problems, some of them are still unconstrained. More details are suggested in a review paper in the field by [197].

## 6 Scientometric Analysis (RQ3- RQ6)

A scientometric analysis is conducted to scientifically measure and analyze the literature in a particular field of study and has attracted much attention from researchers 119–208]. To perform the analysis in this work, VOSviewer [51] and RStudio were used. The following sub-sections provide new insight into the scientometric analysis in the field.

### 6.1 Citation Statistics

Figure 7 displays the trend of published documents, which shows that the number of documents in the field significantly increased from 2003 until the end of 2021 (just above 470 documents).

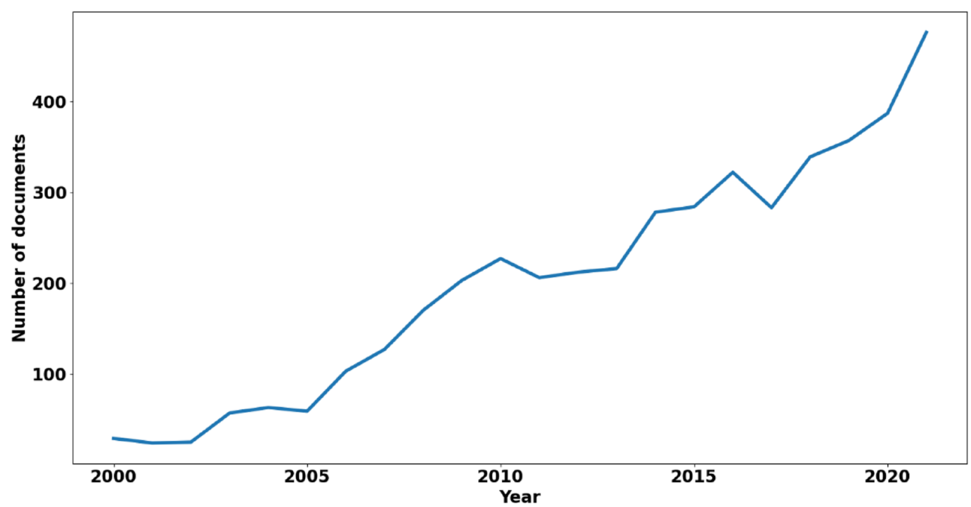


**Fig. 7** Trend of published documents

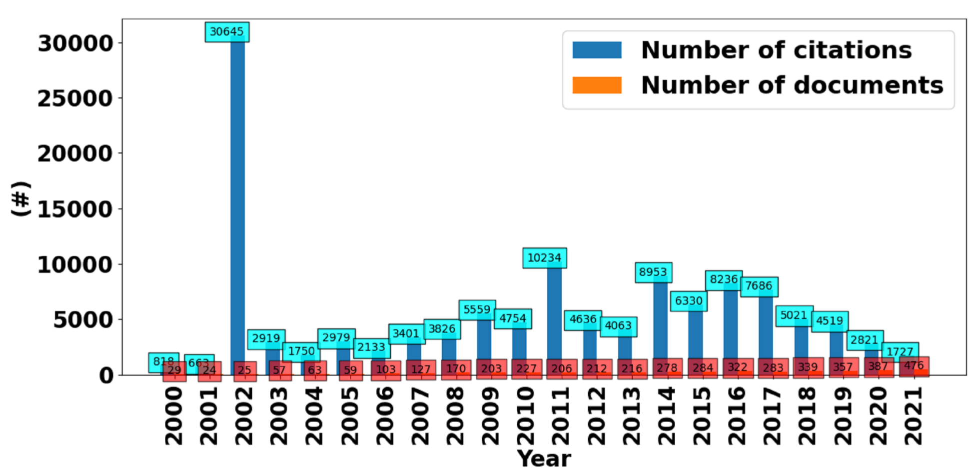


**Fig. 8** Combo chart of number of documents vs. total citations (Scopus)

**Table 4** Citations analysis based on document type

| Document type | TP | % | AU | APP | TC2021 | CPP2021 |
|---|---|---|---|---|---|---|
| Article | 522 | 71.02 | 1362 | 2.60 | 43,904 | 84.10 |
| Proceedings paper | 220 | 29.93 | 469 | 2.13 | 1,543 | 7.01 |
| Review | 16 | 2.17 | 20 | 1.25 | 806 | 50.37 |
| Other items | 23 | 3.12 | 134 | 5.82 | 468 | 20.34 |

TP, AU, APP, TC2020, and CPP2020 present total number of articles; total number of authors; total number of authors for each publication; total citations from WOS since publication year to the end of 2020; total citations for each paper, respectively; Other items: early access and letters [237, 238].

Figure 8 presents a combo chart of the number of documents vs. total citations. In 2002, the most citations was achieved (the paper entitled: "A fast and elitist multi-objective genetic algorithm: NSGA-II" [20] has received more than 43,000 citations, according to Scopus). It is apparent that the number of citations has increased dramatically according to the trend.

According to the WOS, the number of citations of the top articles in the field was analyzed and is presented in Supplementary C (Fig. 1). Of the 735 related documents in WOS, about 45,824 citations were identified from the related papers, with an average of 1992.35 citations per year and an average of 62.35 citations per item. [20, 209, 210] are the top 3 cited articles with 20,013, 2609, and 1591 citations in WOS, respectively.

## 6.2 Statistics Based on Document Types

Among the document types, including articles, proceedings papers, reviews, and other items indexed by WOS, a total of 735 publications on constraint handling multi-objective population-based optimization algorithms were found (Table 4). From the search, articles were the most popular document type, comprising a total of 522 articles (71.02% of 735 documents) with 2.60 authors per publication (APP). Also, articles as the document type had the highest CPP2021 of 84.10, followed by proceedings papers with TP of 220 (29.93% of contributions and APP = 2.13). Moreover, there is a significant difference between the TC2021 article and the proceedings paper.

Figure 9 presents the distribution of documents based on different types, according to WOS. It is clear from the figure that conference papers have the most contributions before 2010, followed by articles. However, since 2010, articles have had the most contributions in the field. It is also interesting to note that book/book chapters have been published since 2000. However, most book/book chapters have been published after 2010.

## 6.3 Publication Statistics Based on Journal

Table 5 presents the top 20 journals that have published the greatest number of constraint handling multi-objective population-based algorithms papers based on Scopus. Accordingly, Lecture Notes In Computer Science (117), Applied Soft Computing Journal (57), and Swarm and Evolutionary

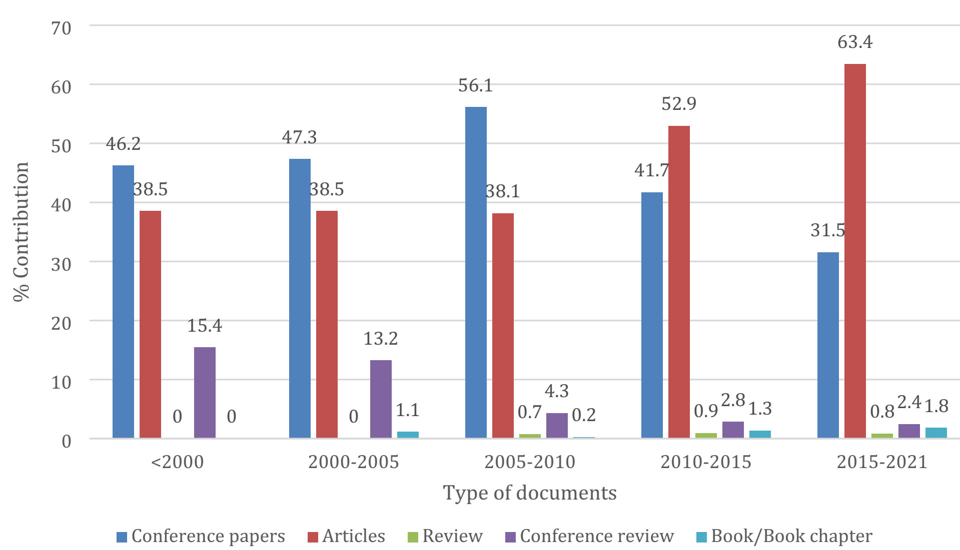


**Fig. 9** Type of research outputs

**Table 5** The top 20 sources that have published the greatest number of constraint handling multi-objective population-based algorithms (Scopus)

| # | Scopus | # of Documents | # | Scopus | # of documents |
|---|---|---|---|---|---|
| 1 | Lecture notes in computer science | 117 | 11 | IEEE Access | 32 |
| 2 | Applied soft computing journal | 57 | 12 | Swarm and evolutionary computation | 30 |
| 3 | "International journal of electrical power and energy systems" | 27 | 13 | Engineering optimization | 21 |
| 4 | "Kongzhi Yu Juece control and decision" | 13 | 14 | Soft computing | 16 |
| 5 | Energy conversion and management | 12 | 15 | Studies in computational intelligence | 16 |
| 6 | IEEE transactions on cybernetics | 12 | 16 | Advances in intelligent systems and computing | 15 |
| 7 | Structural and multidisciplinary optimization | 13 | 17 | Communications in computer and information science | 14 |
| 8 | IEEE transactions on evolutionary computation | 27 | 18 | Engineering applications of artificial intelligence | 14 |
| 9 | Electric power systems research | 10 | 19 | Energy | 13 |
| 10 | Applied intelligence | 12 | 20 | Information sciences | 13 |

**Table 6** The top 10 productive WOS categories

| # | Web of Science category | TP | AU | APP | TC2021 | CPP2021 |
|---|---|---|---|---|---|---|
| 1 | "Computer science" artificial intelligence" | 271 | 628 | 2.31 | 35,074 | 129.42 |
| 2 | "Engineering electrical" electronic" | 171 | 463 | 2.70 | 3688 | 21.56 |
| 3 | "Computer science" interdisciplinary applications" | 92 | 243 | 2.64 | 2691 | 29.25 |
| 4 | "Operations research" management science" | 61 | 131 | 2.14 | 1541 | 25.26 |
| 5 | "Computer science" theory methods" | 171 | 385 | 2.25 | 32,492 | 190.011 |
| 6 | "engineering multidisciplinary" | 64 | 167 | 2.60 | 2377 | 37.14 |
| 7 | "Mathematical interdisciplinary applications" | 45 | 116 | 2.57 | 645 | 14.33 |
| 8 | "Energy fuels" | 41 | 122 | 2.97 | 950 | 23.17 |
| 9 | "Computer science information systems" | 48 | 124 | 2.58 | 746 | 15.54 |
| 10 | "Automation control systems" | 60 | 155 | 2.58 | 1178 | 19.63 |

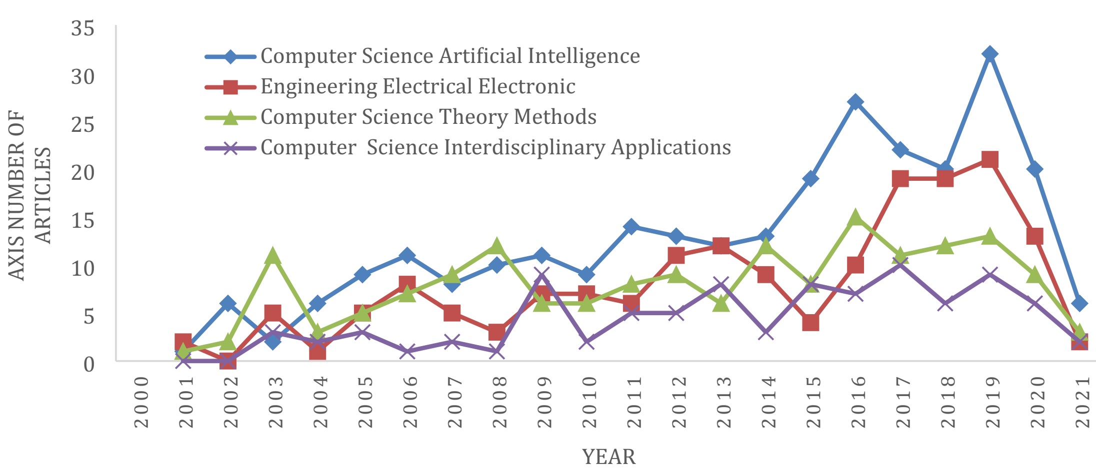


**Fig. 10** Comparison of the development trends of the top four productive WOS categories

Computation (30) are most are most utilized, which predominate in the field of optimization and evolutionary computations.

A total of 735 articles were published in 399 journals, which are classified among the 51 WOS categories in SCI-EXPANDED. Table 6 lists the 10 most productive WOS

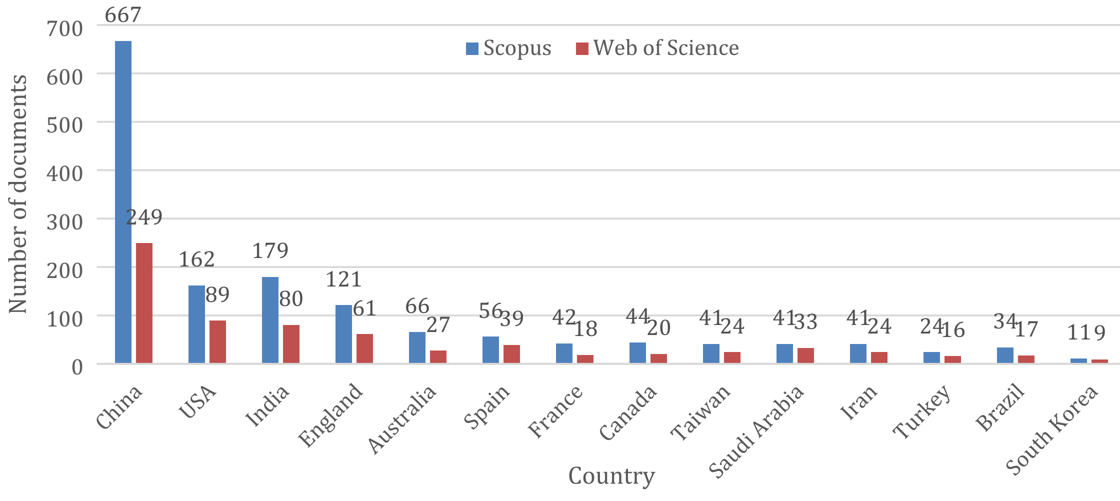


**Fig. 11** Research output of top 10 most productive countries across all databases

categories. A total of 271 articles (36.87% of 735 articles) were published in the first category (Computer Science Artificial Intelligence), of which 83.39% were published in Engineering Electrical Electronic (23.26%) and Computer Science Theory Methods (23.26%). Comparing the top 10 categories, the highest CPP2021 of articles published in the Computer Science Theory Methods category is 190.011, which includes the paper entitled: "A fast and elitist multi-objective genetic algorithm: NSGA-II" by [20], and the highest APP for articles published in the Energy Fuels category is 2.97.

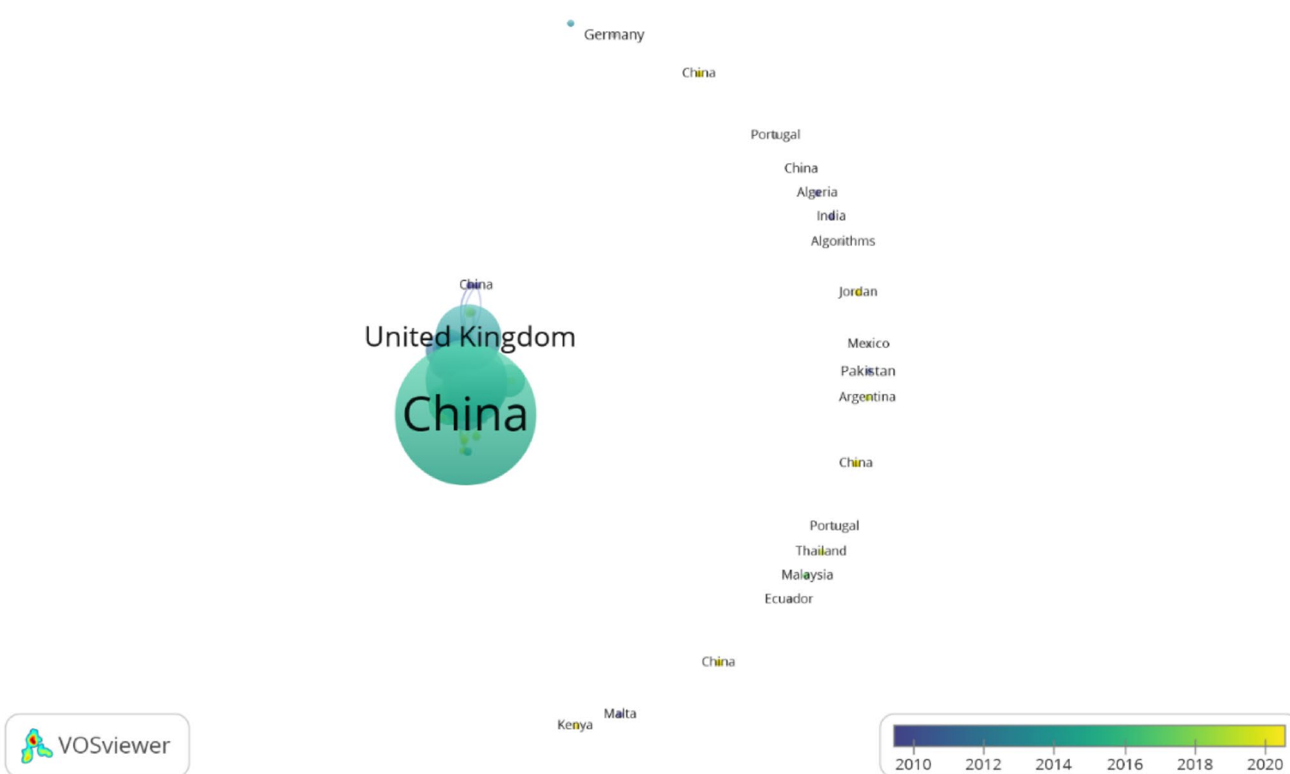


**Fig. 12** Country network visualization

Figure 10 provides a comparison of the development trends of the top four productive WOS categories, including "Computer Science Artificial Intelligence", "Engineering Electrical Electronic", "Computer Science Theory Methods", and "Computer Science Interdisciplinary Applications". Between 2001 and 2021, Computer Science Artificial Intelligence was the most predominant category and has possessed the highest number of publications since 2004, excluding the period between 2007 and 2008. The three other categories possess fluctuations between 2001 and 2021, and as of writing this paper, "Computer Science Theory Methods" and "Engineering Electrical Electronic" have the same TP of 171.

### 6.4 Publication Statistics by Countries

From Fig. 11, China, India, and the USA are the top three active countries in the field according to Scopus (respectively), while China, the USA, and India are the top 3 active territories in the field based on WOS, respectively. It is pertinent to mention that the USA is ranked second based on WOS, but India is ranked second, according to Scopus. Also, it can be seen that there is a significant difference between the first rank (China) and second rank (India) based on the number of publications indexed by Scopus. Moreover, Fig. 12 presents the collaboration among countries, where the links across the circles depict the collaborations, and the circles' size represents the countries' activities in the field. The green and yellow colors present the keywords that have been used recently, while the dark blue indicates those used earlier (around 2008).

Figure 13 displays the growth rate of the top 5 active countries in comparison to the world. While China and the USA have smooth trends between 2000 and 2021, India, the UK, and Australia show some fluctuations. Between 2002 and 2003, India presented the highest growth rate, then the trend continued smoothly until 2014, when it increased until 2015. The trend for the UK shows two growths between 2002–2003 and 2007–2008. While the number of articles published by Australia is much less than the four other countries, there was a significant rise between 2015 and 2016.

### 6.5 Statistics Based on the Subject Area

Figure 14 presents the distribution of articles based on the subject area. Computer science, Engineering, and Mathematics possess the most contributions, with 936, 619, and 580 published articles, respectively. Comparatively, Pharmacology, Medicine, and Economics own the least contributions, with 1, 4, and 6 published documents in the field, respectively.

### 6.6 Statistics Based on Authors

Figures 15 shows the top authors with the most publication according to Scopus (Supplementary C, Figure 2 presents statistics based on WOS). Kalyanmoy Deb from "Michigan State University (USA)", Ray T. from "University of New South Wales (Australia)", and Carlos A. Coello Coello from

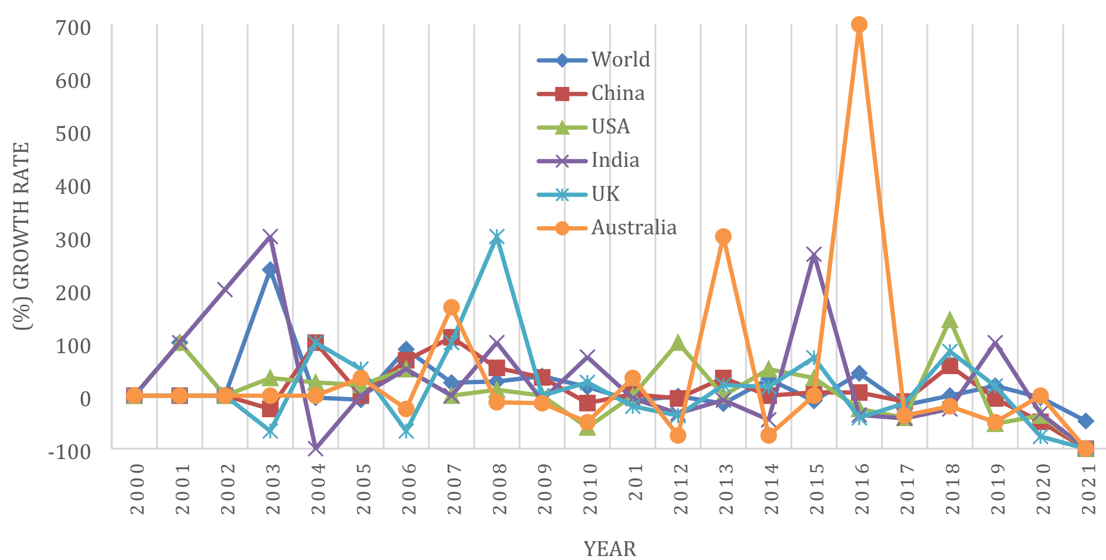


**Fig. 13** Growth rate of published documents for the top 5 countries

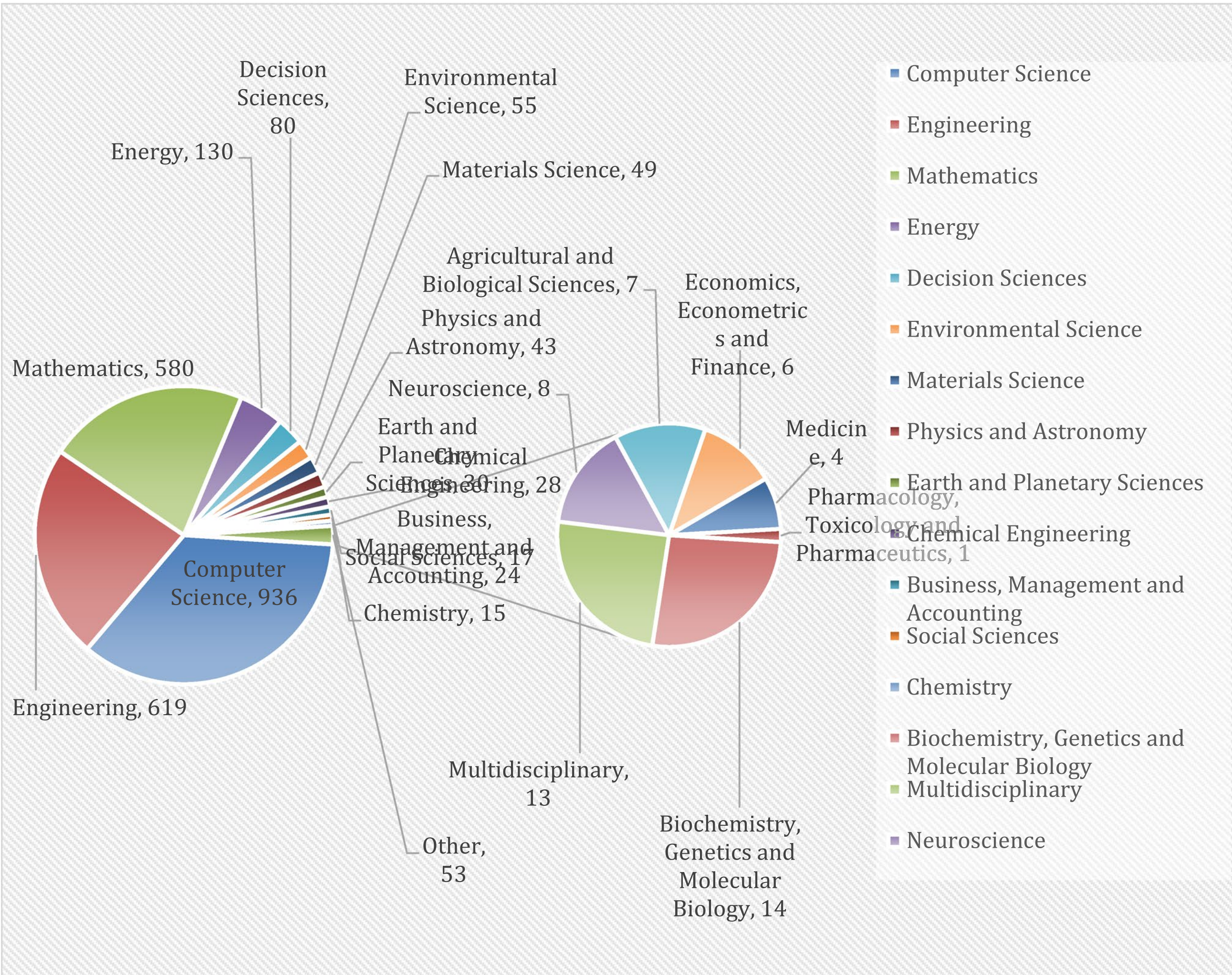


**Fig. 14** Distribution based on the subject area (Scopus)

"Cinvestav-IPN (Mexico)" with 38, 32, and 28 publications are the top 3 authors in the field indexed by Scopus. WANG Y from "City University Hong Kong (Hong Kong)", Carlos A. Coello Coello from "Cinvestav-IPN (Mexico)", and Ray T. from "University of New South Wales (Australia)" are the top 3 authors in the area with 21, 20, and 17 documents (indexed by WOS), respectively. According to WOS, 1717 authors have worked on constraint multi-objective population-based optimization.

In total, 0.5241% of authors own more than 10 documents; 1.6307% possess between 5 and 10 documents; 4.5428% have between 3 and 5 papers; 11.7647% own 2 papers; and 81.5377% possess 1 document (Fig. 16). Figure 17 presents the collaboration among the authors, where links across the circles depict the collaborations, and the circles' size shows the authors activities in the field. In addition, the yellow color represents recent activity, and the dark blue color depicts the contributions prior to 2014.

### 6.7 Statistics on Keywords

Keywords indicate the basic parts of a certain field of research and could offer insight into the organization and knowledge provided in the articles. Figure 18 provides an overlay visualization of the co-occurrence analyses via a network map based on the Scopus database. Each node in the network represents a keyword, and the link between nodes indicates the co-occurrence of the keywords. The top keywords in Scopus include multi-objective optimization, Pareto optimal solution, evolutionary algorithm, artificial intelligence, machine design, stochastic systems, distributed power generation, and reliability. The color of each circle represents the identified cluster, and each circle's size illustrates the keywords' importance. Table 7 presents the top keywords of 1-word, 2-word, and 3-word lengths extracted from Scopus. Specifically, optimization, algorithm, and scheduling are the top 1-word length keywords indexed by

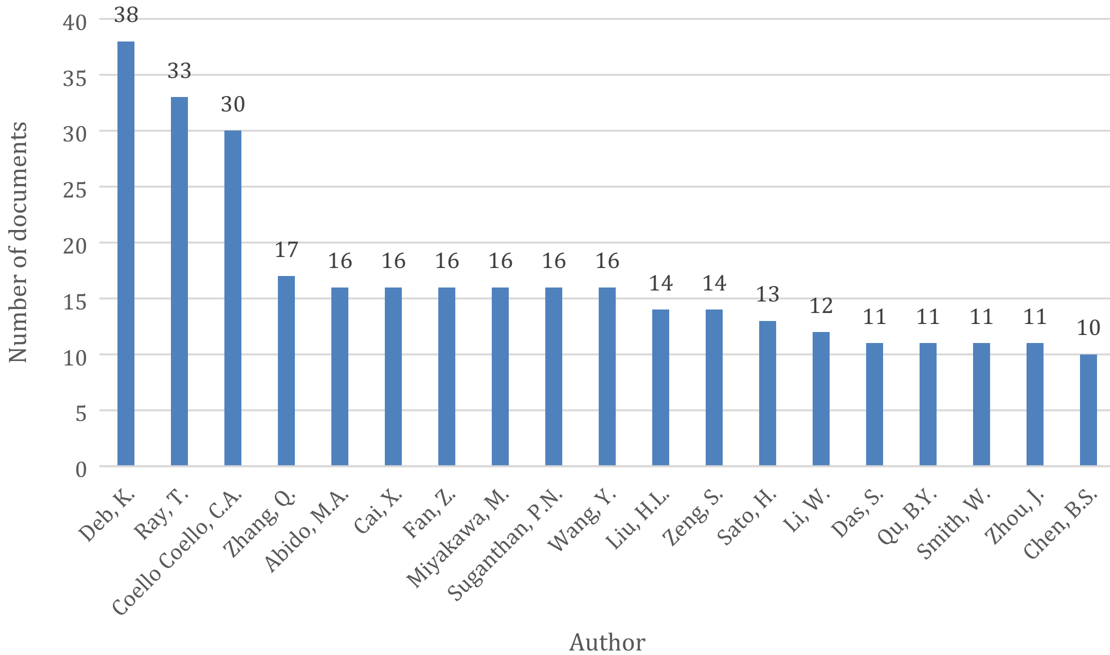


**Fig. 15** The most active authors in the field (Scopus)

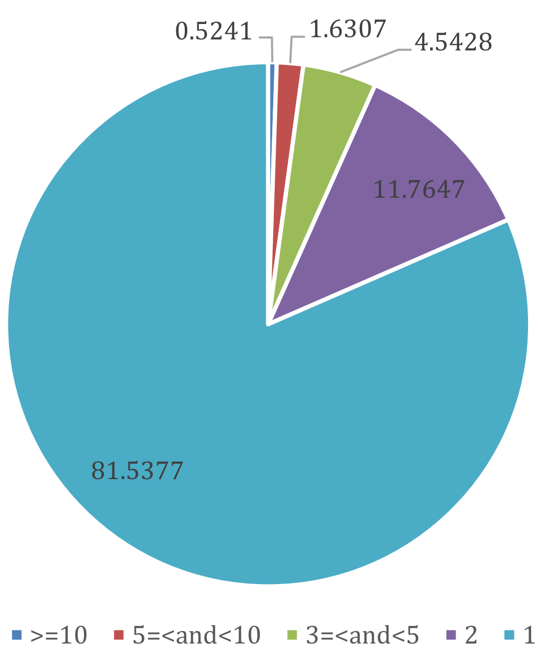


**Fig. 16** Contribution of authors based on the number of documents

Scopus; genetic algorithm, constraint handling, and constrained optimization are the top 2-word length keywords; and constraint-handling techniques, Particle Swarm Optimization (PSO), and multi-objective optimization are the top 3-word length keywords indexed by Scopus.

### 6.8 Publication Statistics by Number of Pages (Pages Count)

As of writing this paper, May of 2021, approximately 22395.8 pages of documents on constraint handling multi-objective population-based algorithms were published, with an average of 13.0435 pages per paper. About 22.53931% of the articles possess between 10 and 15 pages; 12.17239% of the manuscripts are between 15 and 20 pages; 39.07979 % of the papers are between 5 and 10 pages; and 67.09377% of the manuscripts are between 5 and 20 pages. Figure 19 presents the distribution of the manuscripts based on page count.

## 7 Summary and Future Research (RQ7)s

The paper presents an analysis and overview of CHTs applied to multi-objective population-based algorithms. The first part of the paper defines the main idea of CHTs, and the second part discusses a detailed scientometric analysis of the field. Some important technical points are extracted as follows:

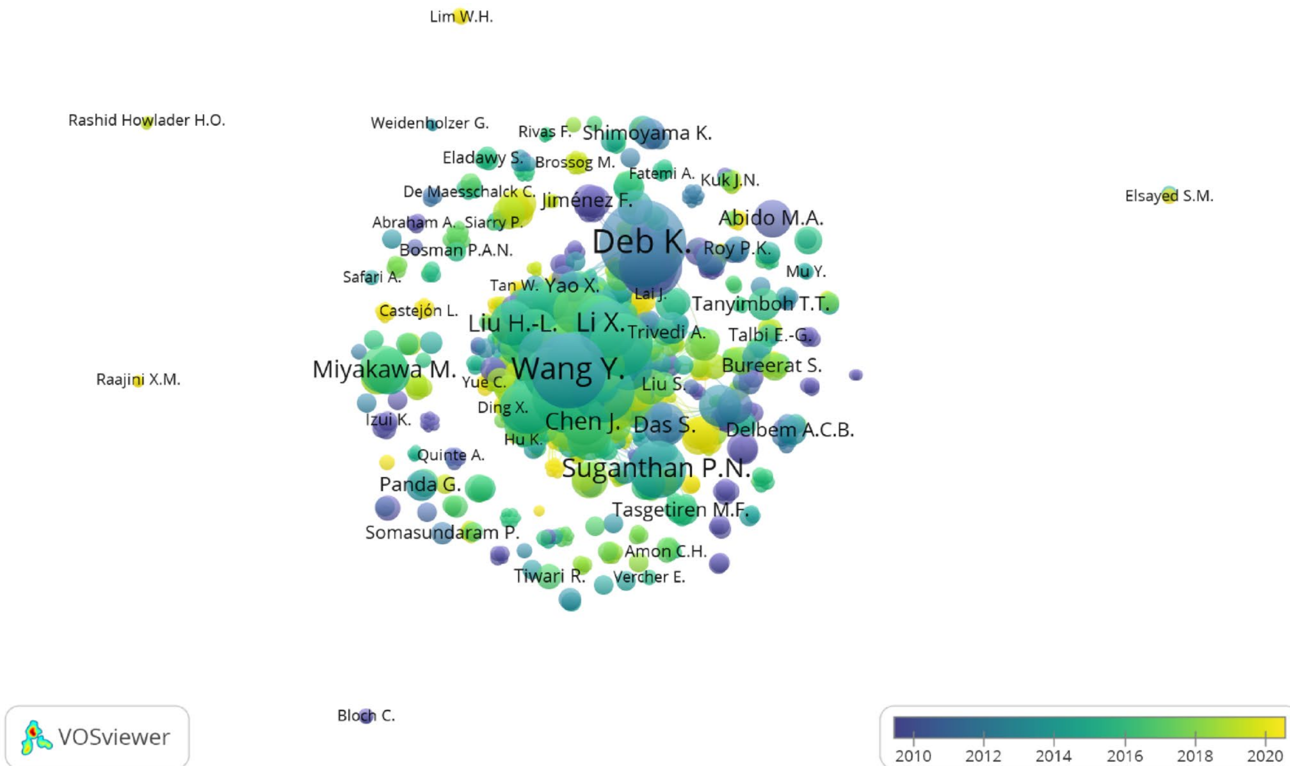


**Fig. 17** Collaboration among the authors (overlay visualizatio

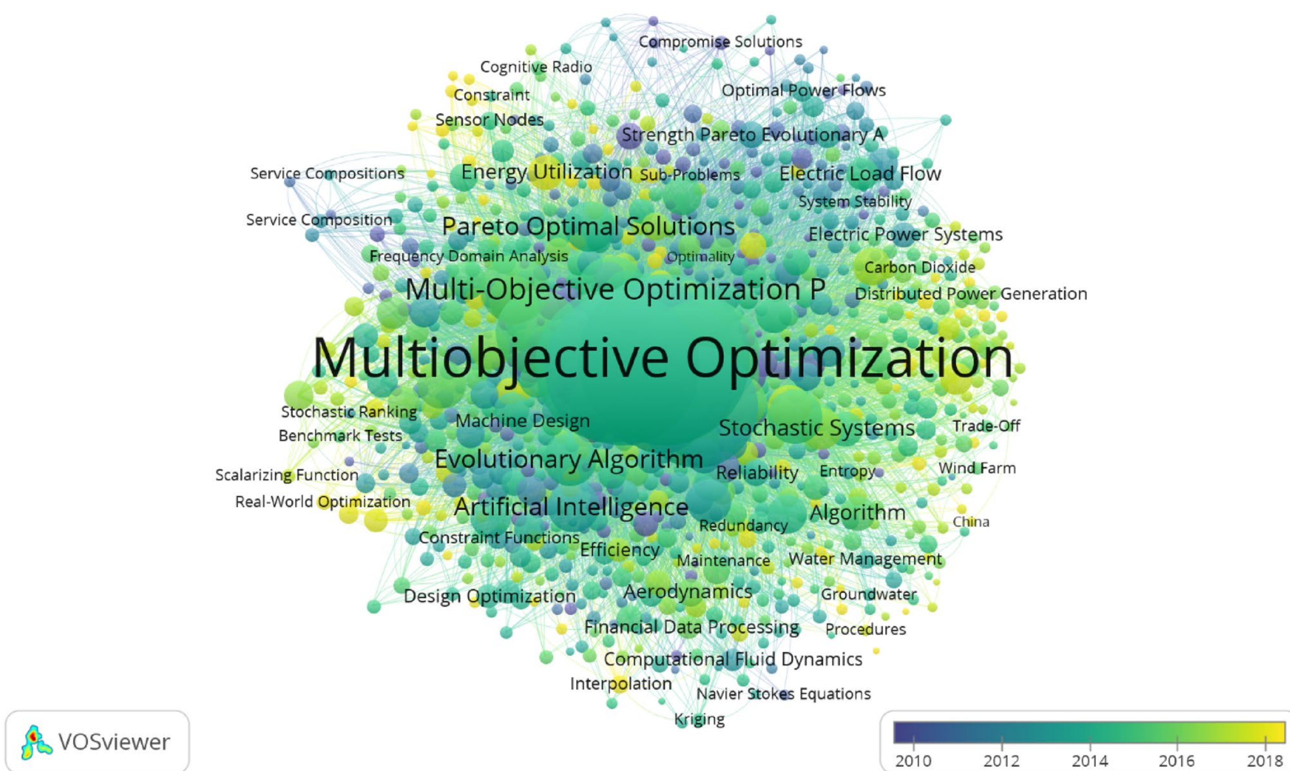


**Fig. 18** Network visualization of keywords

**Table 7** Top 1-,2-, and 3- word keywords used in the field

| # | 1-Word | Frequency | 2-Word | Frequency | 3-Word | Frequency |
|---|---|---|---|---|---|---|
| 1 | Optimization | 680 | Genetic algorithms | 367 | Constraint-handling techniques | 74 |
| 2 | Algorithms | 360 | Constraint handling | 184 | Particle swarm optimization (PSO) | 565 |
| 3 | Scheduling | 141 | Constrained optimization | 1071 | Multi-objective optimization | 467 |
| 4 | NSGA-II | 97 | Multi-objective optimization | 1339 | Particle swarm optimization | 205 |
| 5 | Design | 96 | Evolutionary algorithms | 1081 | Constrained multi-objective optimization | 68 |
| 6 | Algorithm | 59 | Differential evolution | 208 | Electric load dispatching | 66 |
| 7 | Reliability | 33 | Problem solving | 239 | Multi-objective optimization problem | 222 |
| 8 | Investments | 33 | Multi-objective | 307 | Differential evolution algorithms | 71 |
| 10 | Benchmarking | 113 | Decision making | 135 | Pareto optimal solutions | 121 |
| 12 | Costs | 57 | Pareto principle | 281 | Constrained multi-objective optimizations | 213 |

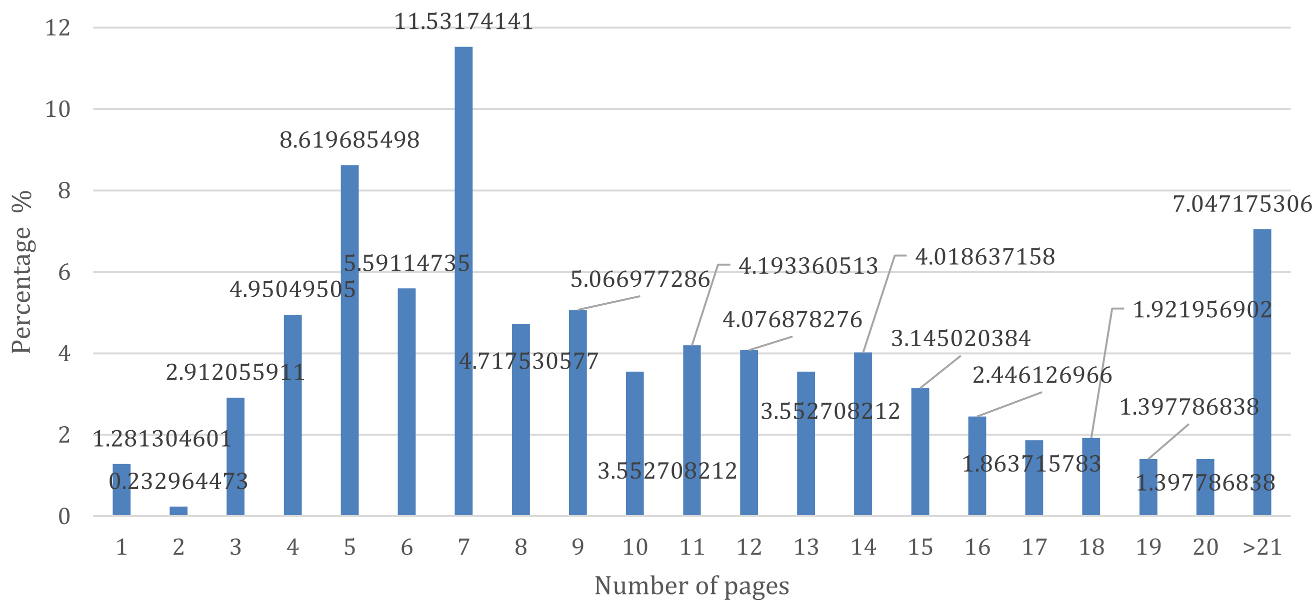


**Fig. 19** Distribution of documents based on page count

- In the death penalty method, no information is used from infeasible points.
- The static penalty method is problem-dependent and may need several penalty parameters.
- Dynamic penalty method may converge to either an infeasible or feasible solution that is far from the global optimum.
- The main disadvantage of the annealing penalty method is its sensitivity to its factors' values.
- Setting parameters in the adaptive penalty method is difficult, and the method needs the definitions of additional parameters.
- The additional parameters may affect the fitness function evaluations in the self-adaptive penalty method.
- The main difficulty in SGA is selecting the penalty factors for each sub-population.
- If the population is completely infeasible, choose solutions with a smaller overall constraint violation.
- Retaining a proportion of infeasible solutions in the population may enhance the convergence and diversity of the algorithm.
- Two types of CHTs, namely repair methods and special genetic operators, focus only on the feasible space.
- Feasible solutions could be used to repair infeasible solutions (repairing population).
- According to the constraint dominance principle, the feasible solution is always preferred over the infeasible solution, which may cause loss of important information from infeasible individuals.

**Table 8** Top 5 keywords in 2019 and 2021

| # | Keywords (Scopus) | Frequency |
|---|---|---|
| 1 | Pareto principle | 65 |
| 2 | Genetic algorithms | 72 |
| 3 | Differential evolution | 45 |
| 4 | Particle swarm optimization (PSO) | 132 |
| 5 | Economic and social effects | 34 |
| 6 | Benchmarking | 32 |
| 7 | Decision making | 36 |
| 8 | Energy utilization | 28 |
| 9 | Scheduling | 39 |
| 10 | Pareto optimal solutions | 24 |

**Table 9** Top 5 research fields in 2019 and 2021

| # | Research fields (Scopus) | (%) Contribution |
|---|---|---|
| 1 | Engineering | 24.3 |
| 2 | Computer science | 31.8 |
| 3 | Mathematics | 17.2 |
| 4 | Energy | 5.9 |
| 5 | Decision sciences | 4.1 |
| 6 | Materials science | 4.1 |
| 7 | Business, management and accounting | 1 |
| 8 | Environmental science | 2.1 |
| 9 | Physics and astronomy | 2.8 |
| 10 | Earth and planetary sciences | 1.4 |

- Retaining a huge number of infeasible solutions may cause low convergence speed.
- Although special operators are known to be highly comparative CHT, their applicability is limited, which makes this technique difficult to run.
- Decoder is an interesting CHTs, but it involves a high computational cost and, thus, is now rarely used.
- Although the ensemble CHT has a competitive performance, the method is parameter-dependent.
- Although the stochastic ranking method has been employed in several nature-inspired algorithms, it is not often used for the multi-objective version of the algorithms.
- Epsilon constraint method has been known as a powerful CHT, however, in some cases, premature convergence has been reported, while other works report that the method relies on gradient-based mutation.
- Using multi-objective concept as a CHT may require gradient calculation.
- Recently, feasibility rules have been recognized as one of the most powerful CHTs, which are simple and flexible; however, one of the major disadvantages of this method is premature convergence since this technique favors feasible solutions.

As a future direction, the authors have identified the top 5 most-used keywords and research fields in the last three years (2019–2021) based on Scopus. Tables 8 and 9 show the mentioned keywords and research fields for this time period. It is obvious that multi-objective optimization, constraint optimization, and evolutionary algorithms are the most famous keywords in the last three years. It should be noted that CHTs for multi-objective optimization has not received much attention compared with single-objective optimization. It is suggested that researchers focus on such methods in future works. Also, the BU technique, which is able to handle constraints directly, possesses the potential to couple with a multi-objective evolutionary algorithm (MOEA) as well. Furthermore, it is suggested to focus on constraint handling techniques for many-objective optimization problems (with more than three objectives) as it is not received much attention. In addition, according to Tables 9 and, GA, DE, and PSO remain the top 3 algorithms, which are expected to be further explored in the future. Moreover, Engineering, Computer Science, and Mathematics have been the top 3 research fields in the last two years, and it is projected that research work will advance in these areas in the future. It is also recommended to review the applications of constrained multi-objective evolutionary algorithms in different sectors; including engineering design problems [212], scheduling optimization problems [176] [214–216], and resource optimization problems [217].

## 8 Discussion and Conclusion

Constraint population-based optimization involves using a population-based algorithm combined with a CHT to solve a constraint optimization problem. The first part of the paper defines the main idea of CHTs, and the second part discusses detailed scientometric analysis of the field. It is noteworthy that most of the mentioned studies in the literature focused on CHTs for single-objective optimization with little attention to multi-objective optimization. This paper presents an analysis and evaluation of the CHTs, focusing on multi-objective optimization population-based algorithms, which support evolutionary and swarm intelligence algorithms. To the best of our knowledge, this study is the first analysis of relevant journals evaluated over the most relevant journals, keywords, authors, and articles in this field. All related papers, including research articles, reviews, book/book chapters, conference papers, etc., were extracted and analyzed. Publication statistics by year, journal, country, affiliation, author, number of pages, number of authors, and keywords are discussed in this paper as follows:

- According to WOS, 45,824 citations have been received by the related papers, which is an average of 1992.35 citations per year and an average of 62.35 citations per item in WOS.
- Based on WOS, articles were the most popular document type, with a total of 522 articles (71.02%), and 2.60 authors per publication.
- Articles as the document type had the highest CPP2021 of 84.10, followed by proceedings papers with TP of 220 (29.93% of contributions and APP = 2.13).
- Conference papers have the most contributions before 2010 followed by articles. However, since 2010, articles have had the most contributions in the field.
- A total of 271 articles (36.87% of the total), with 2.31 authors per publication (on average), were published in the Computer Science Artificial Intelligence category, according to WOS.
- In total, 271 articles (36.87% of 735 articles) were published in the first category (Computer Science Artificial Intelligence), and a total of 83.39% were published in the first three categories: Engineering Electrical Electronic (23.26%) and Computer Science Theory Methods (23.26%).
- The highest CPP2021 of articles published in Computer Science Theory Methods is 190.011, which includes the paper "A fast and elitist multi-objective genetic algorithm: NSGA-II" by [20], and the highest APP for articles published in 'Energy fuels' is 2.97.
- "Computer Science Artificial Intelligence," "Engineering Electrical Electronic," "Computer Science Theory Methods," and "Computer Science Interdisciplinary Applications" were the top 4 productive WOS categories in the field.
- China, USA, and India were the top three active countries in the field, according to WOS.
- Computer science, Engineering, and Mathematics have the most contributions, with 936, 619, and 580 published articles, respectively. Pharmacology, Medicine, and Economics own the least contributions, with 1, 4, and 6 published documents in the field, according to Scopus.
- Kalyanmoy Deb from "Michigan State University (USA)", Ray T. from "University of New South Wales (Australia)", and Carlos A. Coello Coello from "Cinvestav-IPN (Mexico)" are the top 3 authors in the field with 38, 32, and 28 publications (indexed by Scopus), respectively. WANG Y from "City University Hong Kong (Hong Kong)", Carlos A. Coello Coello from "Cinvestav-IPN (Mexico)", and Ray T. from "University of New South Wales (Australia)" are the top 3 authors in the area with 21, 20, and 17 documents (indexed by WOS), respectively.
- Almost 0.5241% of authors own more than 10 documents; 1.6307% possess between 5 and 10 documents; 4.5428% have between 3 and 5 papers; 11.7647% of authors own 2 papers; and 81.5377% of authors possess 1 document.
- Approximately 22.53931% of the articles possess between 10 and 15 pages; 12.17239% of the manuscripts are between 15 and 20 pages; 39.07979% of the papers are between 5 and 10 pages; and 67.09377% of the manuscripts are between 5 and 20 pages.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s11831-022-09859-9.

**Author Contributions** Conceptualization, IR and AH; methodology, IR software, IR; validation, AHG, FC and EM-M; formal analysis, IR; data curation, IR; writing—original draft preparation, IR—review and editing, AHG, FC and EM-M; supervision, AHG, FC.

**Funding** Open access funding provided by Óbuda University. This research received no external funding.

## Declarations

**Conflicts of interest** The authors declare no conflict of interest.



## References

1. Behmanesh R, Rahimi I, Gandomi AH (2021) Evolutionary many-objective algorithms for combinatorial optimization problems: a comparative study. Arch Comput Methods Eng 28(2):673–688
2. Deb K (2014) Multi-objective optimization Search methodologies. Search Methodologies. Springer, New York
3. Marler RT, Arora JS (2004) Survey of multi-objective optimization methods for engineering. Struct Multidiscip Optim 26(6):369–395
4. Coello CAC, Lamont GB, Van Veldhuizen DA et al (2007) Evolutionary algorithms for solving multi-objective problems. Springer, New York
5. Deb K (2011) Multi-objective optimisation using evolutionary algorithms: an introduction. In: Wang L, Ng AHC, Deb K (eds)

Multi-objective evolutionary optimisation for product design and manufacturing. Springer, London

6. Corne DW, Knowles JD, Oates MJ (2000) The Pareto envelope-based selection algorithm for multiobjective optimization. In: Schoenauer M, Deb K, Rudolph G, Yao X, Lutton E, Merelo JJ, Schwefel H-P (eds) International Conference on Parallel Problem Solving from Nature. Springer, Berlin
7. Gharehchopogh FS, Shayanfar H, Gholizadeh H (2020) A comprehensive survey on symbiotic organisms search algorithms. Artif Intell Rev 53(3):2265–2312
8. Gharehchopogh FS, Gholizadeh H (2019) A comprehensive survey: whale optimization algorithm and its applications. Swarm Evol Comput 48:1–24
9. Ghafori S, Gharehchopogh FS (2021) Advances in spotted hyena optimizer: a comprehensive survey. Arch Comput Methods Eng. https://doi.org/10.1007/s11831-021-09624-4
10. Gharehchopogh FS (2022) Advances in tree seed algorithm: a comprehensive survey. Arch Comput Methods Eng. https://doi.org/10.1007/s11831-022-09804-w
11. Horn, J., Nafpliotis, N., & Goldberg, D. E. (1994). A niched Pareto genetic algorithm for multiobjective optimization. Proceedings of the First IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence. 82–87.
12. Binh, T. T., & Korn, U. (1997a). MOBES: A multiobjective evolution strategy for constrained optimization problems. The Third International Conference on Genetic Algorithms (Mendel 97), 25, 27.
13. Fonseca CM, Fleming PJ (1998) Multiobjective optimization and multiple constraint handling with evolutionary algorithms I a unified formulation. IEEE Trans Syst, Man, Cybern-Part A 28(1):26–37
14. Jiménez F, Verdegay JL (1999) Evolutionary techniques for constrained multiobjective optimization problems. In: Workshop on multi-criterion optimization using evolutionary methods GECCO-1999
15. Goldberg DE, Deb K (1991) A comparative analysis of selection schemes used in genetic algorithms In Foundations of genetic algorithms. Elsevier, London
16. Coello Coello CA, Christiansen AD (1999) MOSES: a multiobjective optimization tool for engineering design. Eng Optim 31(3):337–368
17. Deb K (2000) An efficient constraint handling method for genetic algorithms. Comput Methods Appl Mech Eng 186(2–4):311–338
18. Ray T, Tai K, Seow C (2001) An evolutionary algorithm for multiobjective optimization. Eng Optim 33(3):399–424
19. Jimenez, F., Gómez-Skarmeta, A. F., Sánchez, G., & Deb, K. (2002a). An evolutionary algorithm for constrained multiobjective optimization. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), 2, 1133–1138.
20. Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197
21. Coello CAC (2002) Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Comput Methods Appl Mech Eng 191(11–12):1245–1287
22. Angantyr A, Andersson J, Aidanpaa JO (2003) Constrained optimization based on a multiobjective evolutionary algorithm. The 2003 Congress on Evolutionary Computation, 2003. CEC'03., 3, 1560–1567
23. Chafekar D, Xuan J, Rasheed K (2003) Constrained multiobjective optimization using steady state genetic algorithms. In: Cantú-Paz E, Foster JA, Deb K, Davis LD, Roy R, O'Reilly U-M, Beyer H-G, Standish R, Kendall G, Wilson S, Harman M, Wegener J, Dasgupta D, Potter MA, Schultz AC, Dowsland KA, Jonoska N, Miller J (eds) Genetic and Evolutionary Computation Conference. Springer, Berlin
24. Zou X-F, Liu M-Z, Wu Z-J, Kang L-S (2004) A robust evolutionary algorithm for constrained multi-objective optimsssszation problems. J Comput Res Dev 41(6):985–990
25. Young N (2005) Blended ranking to cross infeasible regions in constrainedmultiobjective problems. International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06), 2, 191–196.
26. Venkatraman S, Yen GG (2005) A generic framework for constrained optimization using genetic algorithms. IEEE Trans Evol Comput 9(4):424–435
27. Cai Z, Wang Y (2006) A multiobjective optimization-based evolutionary algorithm for constrained optimization. IEEE Trans Evol Comput 10(6):658–675
28. Min H-Q, Zhou Y, Lu Y, Jiang J (2006) An evolutionary algorithm for constrained multi-objective optimization problems. IEEE Asia-Pacific Conf Serv Comput. https://doi.org/10.1109/APSCC.2006.30
29. Harada, K., Sakuma, J., Ono, I., & Kobayashi, S. (2007a) Constraint-handling method for multi-objective function optimization: Pareto descent repair operator. International Conference on Evolutionary Multi-Criterion Optimization. 156–170.
30. Wang Y, Cai Z, Zhou Y, Zeng W (2008) An adaptive tradeoff model for constrained evolutionary optimization. IEEE Trans Evol Comput 12(1):80–92
31. Kaveh A, Talatahari S (2009) Particle swarm optimizer, ant colony strategy and harmony search scheme hybridized for optimization of truss structures. Comput Struct 87(5–6):267–283
32. Ray T, Singh HK, Isaacs A, Smith W (2009) Infeasibility driven evolutionary algorithm for constrained optimization. In: Mezura-Montes E (ed) Constraint-handling in evolutionary optimization. Springer, Berlin
33. Tulshyan, R., Arora, R., Deb, K., & Dutta, J. (2010). Investigating EA solutions for approximate KKT conditions in smooth problems. Proceedings of the 12th Annual Conference on Genetic and Evolutionary Computation, 689–696.
34. Mezura-Montes E, Coello CAC (2011) Constraint-handling in nature-inspired numerical optimization: past, present and future. Swarm Evol Comput 1(4):173–194
35. Michalewicz Z, Schoenauer M (1996) Evolutionary algorithms for constrained parameter optimization problems. Evol Comput 4(1):1–32
36. Takahama, T., Sakai, S., & Iwane, N. (2005). Constrained optimization by the $\varepsilon$ constrained hybrid algorithm of particle swarm optimization and genetic algorithm. Australasian Joint Conference on Artificial Intelligence, 389–400.
37. Deb, K., & Datta, R. (2010). A fast and accurate solution of constrained optimization problems using a hybrid bi-objective and penalty function approach. IEEE Congress on Evolutionary Computation, 1–8.
38. Xiao J, Xu J, Shao Z, Jiang C, Pan L (2007) A genetic algorithm for solving multi-constrained function optimization problems based on KS function. IEEE Congr Evolut Comput. https://doi.org/10.1109/CEC.2007.4425060
39. Mallipeddi R, Suganthan PN (2010) Ensemble of constraint handling techniques. IEEE Trans Evol Comput 14(4):561–579
40. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82
41. Gandomi AH, Yang X-S (2012) Evolutionary boundary constraint handling scheme. Neural Comput Appl 21(6):1449–1462

42. Eskandar H, Sadollah A, Bahreininejad A, Hamdi M (2012) Water cycle algorithm–a novel metaheuristic optimization method for solving constrained engineering optimization problems. Comput Struct 110:151–166
43. Sadollah A, Bahreininejad A, Eskandar H, Hamdi M (2013) Mine blast algorithm: a new population based algorithm for solving constrained engineering optimization problems. Appl Soft Comput 13(5):2592–2612
44. Hamza NM, Sarker RA, Essam DL, Deb K, Elsayed SM (2014) A constraint consensus memetic algorithm for solving constrained optimization problems. Eng Optim 46(11):1447–1464
45. Jiao L, Luo J, Shang R, Liu F (2014) A modified objective function method with feasible-guiding strategy to solve constrained multi-objective optimization problems. Appl Soft Comput 14:363–380
46. Padhye N, Mittal P, Deb K (2015) Feasibility preserving constraint-handling strategies for real parameter evolutionary optimization. Comput Optim Appl 62(3):851–890
47. Garg H (2016) A hybrid PSO-GA algorithm for constrained optimization problems. Appl Math Comput 274:292–305
48. Lu Z, Deb K, Singh H (2018) Balancing survival of feasible and infeasible solutions in constraint evolutionary optimization algorithms. IEEE Congr Evolut Comput (CEC) 2018:1–8
49. Gandomi AH, Deb K (2020) Implicit constraints handling for efficient search of feasible solutions. Comput Methods Appl Mech Eng 363:112917. https://doi.org/10.1016/j.cma.2020.112917
50. Van Eck NJ, Waltman L (2010) Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 84(2):523–538
51. Van Eck NJ, Waltman L (2013) VOSviewer manual. Univeristeit Leiden 1(1):1–53
52. Koziel S, Michalewicz Z (1998) A decoder-based evolutionary algorithm for constrained parameter optimization problems. In: Eiben AE, Bäck T, Schoenauer M, Schwefel H-P (eds) International Conference on Parallel Problem Solving from Nature. Spring, Berlin
53. Kim DG, Husbands P (1997) Riemann mapping constraint handling method for genetic algorithms. Technical Report CSRP 469, COGS, University of Sussex, UK
54. Kim DG, Husbands P (1998) Landscape changes and the performance of Mapping Based Constraint handling methods. In: Eiben AE, Bäck T, Schoenauer M, Schwefel H-P (eds) International Conference on Parallel Problem Solving from Nature. Spring, Berlin
55. Koziel S, Michalewicz Z (1999) Evolutionary algorithms, homomorphous mappings, and constrained parameter optimization. Evol Comput 7(1):19–44
56. Michalewicz Z (2013) Genetic algorithms+ data structures= evolution programs. Springer Science & Business Media. Berlin: Springer
57. Schoenauer M, Michalewicz Z (1996) Evolutionary computation at the edge of feasibility. In: Voigt H-M, Ebeling W, Rechenberg I, Schwefel H-P (eds) International Conference on Parallel Problem Solving from Nature. Springer, Berlin
58. Schoenauer, M., & Michalewicz, Z. (1997). Boundary Operators for Constrained Parameter Optimization Problems. ICGA, 322–329.
59. Coello, C. A. C. (2017). Constraint-handling techniques used with evolutionary algorithms. Proceedings of the Genetic and Evolutionary Computation Conference Companion, 675–701.
60. Kramer O (2010) A review of constraint-handling techniques for evolution strategies. Appl Comput Intell Soft Comput. https://doi.org/10.1155/2010/185063
61. Mezura-Montes E, Coello CAC (2005) A simple multimembered evolution strategy to solve constrained optimization problems. IEEE Trans Evol Comput 9(1):1–17
62. Coello, C. A. C., Christiansen, A. D., & Aguirre, A. H. (1995). Multiobjective design optimization of counterweight balancing of a robot arm using genetic algorithms. Proceedings of 7th IEEE International Conference on Tools with Artificial Intelligence, 20–23.
63. Homaifar A, Qi CX, Lai SH (1994) Constrained optimization via genetic algorithms. SIMULATION 62(4):242–253
64. Jordehi AR (2015) A review on constraint handling strategies in particle swarm optimisation. Neural Comput Appl 26(6):1265–1275
65. Joines, J. A., & Houck, C. R. (1994). On the use of non-stationary penalty functions to solve nonlinear constrained optimization problems with GA's. Proceedings of the First IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence, 579–584.
66. Ben Hadj-Alouane A, Bean JC (1997) A genetic algorithm for the multiple-choice integer program. Oper Res 45(1):92–101
67. Woldesenbet YG, Yen GG, Tessema BG (2009) Constraint handling in multiobjective evolutionary optimization. IEEE Trans Evol Comput 13(3):514–525
68. Qu BY, Suganthan PN (2011) Constrained multi-objective optimization algorithm with an ensemble of constraint handling methods. Eng Optim 43(4):403–416
69. Carlson, S. E., & Shonkwiler, R. (1998). Annealing a genetic algorithm over constraints. SMC'98 Conference Proceedings. 1998 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 98CH36218), 4, 3931–3936.
70. Powell, D., & Skolnick, M. M. (1993a). Using genetic algorithms in engineering design optimization with non-linear constraints. Proceedings of the 5th International Conference on Genetic Algorithms, 424–431.
71. Hinterding, R., & Michalewicz, Z. (1998). Your brains and my beauty: parent matching for constrained optimisation. 1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No. 98TH8360), 810–815.
72. Jan MA, Khanum RA (2013) A study of two penalty-parameterless constraint handling techniques in the framework of MOEA/D. Appl Soft Comput 13(1):128–148
73. Takahama T, Sakai S (2005) Constrained optimization by $\varepsilon$ constrained particle swarm optimizer with $\varepsilon$-level control In Soft computing as transdisciplinary science and technology. Springer, Berlin
74. Powell, D., & Skolnick, M. M. (1993b). Using genetic algorithms in engineering design optimization with non-linear constraints. Proceedings of the 5th International Conference on Genetic Algorithms, 424–431.
75. Asafuddoula M, Ray T, Sarker R, Alam K (2012) An adaptive constraint handling approach embedded MOEA/D. IEEE Congr Evolut Comput 2012:1–8
76. Mezura-Montes E, Coello CAC, Tun-Morales EI (2004) Simple feasibility rules and differential evolution for constrained optimization. Mexican Int Conf Artif Intell. https://doi.org/10.1007/978-3-540-24694-7_73
77. Mezura-Montes, E., Velázquez-Reyes, J., & Coello Coello, C. A. (2005). Promising infeasibility and multiple offspring incorporated to differential evolution for constrained optimization. Proceedings of the 7th Annual Conference on Genetic and Evolutionary Computation, 225–232.
78. Jaimes AL, Coello CAC, Aguirre H, Tanaka K (2011) Adaptive objective space partitioning using conflict information for many-objective optimization. In: Takahashi RHC, Deb K, Wanner EF,

Greco S (eds) International Conference on Evolutionary Multi-Criterion Optimization. Springer, Berlin

79. Kukkonen S, Lampinen J (2006) Constrained real-parameter optimization with generalized differential evolution. IEEE Int Conf on Evolut Comput 2006:207–214
80. Lampinen, J. (2002a). A constraint handling approach for the differential evolution algorithm. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), 2, 1468–1473.
81. Mezura-Montes E, Palomeque-Ortiz AG (2009) Parameter control in differential evolution for constrained optimization. IEEE Congr Evolut Comput 2009:1375–1382
82. Mezura-Montes E, Palomeque-Ortiz AG (2009) Self-adaptive and deterministic parameter control in differential evolution for constrained optimization. In: Mezura-Montes E (ed) Constraint-Handling in Evolutionary Optimization. Springer, Berlin
83. Mezura-Montes E, Velázquez-Reyes J, Coello CAC (2006) Modified differential evolution for constrained optimization. IEEE Int Conf Evolut Comput. https://doi.org/10.1109/CEC.2006.1688286
84. Zielinski K, Vudathu SP, Laur R (2008) Influence of different deviations allowed for equality constraints on particle swarm optimization and differential evolution. In: Zielinski K, Vudathu SP, Laur R (eds) Nature Inspired Cooperative Strategies for Optimization (NICSO 2007). Springer, Berlin
85. Lampinen, J. (2002b). A constraint handling approach for the differential evolution algorithm. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), 2, 1468–1473.
86. Jiang H (2017) Efficiency measurement and improvement of housing provident fund in China. Int J Wireless Mobile Comput 12(3):259–269
87. Si C, Hu J, Lan T, Wang L, Wu Q (2017) A combined constraint handling framework: an empirical study. Memetic Comput 9(1):69–88
88. Mezura-Montes E, Flores-Mendoza JI (2009) Improved particle swarm optimization in constrained numerical search spaces In Nature-inspired algorithms for optimisation. Springer, Berlin
89. Karaboga D, Basturk B (2007) Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In: Melin P, Castillo O, Aguilar LT, Kacprzyk J, Pedrycz W (eds) International Fuzzy Systems Association World Congress. Springer, Berlin
90. Karaboga D, Akay B (2011) A modified artificial bee colony (ABC) algorithm for constrained optimization problems. Appl Soft Comput 11(3):3021–3031
91. Elsayed SM, Sarker RA, Essam DL (2010) A comparative study of different variants of genetic algorithms for constrained optimization. In: Deb K, Bhattacharya A, Chakraborti N, Chakroborty P, Das S, Dutta J, Gupta SK, Jain A, Aggarwal V, Branke J, Louis SJ, Tan KC (eds) Asia-Pacific Conference on Simulated Evolution and Learning. Springer, Berlin
92. Wang Y, Cai Z (2009) A hybrid multi-swarm particle swarm optimization to solve constrained optimization problems. Front Comput Sci China 3(1):38–52
93. Elsayed SM, Sarker RA, Essam DL (2011) GA with a new multi-parent crossover for constrained optimization. IEEE Congr Evolut Comput (CEC) 2011:857–864
94. Aragón VS, Esquivel SC, Coello CAC (2007) A novel model of artificial immune system for solving constrained optimization problems with dynamic tolerance factor. Mexican Int Conf Arti Intell. https://doi.org/10.1007/978-3-540-76631-5_3
95. Aragón VS, Esquivel SC, Coello CAC (2007) Artificial immune system for solving constrained optimization problems. Intel Artif Rev Iberoam de Intell Artif 11(35):55–66
96. Bernardino HS, Barbosa HJC, Lemonge ACC (2007) A hybrid genetic algorithm for constrained optimization problems in mechanical engineering. IEEE Congr Evolut Comput 2007:646–653
97. Coello, C. A. C., & Cortés, N. C. (2002). A parallel implementation of an artificial immune system to handle constraints in genetic algorithms: Preliminary results. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), 1, 819–824.
98. Cruz-Cortés N (2009) Handling constraints in global optimization using artificial immune systems: A survey. In: Mezura-Montes E (ed) Constraint-Handling in Evolutionary Optimization. Springer, Berlin, pp 237–262
99. Hajela P, Lee J (1996) Constrained genetic search via schema adaptation: an immune network solution. Struct Optim 12(1):11–15
100. Liu, B., Ma, H., Zhang, X., & Zhou, Y. (2007). A memetic co-evolutionary differential evolution algorithm for constrained optimization. 2007 IEEE Congress on Evolutionary Computation, 2996–3002.
101. Liu J, Zhong W, Jiao L (2007) An organizational evolutionary algorithm for numerical optimization. IEEE Trans, Syst, Man Cybern Part B (Cybern) 37(4):1052–1064
102. Ma H, Simon D (2011) Blended biogeography-based optimization for constrained optimization. Eng Appl Artif Intell 24(3):517–525
103. Mezura-Montes, E., & Hernández-Ocaña, B. (2009). Modified bacterial foraging optimization for engineering design. Proceedings of the Artificial Neural Networks in Enginnering Conference (ANNIE'2009), 19, 357–364.
104. Peng C, Liu H-L, Gu F (2017) An evolutionary algorithm with directed weights for constrained multi-objective optimization. Appl Soft Comput 60:613–622
105. Ning W, Guo B, Yan Y, Wu X, Wu J, Zhao D (2017) Constrained multi-objective optimization using constrained non-dominated sorting combined with an improved hybrid multi-objective evolutionary algorithm. Eng Optim 49(10):1645–1664
106. Yang Y, Liu J, Tan S (2020) A constrained multi-objective evolutionary algorithm based on decomposition and dynamic constraint-handling mechanism. Appl Soft Comput 89:106104
107. Li H, Zhang Q, Deng J (2016) Biased multiobjective optimization and decomposition algorithm. IEEE Transa Cybern 47(1):52–66
108. Li J-P, Wang Y, Yang S, Cai Z (2016) A comparative study of constraint-handling techniques in evolutionary constrained multiobjective optimization. IEEE Congr Evolut Comput (CEC) 2016:4175–4182
109. Fan Z, Li W, Cai X, Li H, Wei C, Zhang Q, Deb K, Goodman E (2019) Push and pull search for solving constrained multi-objective optimization problems. Swarm Evol Comput 44:665–679
110. Liu Z-Z, Wang Y (2019) Handling constrained multiobjective optimization problems with constraints in both the decision and objective spaces. IEEE Trans Evol Comput 23(5):870–884
111. Runarsson TP, Yao X (2000) Stochastic ranking for constrained evolutionary optimization. IEEE Trans Evol Comput 4(3):284–294
112. Leguizamon G, Coello CAC (2008) Boundary search for constrained numerical optimization problems with an algorithm inspired by the ant colony metaphor. IEEE Trans Evol Comput 13(2):350–368
113. Fonseca LG, Capriles PVSZ, Barbosa HJC, Lemonge ACC (2007) A stochastic rank-based ant system for discrete structural optimization. IEEE Swarm Intell Symp 2007:68–75
114. Leguizamón, G., & Coello, C. A. C. (2007). A boundary search based ACO algorithm coupled with stochastic ranking. 2007 IEEE Congress on Evolutionary Computation, 165–172.

115. Fan Z, Liu J, Sorensen T, Wang P (2008) Improved differential evolution based on stochastic ranking for robust layout synthesis of MEMS components. IEEE Trans Industr Electron 56(4):937–948
116. Liu, J., Fan, Z., & Goodman, E. (2009). SRaDE: An adaptive differential evolution based on stochastic ranking. Proceedings of the 11th Annual Conference on Genetic and Evolutionary Computation, 1871–1872.
117. Liu, R., Li, Y., Zhang, W., & Jiao, L. (2009). Stochastic ranking based differential evolution algorithm for constrained optimization problem. In Proceedings of the first acm/sigevo summit on genetic and evolutionary computation (pp. 887–890).
118. Mallipeddi, R., Suganthan, P. N., & Qu, B.-Y. (2009). Diversity enhanced adaptive evolutionary programming for solving single objective constrained problems. 2009 IEEE Congress on Evolutionary Computation, 2106–2113.
119. Vodopija, A., Oyama, A., & Filipič, B. (2019a). Ensemble-based constraint handling in multiobjective optimization. Proceedings of the Genetic and Evolutionary Computation Conference Companion, 2072–2075.
120. Vodopija, A., Oyama, A., & Filipič, B. (2019b). Ensemble-based constraint handling in multiobjective optimization. Proceedings of the Genetic and Evolutionary Computation Conference Companion, 2072–2075.
121. Mallipeddi R, Suganthan PN (2010) Differential evolution with ensemble of constraint handling techniques for solving CEC 2010 benchmark problems. IEEE Congr Evolut Comput. https://doi.org/10.1109/CEC.2010.5586330
122. Tasgetiren MF, Suganthan PN, Pan Q-K, Mallipeddi R, Sarman S (2010) An ensemble of differential evolution algorithms for constrained function optimization. IEEE Congr Evolut Comput. https://doi.org/10.1109/CEC.2010.5586396
123. Li, L. D., Li, X., & Yu, X. (2008). A multi-objective constraint-handling method with PSO algorithm for constrained engineering optimization problems. 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), 1528–1535
124. Reynoso-Meza, G., Blasco, X., Sanchis, J., & Mart\'\inez, M. (2010). Multiobjective optimization algorithm for solving constrained single objective problems. IEEE Congress on Evolutionary Computation, 1–7.
125. Wang Y, Liu H, Cai Z, Zhou Y (2007) An orthogonal design based constrained evolutionary optimization algorithm. Eng Optim 39(6):715–736
126. Samanipour F, Jelovica J (2020) Adaptive repair method for constraint handling in multi-objective genetic algorithm based on relationship between constraints and variables. Appl Soft Comput 90:106143
127. Long Q (2014) A constraint handling technique for constrained multi-objective genetic algorithm. Swarm Evol Comput 15:66–79
128. Deb K (1999) Multi-objective genetic algorithms: problem difficulties and construction of test problems. Evol Comput 7(3):205–230
129. Srinivas N, Deb K (1994) Muiltiobjective optimization using nondominated sorting in genetic algorithms. Evol Comput 2(3):221–248
130. Bäck T, Fogel DB, Michalewicz Z (2018) Evolutionary computation 1. In: Baeck T, Fogel DB, Michalewicz Z (eds) Basic algorithms and operators. CRC Press, Florida
131. Poon PW, Carter JN (1995) Genetic algorithm crossover operators for ordering applications. Comput Oper Res 22(1):135–147
132. Ngo CY, Li VOK (1998) Fixed channel assignment in cellular radio networks using a modified genetic algorithm. IEEE Trans Veh Technol 47(1):163–172
133. Salcedo-Sanz S, Camps-Valls G, Pérez-Cruz F, Sepúlveda-Sanchis J, Bousoño-Calzón C (2004) Enhancing genetic feature selection through restricted search and Walsh analysis. IEEE Trans Syst, Man, Cybern Part C (Appl Rev) 34(4):398–406
134. Dengiz B, Altiparmak F, Smith AE (1997) Local search genetic algorithm for optimal design of reliable networks. IEEE Trans Evol Comput 1(3):179–188
135. Kou L, Markowsky G, Berman L (1981) A fast algorithm for steiner trees. Acta Informatica 15(2):141–145
136. Agustín-Blas LE, Salcedo-Sanz S, Ortiz-García EG, Portilla-Figueras A, Pérez-Bellido ÁM (2009) A hybrid grouping genetic algorithm for assigning students to preferred laboratory groups. Expert Syst Appl 36(3):7234–7241
137. Falkenauer E (1993) The grouping genetic algorithms: widening the scope of the GA's. JORBEL-Belgian J Oper Res, Stat, Comput Sci 33(1–2):79–102
138. Krasnogor N, Smith J (2005) A tutorial for competent memetic algorithms: model, taxonomy, and design issues. IEEE Trans Evol Comput 9(5):474–488
139. Salcedo-Sanz S (2009) A survey of repair methods used as constraint handling techniques in evolutionary algorithms. Comput Sci Rev 3(3):175–192
140. Suh, J.-Y., & Van Gucht, D. (1987). Incorporating heuristic information into genetic search. Genetic Algorithms and Their Applications: Proceedings of the Second International Conference on Genetic Algorithms: at the Massachusetts Institute of Technology, Cambridge, MA.
141. Talbi E-G (2016) Combining metaheuristics with mathematical programming, constraint programming and machine learning. Ann Oper Res 240(1):171–215
142. Lai WK, Coghill GG (1996) Channel assignment through evolutionary optimization. IEEE Trans Veh Technol 45(1):91–96
143. Ngo CY, Li VOK (2003) Centralized broadcast scheduling in packet radio networks via genetic-fix algorithms. IEEE Trans Commun 51(9):1439–1441
144. Esbensen H (1995) Computing near-optimal solutions to the steiner problem in a graph using a genetic algorithm. Networks 26(4):173–185
145. Coello, C. A. C., & Carlos, A. (1999). A survey of constraint handling techniques used with evolutionary algorithms. Lania-RI-99–04, Laboratorio Nacional de Informática Avanzada.
146. Geng H, Zhang M, Huang L, Wang X (2006) Infeasible elitists and stochastic ranking selection in constrained evolutionary multi-objective optimization. In: Wang T-D, Li X, Chen S-H, Wang X, Abbass H, Iba H, Chen G-L, Yao X (eds) Asia-Pacific Conference on Simulated Evolution and Learning. Springer, Berlin, pp 336–344
147. Ying W-Q, He W-P, Huang Y-X, Li D-T, Wu Y (2016) An adaptive stochastic ranking mechanism in MOEA/D for constrained multi-objective optimization. Int Conf Info Syst Artif Intell (ISAI) 2016:514–518
148. Liu, Y., Li, X., & Hao, Q. (2019). A new constrained multi-objective optimization problems algorithm based on group-sorting. Proceedings of the Genetic and Evolutionary Computation Conference Companion, 221–222.
149. Liu Z-Z, Wang Y, Wang B-C (2019) Indicator-based constrained multiobjective evolutionary algorithms. IEEE Trans Syst, Man, Cybern: Syst 51(9):5414–5426
150. Gu Q, Wang Q, Xiong NN, Jiang S, Chen L (2021) Surrogate-assisted evolutionary algorithm for expensive constrained multi-objective discrete optimization problems. Complex Intell Syst. https://doi.org/10.1007/s40747-020-00249-x
151. Isaacs A, Ray T, Smith W (2008) Blessings of maintaining infeasible solutions for constrained multi-objective optimization problems. IEEE Congr Evolut Comput 2008:2780–2787

152. Zhou Y, Zhu M, Wang J, Zhang Z, Xiang Y, Zhang J (2018) Tri-goal evolution framework for constrained many-objective optimization. IEEE Trans Syst, Man, Cybern: Syst 50(8):3086–3099
153. Saxena DK, Ray T, Deb K, Tiwari A (2009) Constrained many-objective optimization: a way forward. IEEE Congr Evolut Comput 2009:545–552
154. Zapotecas Martinez, S., Arias Montano, A., & Coello Coello, C. A. (2014). Constrained multi-objective aerodynamic shape optimization via swarm intelligence. Proceedings of the 2014 Annual Conference on Genetic and Evolutionary Computation, 81–88.
155. Becerra, R. L., Coello Coello, C. A., Hernández-D\'\iaz, A. G., Caballero, R., & Molina, J. (2007). Alternative techniques to solve hard multi-objective optimization problems. Proceedings of the 9th Annual Conference on Genetic and Evolutionary Computation, 754–757.
156. Yang, Z., Cai, X., & Fan, Z. (2014). Epsilon constrained method for constrained multiobjective optimization problems: some preliminary results. Proceedings of the Companion Publication of the 2014 Annual Conference on Genetic and Evolutionary Computation, 1181–1186.
157. Martinez SZ, Coello CAC (2014) A multi-objective evolutionary algorithm based on decomposition for constrained multi-objective optimization. IEEE Congr Evolut Comput (CEC). https://doi.org/10.1109/CEC.2014.6900645
158. Fan Z, Li H, Wei C, Li W, Huang H, Cai X, Cai Z (2016) An improved epsilon constraint handling method embedded in MOEA/D for constrained multi-objective optimization problems. IEEE Symp Ser Comput Intell (SSCI) 2016:1–8
159. Yang Y, Liu J, Tan S, Wang H (2019) A multi-objective differential evolutionary algorithm for constrained multi-objective optimization problems with low feasible ratio. Appl Soft Comput 80:42–56
160. Zapotecas-Mart\'\inez, S., & Ponsich, A. (2020). Constraint handling within moea/d through an additional scalarizing function. Proceedings of the 2020 Genetic and Evolutionary Computation Conference, 595–602.
161. Yang Y, Liu J, Tan S (2021) A partition-based constrained multi-objective evolutionary algorithm. Swarm Evol Comput 66:100940
162. Tian Y, Zhang T, Xiao J, Zhang X, Jin Y (2020) A coevolutionary framework for constrained multiobjective optimization problems. IEEE Trans Evol Comput 25(1):102–116
163. Wang H, Cai T, Li K, Pedrycz W (2021) Constraint handling technique based on Lebesgue measure for constrained multiobjective particle swarm optimization algorithm. Knowl-Based Syst 227:107131
164. Wang, J., Li, Y., Zhang, Q., Zhang, Z., & Gao, S. (2021). Cooperative multiobjective evolutionary algorithm with propulsive population for constrained multiobjective optimization. IEEE Transactions on Systems, Man, and Cybernetics: Systems
165. Liu, Z.-Z., Wang, B.-C., & Tang, K. (2021). Handling Constrained Multiobjective Optimization Problems via Bidirectional Coevolution. IEEE Transactions on Cybernetics.
166. Fan Z, Wang Z, Li W, Yuan Y, You Y, Yang Z, Sun F, Ruan J (2020) Push and pull search embedded in an M2M framework for solving constrained multi-objective optimization problems. Swarm Evol Comput 54:100651
167. Oyama A, Shimoyama K, Fujii K (2007) New constraint-handling method for multi-objective and multi-constraint evolutionary optimization. Trans Japan Soc Aeronaut Space Sci 50(167):56–62
168. Jimenez, F., Gómez-Skarmeta, A. F., Sánchez, G., & Deb, K. (2002b). An evolutionary algorithm for constrained multi-objective optimization. Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), 2, 1133–1138.
169. Caraffini F, Neri F, Iacca G, Mol A (2013) Parallel memetic structures. Inf Sci 227:60–82
170. Caraffini F, Neri F, Picinali L (2014) An analysis on separability for memetic computing automatic design. Inf Sci 265:1–22
171. Datta S, Ghosh A, Sanyal K, Das S (2017) A radial boundary intersection aided interior point method for multi-objective optimization. Inf Sci 377:1–16
172. Morovati V, Pourkarimi L (2019) Extension of Zoutendijk method for solving constrained multiobjective optimization problems. Eur J Oper Res 273(1):44–57
173. Uribe L, Lara A, Schütze O (2020) On the efficient computation and use of multi-objective descent directions within constrained MOEAs. Swarm Evol Comput 52:100617
174. Harada, K., Sakuma, J., Ono, I., & Kobayashi, S. (2007b). Constraint-handling method for multi-objective function optimization: Pareto descent repair operator. International Conference on Evolutionary Multi-Criterion Optimization, 156–170.
175. Qian F, Xu B, Qi R, Tianfield H (2012) Self-adaptive differential evolution algorithm with α-constrained-domination principle for constrained multi-objective optimization. Soft Comput 16(8):1353–1372
176. Li K, Chen R, Fu G, Yao X (2018) Two-archive evolutionary algorithm for constrained multiobjective optimization. IEEE Trans Evol Comput 23(2):303–315
177. Qu, B.-Y., & Suganthan, P. N. (2010). Constrained multi-objective optimization algorithm with diversity enhanced differential evolution. IEEE Congress on Evolutionary Computation, 1–5.
178. Wang Y-N, Wu L-H, Yuan X-F (2010) Multi-objective self-adaptive differential evolution with elitist archive and crowding entropy-based diversity measure. Soft Comput 14(3):193–209
179. Hobbie JG, Gandomi AH, Rahimi I (2021) A comparison of constraint handling techniques on NSGA-II. Arch Comput Methods Eng 28(5):3475–3490
180. Rosenbrock H (1960) An automatic method for finding the greatest or least value of a function. Comput J 3(3):175–184
181. Michalewicz, Z. (1995a). Genetic algorithms, numerical optimization, and constraints. Proceedings of the Sixth International Conference on Genetic Algorithms, 195, 151–158.
182. Himmelblau DM (1972) Applied Nonlinear Programming. McGraw-Hill Book Company, New York
183. Rao SS (2019) Engineering optimization: theory and practice. Wiley, New Jersey
184. Sandgren E (1990) Nonlinear integer and discrete programming in mechanical desigsn optimization. J Mech Des. https://doi.org/10.1115/1.2912596
185. Golinski J (1973) An adaptive optimization system applied to machine synthesis. Mech Mach Theory 8(4):419–436
186. Kvalie D (1967) Optimization of plane elastic grillages. PhD Thesis, Norges Teknisk Naturvitenskapelige Universitet, Norway
187. Yang XS, Gandomi AH (2012) Bat algorithm: a novel approach for global engineering optimization. Engineering Computations. 29(5):464–483
188. Steven G (2002) Evolutionary algorithms for single and multicriteria design optimization. A. Osyczka. Springer Verlag, Berlin, 2002, ISBN 3–7908–1418–01. Structural and Multidisciplinary Optimization, 24(1):88–89
189. Changsen W, Wan C (1991) Analysis of rolling element bearings. Wiley-Blackwell, New Jersey
190. Youn BD, Choi KK (2004) A new response surface methodology for reliability-based design optimization. Comput Struct 82(2–3):241–256

191. Vanderplaats, G. (2002). Very large scale optimization. 8th Symposium on Multidisciplinary Analysis and Optimization, 4809
192. Binh, T. T., & Korn, U. (1997b). MOBES: A multiobjective evolution strategy for constrained optimization problems. The Third International Conference on Genetic Algorithms (Mendel 97), 25, 27
193. Osyczka A, Kundu S (1995) A new method to solve generalized multicriteria optimization problems using the simple genetic algorithm. Struct Optim 10(2):94–99
194. Zitzler E, Deb K, Thiele L (2000) Comparison of multiobjective evolutionary algorithms: empirical results. Evol Comput 8(2):173–195
195. Deb, K., & Srinivasan, A. (2006). Innovization: Innovating design principles through optimization. Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation. 1629–1636
196. Jain H, Deb K (2013) An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: handling constraints and extending to an adaptive approach. IEEE Trans Evol Comput 18(4):602–622
197. Huband S, Hingston P, Barone L, While L (2006) A review of multiobjective test problems and a scalable test problem toolkit. IEEE Trans Evol Comput 10(5):477–506
198. Deb K, Thiele L, Laumanns M, Zitzler E (2005) Scalable test problems for evolutionary multiobjective optimization. In: Abraham A, Jain L, Goldberg R (eds) evolutionary multiobjective optimization. Springer, London
199. Leydesdorff, L., & Milojević, S. (2012). Scientometrics
200. Childress D (2011) Citation tools in academic libraries: best practices for reference and instruction. Ref User Serv Q 51(2):143
201. Estabrooks CA, Derksen L, Winther C, Lavis JN, Scott SD, Wallin L, Profetto-McGrath J (2008) The intellectual structure and substance of the knowledge utilization field: a longitudinal author co-citation analysis, 1945 to 2004. Implement Sci 3(1):49
202. Gandomi AH, Emrouznejad A, Rahimi I (2020) Evolutionary Computation in Scheduling: A Scientometric Analysis. In: Gandomi AH, Emrouznejad A, Jamshidi MM, Deb K, Rahimi I (eds) Evolutionary Computation in Scheduling. Wiley, Hoboken
203. Müßigmann B, von der Gracht H, Hartmann E (2020) Blockchain technology in logistics and supply chain management—a bibliometric literature review from 2016 to january 2020. IEEE Trans Eng Manag 67(4):988–1007
204. Neelam S, Sood SK (2020) A scientometric review of global research on smart disaster management. IEEE Trans Eng Manag 68(1):317–329
205. Rahimi I, Ahmadi A, Zobaa AF, Emrouznejad A, Abdel Aleem SHE (2017) Bigdata optimization in electric power systems: A review. Big Data Analytics in Future Power Systems (2018), CRCPress: Boca Raton, FL, USA: 55–84
206. Rahimi I, Gandomi AH (2021) A comprehensive review and analysis of operating room and surgery scheduling. Arch Comput Methods Eng 28(3):1667–1688
207. Rahimi I, Nematian J (2022) A bibliometric analysis on optimization solution methods applied to supply chain of solar energy. Arch Comput Methods Eng. https://doi.org/10.1007/s11831-022-09736-5
208. Rahimi I, Chen F, Gandomi AH (2021) A review on COVID-19 forecasting models. Neural Comput Appl. https://doi.org/10.1007/s00521-020-05626-8
209. Das S, Suganthan PN (2010) Differential evolution: a survey of the state-of-the-art. IEEE Trans Evol Comput 15(1):4–31
210. Deb K, Jain H (2013) An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. IEEE Trans Evol Comput 18(4):577–601
211. Santana-Quintero LV, Hernández-Díaz AG, Molina J, Coello CAC, Caballero R (2010) DEMORS: a hybrid multi-objective optimization algorithm using differential evolution and rough set theory for constrained problems. Comput Oper Res 37(3):470–480
212. Tawhid MA, Savsani V (2018) A novel multi-objective optimization algorithm based on artificial algae for multi-objective engineering design problems. Appl Intell 48(10):3762–3781s
213. Yang Y, Liu J, Tan S, Wang H (2018) Application of constrained multi-objective evolutionary algorithm in multi-source compressed-air pipeline optimization problems. IFAC-PapersOnLine 51(18):168–173
214. Ma Z, Wang Y (2021) Shift-based penalty for evolutionary constrained multiobjective optimization and its application. IEEE Trans Cybern. https://doi.org/10.1109/TCYB.2021.3069814
215. Chen M-R, Zeng G-Q, Lu K-D (2019) Constrained multiobjective population extremal optimization based economic-emission dispatch incorporating renewable energy resources. Renew Energy 143:277–294
216. El-Shorbagy MA, Mousa AA (2021) Constrained multiobjective equilibrium optimizer algorithm for solving combined economic emission dispatch problem. Complexity. https://doi.org/10.1155/2021/6672131
217. Wang C, Xu R (2020) An angle based evolutionary algorithm with infeasibility information for constrained many-objective optimization. Appl Soft Comput 86:105911
218. Dasgupta, D., & Michalewicz, Z. (2013). Evolutionary algorithms in engineering applications. Springer Science & Business Media.
219. Eiben, A. E., & Van Der Hauw, J. K. (1997). Adaptive penalties for evolutionary graph coloring. European Conference on Artificial Evolution. 95–106.
220. Watanabe K, Hashem MMA (2004) Evolutionary optimization of constrained problems In Evolutionary computations. Springer, Berlin
221. Coello, C. A. C. (1999). Self-adaptive penalties for GA-based optimization. Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), 1, 573–580.
222. Coello CAC (2000) Use of a self-adaptive penalty approach for engineering optimization problems. Comput Ind 41(2):113–127
223. Le Riche, R., Knopf-Lenoir, C., & Haftka, R. T. (1995). A Segregated Genetic Algorithm for Constrained Structural Optimization. ICGA, 558–565.
224. Constantin E (2020) Second-order optimality conditions in locally lipschitz inequality-constrained multiobjective optimization. J Optim Theory Appl 186(1):50–67
225. Eichfelder G, Warnow L (2021) Proximity measures based on KKT points for constrained multi-objective optimization. J Global Optim 80(1):63–86
226. Peng G, Wu H, Wu H, Wolter K (2021) Constrained multiobjective optimization for IoT-enabled computation offloading in collaborative edge and cloud computing. IEEE Internet Th J. https://doi.org/10.1109/JIOT.2021.3067732
227. Yuan, J., Liu, H.-L., Ong, Y.-S., & He, Z. (2021). Indicator-based Evolutionary Algorithm for Solving Constrained Multiobjective Optimization Problems. IEEE Transactions on Evolutionary Computation.
228. Peng C, Liu H-L, Goodman ED (2020) Handling multi-objective optimization problems with unbalanced constraints and their effects on evolutionary algorithm performance. Swarm Evol Comput 55:100676
229. Ma H, Wei H, Tian Y, Cheng R, Zhang X (2021) A multi-stage evolutionary algorithm for multi-objective optimization with complex constraints. Inf Sci 560:68–91

230. Tian, Y., Zhang, Y., Su, Y., Zhang, X., Tan, K. C., & Jin, Y. (2021). Balancing Objective Optimization and Constraint Satisfaction in Constrained Evolutionary Multiobjective Optimization. IEEE Transactions on Cybernetics.
231. Yu K, Liang J, Qu B, Yue C (2021) Purpose-directed two-phase multiobjective differential evolution for constrained multiobjective optimization. Swarm Evol Comput 60:100799
232. Peng C, Liu H-L, Goodman ED (2020) A cooperative evolutionary framework based on an improved version of directed weight vectors for constrained multiobjective optimization with deceptive constraints. IEEE Trans Cybern. https://doi.org/10.1109/TCYB.2020.2998038
233. Cantú VH, Ponsich A, Azzaro-Pantel C (2021) On the use of Gradient-Based Repair Method for Solving Constrained Multiobjective Optimization Problems—A Comparative Study. In: Kulkarni AJ, Mezura-Montes E, Wang Y, Gandomi AH, Krishnasamy G (eds) Constraint Handling in Metaheuristics and Applications. Springer, Berlin
234. Zhu Q, Zhang Q, Lin Q (2020) A constrained multiobjective evolutionary algorithm with detect-and-escape strategy. IEEE Trans Evol Comput 24(5):938–947
235. Abdel-Basset M, Mohamed R, Abouhawwash M (2021) Balanced multi-objective optimization algorithm using improvement based reference points approach. Swarm Evol Comput 60:100791
236. Bouzid SE, Seresstou Y, Raoof K, Omri MN, Mbarki M, Dridi C (2020) MOONGA: multi-objective optimization of wireless network approach based on genetic algorithm. IEEE Access 8:105793–105814
237. Chen H, Ho YS (2015) Highly cited articles in biomass research: a bibliometric analysis. Renew Sustain Energy Rev 49:12–20. https://doi.org/10.1016/j.rser.2015.04.060
238. Ho Y-S (2012) Top-cited articles in chemical engineering in science citation index expanded: a bibliometric analysis. Chin J Chem Eng 20(3):478–488