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A Comprehensive Review on NSGA-II for Multi-Objective Combinatorial Optimization Problems

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ABSTRACT This paper provides an extensive review of the popular multi-objective optimization algorithm NSGA-II for selected combinatorial optimization problems viz. assignment problem, allocation problem, travelling salesman problem, vehicle routing problem, scheduling problem, and knapsack problem. It is identified that based on the manner in which NSGA-II has been implemented for solving the aforementioned group of problems, there can be three categories: Conventional NSGA-II, where the authors have implemented the basic version of NSGA-II, without making any changes in the operators; the second one is Modified NSGA-II, where the researchers have implemented NSGA-II after making some changes into it and finally, Hybrid NSGA-II variants, where the researchers have hybridized the conventional and modified NSGA-II with some other technique. The article analyses the modifications in NSGA-II and also discusses the various performance assessment techniques used by the researchers, i.e., test instances, performance metrics, statistical tests, case studies, benchmarking with other state-of-the-art algorithms. Additionally, the paper also provides a brief bibliometric analysis based on the work done in this study.

INDEX TERMS NSGA-II, combinatorial optimization, multi-objective optimization, genetic algorithms.

I. INTRODUCTION

The Non-Dominated Sorting Genetic Algorithm (NSGA-II) is a powerful decision space exploration engine based on Genetic Algorithm (GA) for solving Multi-objective Optimization Problems (MOOPs). It was initially proposed by Deb *et al.* [1] in the year 2000 in 'International Conference on Parallel Problem Solving from Nature.'

In 2002, it was published as a full-length research article in the journal, IEEE Transactions on Evolutionary Computation [2], and since then, it has been cited more than 20630 times according to IEEE Xplore. Presumably, NSGA-II is the 4th most cited journal article in the database of IEEE Xplore. Further, as per Google scholar, it has been cited more than 35240 times, out of which more than 19600 citations are from web of science. This information is sufficient to show the popularity of NSGA-II for solving MOOPs. During its 20 years of existence, NSGA-II has been implemented on a wide range of MOOPs having continuous as well as discrete variables. However, to the best of the authors' knowledge, there is no comprehensive review of NSGA-II, which can guide the researchers working in this area. To bridge this gap and to acquaint the readers with the versatility of NSGA-II, in this paper, the focus is on the application of NSGA-II and its variants on selected Combinatorial Optimization Problems (COPS): assignment problem, allocation problem, travelling salesman problem (TSP), vehicle routing problem (VRP), scheduling problem, and knapsack problem. We have particularly chosen COPS as in the broad world of optimization, COPs are considered to be one of the most challenging and complex problems. Since most COPs are NP-hard in nature, the computational complexity for solving these problems increases as the problem size increases. Therefore, for such problems, approximate methods such as metaheuristics approaches are preferred over classical methods [3].

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A. COMBINATORIAL OPTIMIZATION PROBLEMS (COPS)

In the early '70s, when metaheuristics such as evolutionary algorithms were proposed to solve COPs, they did not have a significant influence due to the lack of efficient computational facilities [4]. However, with the passage of time and with the advent of fast and high-end computational facilities, many metaheuristics were proposed for solving complex COPs. Literature reveals that a lot of attention has been given to COPs with multiple objectives due to their challenging nature and practical utility.

Multi-objective Combinatorial Optimization Problems (MOCOPs) have been surveyed from time to time by various researchers.

In 1994, Ulungu & Teghem [5] surveyed and suggested the adaptations of metaheuristics to multi-objective environment as a direction of future research. Thereafter, researchers proposed effective heuristics and meta-heuristics to solve MOCOPs.

Coello Coello *et al.* [6] gave a detailed overview of multi-objective combinatorial optimization that included relevant definitions and the basic idea of using metaheuristic for MOCOP. An overview of hybrid approximation methods for MOCOPs can be found in [7] and [8]. According to [8], an approximation algorithm for MOCOPs should necessarily be hybridized, i.e., it should be a combination of an evolutionary algorithm, a neighbourhood search algorithm (local search procedure), and problem-specific components because the universal method for a problem cannot perform better than the technique specially tailored for it. More recently, Liu *et al.* [9] reviewed the literature of multi-objective metaheuristics for multi-objective discrete optimization problems (MODOPs) and provided information about its application areas, test instances, and performance metrics. As a direction of future research, the author suggested reviewing various metaheuristics for different type of MODOPs.

The review studies on COPs in the existing literature either discussed both single and multi-objective versions of a specific COP or only its multi-objective version along with the solution approaches. Some of the reviewed single-objective COPs by the researchers focus on specific areas like blocking flowshop scheduling problem (FSP) [10], permutation FSP [11], non-permutation FSP [12], agricultural land-use allocation [13], facility location problems [14], emergency material scheduling[15], allocation of distributed generation [16], location-routing problems [17], resource allocation for CRAN in 5G and beyond networks [18], VRP [19], cell formation problem [20] and many more.

The selected papers are divided into three categories that are identified based on the implementation of NSGA-II to MOCOPs and are-conventional NSGA-II, modified NSGA-II, and hybrid NSGA-II. The papers under the first category used NSGA-II in its traditional form with the same crossover, mutation, and selection operators [2]. The papers under the second category modified the conventional NSGA-II, mainly in terms of the initialization, selection scheme, crossover and mutation operators, crowding distance operator, constraint handling technique, or some other criteria. Furthermore, the third category contains the papers in which either the conventional NSGA-II or modified NSGA-II is hybridized with a heuristic strategy, a local search operator, a machine learning technique, or another single/multi-objective optimization algorithm. On the other, those papers in which multi-criteria decision-making (MCDM) techniques are applied to the trade-off solutions obtained using conventional NSGA-II are not considered in the third category. In this study, an MCDM technique is viewed as a post-optimization technique for selecting the best-compromised solution. Such papers are studied under the first category and analyzed separately in terms of applied decision-making methods.

In the selected papers, the benchmarking of NSGA-II based algorithms with other state-of-the-art algorithms, the algorithms used for hybridization with NSGA-II, the methods used for the post-Pareto optimality analysis, the number of objective functions involved in the papers are discussed. Additionally, the test instance or datasets, case studies, performance metrics, and statistical tests used in the papers are also analyzed.

In summary, this paper makes the following contributions:

- Provides a detailed analysis of NSGA-II and its variants for solving six selected MOCOPs.
- Discusses the modifications in NSGA-II algorithms.
- Provides a brief bibliometric analysis including information about post-Pareto optimality analysis, number of objective functions, test instances, case studies, performance metrics and statistical tests.
- Future research directions in this field.

Accordingly, the remaining of the paper is organized as follows: Section 2 contains the background of MOOP, MOCOP, concept of Pareto dominance, and NSGA-II, including its basic structure and working procedure. Section 3 provides the research methodology for the study. Section 4 addresses the literature survey, including NSGA-II implementation to MOCOPs, performance assessment, performed case studies, statistical analysis, and post-Pareto optimality analysis. Section 5 is about the analysis of modifications in NSGA-II. Section 6 discusses the bibliometric analysis, and lastly, Section 7 provides the conclusion and future directions drawn from this study.

II. BACKGROUND

In this section, we describe the concepts of MOOP, MOCOP, and Pareto dominance. The basic structure and procedure of NSGA-II are also discussed.

A. MULTI-OBJECTIVE OPTIMIZATION PROBLEM

A MOOP includes a set of n decision variables, k objective functions, and a set of (m inequality and p equality) constraints. The optimization goal is-

$$\text{Min/Max } \; y = f(x) = (f_1(x), f_2(x), \ldots, f_k(x)), \; k \geq 2 \quad (1)$$

$$\text{Subject to } \; g_i(x) \leq 0, i = 1, 2, \ldots, m \quad (2)$$

$$h_j(x) = 0, j = 1, 2, \ldots, p \quad (3)$$

where $x = (x_1, x_2, \ldots, x_n)$ is an n-dimensional decision vector in $X \subseteq R^n$ (R is the set of real numbers), y is a k-dimensional objective vector in R^k, f defines the mapping function, g_i is the i^{th} inequality constraint, and h_j is the j^{th} equality constraint. Further, (2-3) determine the set of all feasible solutions X.

B. MULTI-OBJECTIVE COMBINATORIAL OPTIMIZATION PROBLEM

The MOCOPs form a particular class of MOOPs, that can be formulated as:

$$\text{Min/Max} \quad y = f(x) = (f_1(x), f_2(x), \ldots f_k(x)), \quad k \geq 2 \tag{4}$$

$$\text{Subject to} \quad g_i(x) \leq 0, \; i = 1, 2, \ldots, m \tag{5}$$

$$h_j(x) = 0, \; j = 1, 2, \ldots, p \tag{6}$$

where $x = (x_1, x_2, \ldots, x_n) \in D$ is an n-dimensional vector in decision-space $D = D_1 \times D_2 \times \ldots \times D_n$ (D_n is the domain of x_n), y is a k-dimensional objective vector in R^k, f is the mapping function, g_i is the i^{th} inequality constraint, h_j is the j^{th} equality constraint. The other variables, k, m, and p, represent the numbers of objective functions, inequality constraints, and equality constraints, respectively.

The set S is the set of all feasible solutions that satisfy (5-6) and may describe a combinatorial structure such as spanning trees of a graph, paths, and matching. Some examples of COPs are assignment problem, allocation problem, scheduling problem, VRP, TSP, knapsack problem, sum of subset problem, network design problem, graph-colouring problem, location-routing problem, and facility location problem.

C. CONCEPT OF PARETO DOMINANCE

Let x^1 and x^2 be the two feasible solutions of the multiobjective minimization problem (1). The solution x^1 can be viewed as better than x^2 if the following conditions hold:

1. $f_j(x^1) \leq f_j(x^2)$ for all $j = \{1, 2, \ldots, k\}$
2. $f_j(x^1) < f_j(x^2)$ for at least one $j = \{1, 2, \ldots, k\}$

where k is the number of objective functions, $f_j(x)$ is the j^{th} value of an objective function for decision vector x. In this case, we say that x^1 dominates x^2 (or x^2 is dominated by x^1): x^1 is better than x^2. The relation '$<$' (or '$>$' for maximization problem) can be denoted as a dominance operator $\triangleleft$. $x^1 \triangleleft x^2$ represents x^1 dominates x^2.

When a solution x of (1) is not dominated by any other feasible solutions, it is called a Pareto optimal solution. The set of all Pareto optimal solutions are referred to as a Pareto set. The objective vector corresponding to the Pareto set is defined as a Pareto front, as shown in Fig. 1.

D. NSGA-II

NSGA-II is an improved version of the non-dominated sorting genetic algorithm (NSGA) [21], which has been criticized by researchers due to its limitations such as the absence of elitism, the need to define sharing parameter for diversity preservation, and its high computational complexity. On the other hand, the design of NSGA-II exhibits the property of elitism and does not need any sharing parameter. It uses the crowding distance operator for the mechanism of diversity preservation. Moreover, it is computationally fast and lives up to its name 'Fast Elitist NSGA-II.' The overall complexity of NSGA-II is at most O(MN^2), where M is the number of objective functions, and N is the population size.

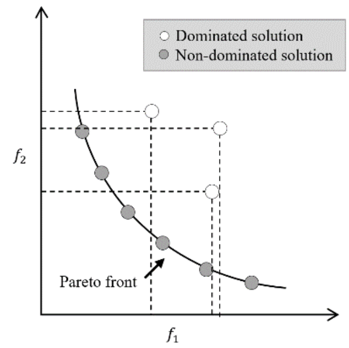

FIGURE 1. Pareto dominance.

1) BASIC STRUCTURE OF NSGA-II

The philosophy of NSGA-II is based on four main principles, which are: Non-Dominated Sorting, Elite Preserving Operator, Crowding Distance and Selection Operator. These are described in brief in the following subsections.

a: NON-DOMINATED SORTING

In this procedure, the population members are sorted using the concept of Pareto dominance. The process of non-dominated sorting begins with assigning the first rank to the non-dominated members of the initial population. These first ranked members are then placed in the first front and removed from the initial population. After that, the non-dominating sorting procedure is performed on the remaining population members. Further, the non-dominated members of the remaining population are assigned the second rank and placed in the second front. This process continues until the whole population members are put on different fronts according to their ranks, as shown in Fig. 2 (a).

b: ELITE-PRESERVING OPERATOR

Elite preserving strategy retains the elite solutions of a population by directly transferring them to the next generation. In other words, the non-dominated solutions found in each generation move on to the next generations till some solutions dominate them.

c: CROWDING DISTANCE

The crowding distance is calculated to estimate the density of solutions surrounding a particular solution. It is the average distance of two solutions on either side of the solution along each of the objectives. On comparing two solutions with different crowding distances, the solution with the large crowded distance is considered to be present in a less crowded region. The crowded distance of the i^{th} solution is the average side-length of the cuboid, as shown in Fig. 2(b). If f_j^i is the j^{th} value of an objective function for the i^{th} individual and, $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values

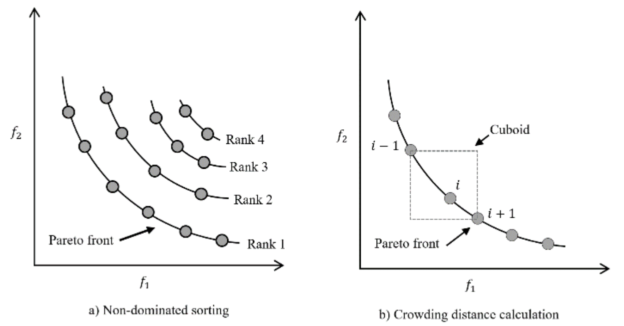

FIGURE 2. Non-dominated sorting procedure and Crowding distance calculation.

respectively of j^{th} objective function among all the individuals. Then, the crowding distance of i^{th} individual is defined as the average distance of two nearest solutions on either side, as given in (7).

$$cd(i) = \sum_{i=1}^{k} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{\max} - f_j^{\min}} \tag{7}$$

where k is the number of objective functions.

d: SELECTION OPERATOR

The population for the next generation is selected using a crowded tournament selection operator, which uses the rank of the population members and their crowding distances for the selection. The rule for selecting one out of two population members for the next generation is-

(i) If both the population members are of different ranks, then the one with the better rank is selected for the next generation

(ii) If both the population members are of the same ranks, then the one with the higher crowding distance is selected for the next generation.

2) PROCEDURE OF NSGA-II

The procedure of NSGA-II begins with generating an initial population P_t of size N. Then, a new population Q_t is created after performing crossover and mutation operations on the population P_t. After that, the population P_t and Q_t are combined to form a new population R_t, and the non-dominated sorting procedure is performed on R_t. Then, the population members of R_t are ranked into different fronts according to their non-domination levels.

The next process is to select N members from R_t to create the next population P_{t+1}. If the size of the first front is greater than or equal to N, then only N members are selected from the least crowded region of the first front to form P_{t+1}. On the contrary, if the size of the first front is less than equal to N, then the members of the first front are directly transferred to the next generation, and the remaining members are taken from the least crowded region of the second front and added to P_{t+1}. If the size of P_{t+1} is still less than N, then the same procedure is followed for the next consecutive fronts until the size of P_{t+1} becomes equal to N. The populations P_{t+2}, P_{t+3}, P_{t+4}, …, for the next generations are constructed using the same procedure until the stopping criteria are not satisfied. The working of NSGA-II is shown in Fig. 3.

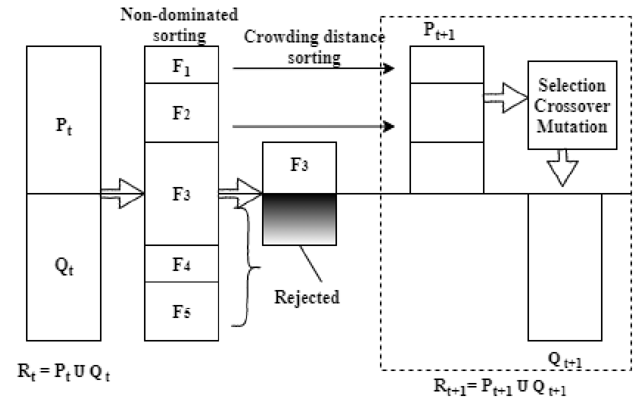

FIGURE 3. Procedure of NSGA-II.

III. RESEARCH METHODOLOGY

A. MATERIAL COLLECTION

This study is conducted using research databases till April 2020 from Science Direct, Taylor & Francis Online, Wiley Online Library, Springer, and IEEE Xplore. The database of Science Direct was searched for article type 'Research articles' with search terms 'NSGA-II, travelling salesman problem,' 'NSGA-II, assignment problem,' 'NSGA-II, allocation problem,' 'NSGA-II, knapsack problem,' 'NSGA-II, vehicle routing problem' and 'NSGA-II, scheduling problem.' The database of Springer was searched for article and conference paper using advance search option with the word 'NSGA-II' and exact phrases 'travelling salesman problem,' 'assignment problem,' 'allocation problem,' 'knapsack problem,' 'vehicle routing problem' and 'scheduling problem.' The database of Taylor & Francis Online was searched using words' 'NSGA-II + travelling salesman problem', 'NSGA-II + assignment problem,' 'NSGA-II + allocation problem,' 'NSGA-II + knapsack problem,' 'NSGA-II + vehicle routing problem,' and 'NSGA-II + scheduling problem' anywhere in the articles. The database of IEEE Xplore was advance searched using the search term 'NSGA-II and travelling salesman problem,' 'NSGA-II and assignment problem,' 'NSGA-II and allocation problem,' 'NSGA-II and knapsack problem,' 'NSGA-II and vehicle routing problem' and 'NSGA-II and scheduling problem' anywhere in the metadata. The database of Wiley Online Library was searched for journal papers with the same procedure as used for the IEEE Xplore database.

The details of the search results are given in Table 1. Out of these, the papers focused on using conventional NSGA-II/ modified NSGA-II/hybrid NSGA-II for solving MOCOPs are considered for the study. Further, only those journals articles are selected, which are published in Science citation index expanded (SCIE) and emerging sources citation index (ESCI) indexed journals. In total, 169 papers got selected for review, of which 135 are journal papers, and the rest 34 are conference papers. The list of journals in which

TABLE 1. Database search results.

Search Results	Science Direct	IEEE Xplore	Wiley Online Library	Taylor & Francis Online	Springer
NSGA-II, Travelling Salesman Problem	206	15	25	46	256
NSGA-II, Assignment Problem	1405	50	821	918	195
NSGA-II, Allocation Problem	1574	102	437	409	282
NSGA-II, Knapsack Problem	175	27	20	23	264
NSGA-II, Vehicle Routing Problem	486	22	73	126	192
NSGA-II, Scheduling Problem	1970	147	394	522	655
Total	5816	363	1770	2044	1844

selected papers are published is shown in Table 2 with their latest impact factors and quartile ranking based on JCR 2019. The number of papers based on different publishers is shown in Table 3. The maximum number of papers are from the Elsevier publisher.

B. CATEGORIZATION OF SELECTED PAPERS

The reviewed papers are initially classified into three categories, conventional NSGA-II, modified NSGA-II, and hybrid NSGA-II based on the implementation of NSGA-II. These three categories are further classified into different sub-categories based on the type of MOCOPs, as shown in Table 4. The miscellaneous category includes the papers based on the combinations of the above six MOCOPs.

IV. REVIEW OF LITERATURE

In COPs' literature, many approximation algorithms are used for solving the MOCOPs, such as, multi-objective discrete artificial bee colony (ABC) [22]–[27]; multi-objective ant colony optimization (MOACO) [28]; improved artificial immune algorithm [29]; MOEA/D [30]; multi-objective memetic algorithm [31]–[34]; water wave optimization [35]; modified particle swarm optimization (PSO) [36], [37]; multi-objective hybrid immune algorithm [38]; GA [39]; grey wolf optimization [40]; cooperative swarm intelligence algorithm for MODOP [41]; multi-objective fruit fly optimization algorithm [42]; multi-objective discrete virus optimization algorithm [43]; NSGA-II & SPEA-II [44] and subpopulation based multi-objective evolutionary algorithm [45]. As this study is focussed on reviewing NSGA-II for MOCOPs, a detailed view of NSGA-II implementations for selected MOCOPs is given in next sub-sections.

TABLE 2. List of journals.

Journal name	Impact factor 2019
Q1	
Information Sciences	5.910
Reliability Engineering and System Safety	5.040
International Journal of Production Research	4.577
Applied Mathematical Modelling	3.633
European Journal of Operational Research	4.213
Applied Soft Computing	5.472
Knowledge-Based Systems	5.921
International Journal of Production Research	4.577
Journal of Cleaner Production	7.246
Transportation Research Part E	4.690
International Journal of Geographical Information Science	3.733
Neural Computing & Applications	4.774
Expert Systems With Applications	5.452
Transportation Research Part C	6.077
Process Safety and Environmental Protection	4.966
Applied Energy	8.848
Automation in Construction	5.669
Engineering with Computers	3.938
Computers & Industrial Engineering	4.135
IEEE Access	3.745
Engineering Applications of Artificial Intelligence	4.201
Applied Mathematics and Computation	3.472
Future Generation Computer Systems	6.125
Journal of Manufacturing Systems	5.105
Swarm and Evolutionary Computation	6.912
Forest Policy and Economics	3.139
ISA Transactions	4.305
Energy	6.082
Mechanical Systems and Signal Processing	6.471
IEEE Transactions on Cybernetics	11.079
IEEE Transactions on Reliability	3.177
Journal of Petroleum Science and Engineering	3.706
Q2	
Journal of the Operational Research Society	2.175
Computer Networks	3.111
International Journal of Disaster Risk Reduction	2.896
Information and Software Technology	2.726
International Journal of Hydrogen Energy	4.939
Journal of Parallel and Distributed Computing	2.296
International Transactions in Operational Research	2.987
Computer Communications	2.816
Soft Computing	3.050
Wireless Network	2.659
The International Journal of Advanced Manufacturing Technology	2.633
Transportation Research Part D	4.577
Computers & Operations Research	3.424
Quality Technology & Quantitative Management	2.231
Journal of Systems Architecture	2.552
Cluster Computing	3.458
Q3	
Computers and Electrical Engineering	2.663
IEEE Transactions on Engineering Management	2.784
Journal of Scheduling	1.765
Operational Research - An International Journal	1.759
Journal of Central South University	1.249
Journal of Heuristics	1.577
Journal of Network and Systems Management	2.250
Microelectronics Journal	1.405
Transportation Letters	1.840
Q4	
Sadhana	0.849
Electric Power Components and Systems	0.824
Journal of Asian Architecture and Building Engineering	0.384
Wireless Personal Communications	1.061
Journal of Systems Engineering and Electronics	0.907
International Journal of Network Management	1.338
Journal of Statistical Computation and Simulation	0.918
Journal of Systems Science and Complexity	0.926
ESCI	
Operations Research for Health Care	NA
Geo-spatial Information Science	NA
Journal of Industrial and Production Engineering	NA
Journal of the Operations Research Society of China	NA

TABLE 3. Number of papers from different publishers.

Publisher	Number of Papers
Elsevier	81
IEEE	44
Springer	23
Taylor & Francis	19
Wiley Online Library	2

TABLE 4. Classification of papers based on different categories.

Problem Type	Conventional NSGA-II	Modified NSGA-II	Hybrid NSGA-II
Assignment Problem	5	11	4
Allocation Problem	1	22	5
Scheduling Problem	4	35	31
Travelling Salesman Problem	-	1	6
Vehicle Routing Problem	1	8	5
Knapsack Problem	1	8	2
Miscellaneous	2	12	5

A. NSGA-II FOR MOCOPS

In the literature, NSGA-II was applied to solve the MOCOPs in conventional, modified, or hybrid forms. The modifications are often done due to the unsuitability of the conventional NSGA-II for the problems in terms of chromosome representation, crossover operator, and mutation operator. The modification and hybridization aim to improve the efficiency of NSGA-II for a particular problem or a class of problems. These improvements in NSGA-II need validation, which is done by comparing it with other state-of-the-art algorithms, including NSGA-II.

In this section, the implementation of NSGA-II to six selected MOCOPs is discussed. The basic definitions of these problems are given in Table 5.

From the searched literature, the problems considered under the category of assignment problems are generalized assignment problem [46], cell formulation problem [47]–[49], critical job assignment problem [50], load balancing of network traffic [51], platform-assignment problem [52], [53], frequency assignment problem [54], multi-stage weapon target assignment (MWTA) problem [55]–[57], location problem [58], [59], land-use optimization [60], optimal configuration selection [61], optimal transmission line assignment [62], multi-skilled worker assignment problem [63], spectrum assignment problem [64] and multi-stage assignment optimization for emergency rescue teams [65].

The problems categorized as allocation problems are resource allocation problem (RAP) [66]–[72], redundancy allocation problem (denoted as ReAP) [73]–[85], reliability redundancy allocation problem [86], buffer allocation [87], order allocation planning [88], land allocation [89], allocation of D-STATCOM in DSs [90], channel allocation in mobile computing [91], agile team allocation problem [92] and continuous berth allocation problem [93].

In the category of knapsack problems, the problems such as search based requirements selection [94], RAP [95], [96], optimal selection of safety measures in oil and gas facilities [97] and multi/many objective knapsack problem [98]–[104] are included.

The pickup and delivery problem [105], multiple TSP [106], GEO satellite mission planning problem [107], and [108]–[110], [45] come under the category of TSPs.

The other problems such as pollution routing problem [111], [112], ship weather routing problem [113], urban freight transportation planning problem [114], many-objective dynamic route planning [115], VRP with demand responsive transport [116], [117], VRP with time windows [118], and other routing problems [119]–[124] are considered under the category of VRPs.

Lastly, the scheduling problems which is the most discussed category of MOCOPs consists of open shop scheduling problem [125], [126], job shop scheduling problem (JSSP) [127]–[132], FSP [133]–[138], project scheduling problem (PSP) [139], resource constrained PSP (RCPSP) [140]–[145], timetabling problem [146], cross-docking scheduling problem [147], task scheduling problem [148]–[154], machine scheduling problem [155]–[161], satellite range scheduling problem [162], multi-objective satellite data transmission scheduling problem [163], satellite scheduling of large areal tasks [164], operating room scheduling [165], [166], harvest scheduling problem [167], energy-efficiency scheduling problem [168], [169] scheduling of demand response programs [170], [171], economic dispatch problem [172], order scheduling problem [173], preventive maintenance scheduling [174], [175] resource-constrained discrete time-cost-resource optimization [176], time-cost-quality trade-off problem [177], [178], production-distribution scheduling problem, [179], job scheduling in computational grid [180], contraflow scheduling problem [181], practical scheduling release times in steel plants [182], real-time routing selection [183], resource scheduling in fog computing [184], inter-site earthmoving optimization [185], process planning and scheduling [186]–[188], cross-trained workers scheduling [189], cross-docking scheduling [190], workforce scheduling problem [191], multi-objective optimized operation of integrated energy system with hydrogen storage [192] and multi-objective integrated optimization of configuration generation and scheduling [193].

The remaining problems, which are combinations of the above six MOCOPs, are considered under the category of miscellaneous problems. The problems included in this category are resource allocation supply chain scheduling and VRP [194], resource allocation and activity scheduling for fourth-party logistics [195], sustainable hub location-scheduling problem for perishable food supply chain [196], routing and scheduling of ships [197], location-routing problem [118], [198]–[202], integrated maintenance scheduling and VRP [203], travelling thief problem [204], lock scheduling and berth allocation [205], assignment-allocation [206], nursing home location-allocation problem [207], location-allocation

TABLE 5. Definitions of combinatorial problems.

Problem	Definition
Assignment Problem	In this problem, n tasks are to be assigned to n agents, such that an agent can perform at most one task, and a task can be performed by at most one agent such that the total cost of assigning the tasks to the agents is minimized.
Allocation Problem	This problem is concerned with the allocation of limited resources among the activities such that the return from the activities is maximized.
Travelling Salesman Problem (TSP)	In TSP, a salesperson has to visit a given set of cities (each city exactly once) and return to the origin city with an objective to find the shortest route.
Vehicle Routing Problem (VRP)	The VRP is the generalization of the TSP. In VRP, the objective is to find the optimal set of routes for a fleet of vehicles to serve a set of customers satisfying the given constraints.
Scheduling Problem	The task is to determine the processing sequence of a set of N jobs on a set of M machines such that a given criterion is optimized. The scheduling problems are categorized into different groups concerning the machine environment (job shop, flow shop, open shop, etc.), job characteristics (no. wait, setup times, precedence, etc.), and optimality criteria (makespan, total flowtime, etc.).
Knapsack Problem	The objective of this problem is the selection of P out of Q items for the knapsack of a fixed capacity W, where each item i has a fixed weight w_i and a fixed value v_i such that the total value of the selected items is maximized.

TABLE 6. Summary of reviewed papers using conventional NSGA-II for MOCOPs.

Ref.	Problem	k	Test problems	Compared algorithms
[51]	Assignment Problem	2	-	-
[49]		5	-	MOPSO, WSM & ECM
[58]		2	-	-
[65]		2	Designed Experimental Scenarios	GA
[53]		3	20 new instances were proposed based on random data	GRASP
[80]	Allocation Problem	2	Cold standby & Hot standby system	SPEA-II
[154]	Scheduling Problem	2	Randomly Generated	NSPSO
[171]		2	-	NSGA-II different configurations
[185]		2	-	-
[174]		2	Designed Numerical Example	-
[97]	Knapsack Problem	2	-	-
[122]	VRP	2	Solomon datasets[1]	NSGA-II with different DM preferences
[199]	Miscellaneous	3	Randomly Generated	MOPSO
[197]		2	Problem instances are developed	MOPSO

problem [208], high-level synthesis problem [209], industrial hazardous waste location- routing problem [210], and multi-objective RWA network design problem [211].

1) CONVENTIONAL NSGA-II FOR MOCOPS

This section presents a detailed study of the conventional NSGA-II implementation to MOCOPS. The summary of the related literature is shown in Table 6.

a: ASSIGNMENT PROBLEM

In [49], Azadeh *et al.* utilized NSGA-II to solve a large-sized cell formation problem, a traditional problem of assignment of parts, operators, and machines to the cells. In this study, the operators' personality and decision-making styles, expertise in dealing with machines, and job security are also incorporated, which demonstrates the novelty of the proposed model. The results were validated using NSGA-II, multi-objective PSO (MOPSO), weighted sum method (WSM), and epsilon constraint method (ECM). Out of these methods, the metaheuristic approaches outperformed the classical approaches.

Zhang *et al.* [65] used NSGA-II to optimize multi-stage assignment for emergency rescue teams in the disaster chain. The proposed NSGA-II performed better than GA when compared using scenarios designed for experiments.

In [53], NSGA-II outperformed the Greedy randomized adaptive search procedure (GRASP) to solve a multi-objective oil platform location problem. Other implementations of NSGA-II to assignment problems include the load balancing of network traffic [51] and the bi-objective facility location problem [58].

b: ALLOCATION PROBLEM

Attar *et al.* [80] suggested NSGA-II for free distributed repairable multi-state availability-ReAP. The proposed approach was compared with the strength Pareto evolutionary algorithm (SPEA-II) under cold standby and hot standby scenarios using accuracy and diversity metrics. The findings obtained from the statistical analysis showed that NSGA-II was superior to SPEA-II

c: VEHICLE ROUTING PROBLEM

In [122], the researchers proposed NSGA-II with a novel framework to solve multi-objective capacitated VRP. The reference value method and ranking objective method were used to prune the size of the Pareto optimal solutions according to the preferences of the decision-maker. The efficiency of the algorithm was demonstrated using Solomon datasets, a standard instance for the capacitated VRP.

d: SCHEDULING PROBLEM

In [154], the researchers compared NSGA-II and NSPSO for Distributed heterogeneous computing systems on benchmark instances using standard performance metrics.

The compromised optimal schedules obtained by NSGA-II have better quality than the other approach.

The authors in [174] proposed a new multi-objective nonlinear model for preventive maintenance scheduling for offshore wind farms.

Here, NSGA-II was implemented to obtain the trade-off between two conflicting objectives, maximum utilization, and minimum costs.

In [185], NSGA-II was used to plan the inter-site earthmoving in which it deals with two conflicting objectives of minimizing earthmoving costs associated with cut and fill sites along with satisfactory construction schedules.

In [171], NSGA-II configurations based on different number of function evaluations were applied to solve the scheduling problem of demand resource programs in retail electricity markets. Here, the performance of the algorithm increases as the number of function evaluations increases.

e: KNAPSACK PROBLEM

In [97], two mathematical models for optimal selection of safety measures in oil and gas facilities are developed, solutions of which are obtained using NSGA-II

f: MISCELLANEOUS

Rabbani *et al.* [199] applied NSGA-II and MOPSO to the newly proposed industrial waste location-routing problem, which includes three objectives, minimization of total costs, total risk, and transportation risk for all routes. The above algorithms are applied to randomly-generated test instances for comparison based on the quantity of non-dominated solutions, CPU time, spacing, and diversity metrics using a statistical t-test. Out of these, NSGA-II outperformed MOPSO for the first three performance measures.

De *et al.* in [197] introduced a new MINLP model for the routing and scheduling of ships and solved it using NSGA-II and MOPSO. The Problem instances are developed for the verification of the proposed model and comparison of the algorithms. NSGA-II was claimed to be computationally more efficient than MOPSO for large-sized instances.

2) MODIFIED NSGA-II FOR MOCOPS

In some MOOPs, NSGA-II cannot be applied directly due to their different problem structure. For solving such problems, NSGA-II can be modified according to their requirement. Also, the performance and efficiency of conventional NSGA-II can be further improved using modifications related to initial population generation, mutation and crossover operator, crowding distance operator, selection mechanism, constraint handling technique, and many other criteria. This section presents a detailed study of the implementation of modified NSGA-II to MOCOPS. The summary of the related literature is shown in Table 7.

a: ASSIGNMENT PROBLEM

Lian *et al.* [63] proposed a new multi-objective model for the assignment of multi-skilled workers to seru production systems, considering heterogeneous workers with different work skills. NSGA-II based algorithm was tested on medium size numerical examples and applied to the proposed model. The seru swap crossover strategy and a mutation strategy designed according to the given problem were used as genetic operators for the proposed NSGA-II.

Li *et al.* [55] performed a comparative analysis of two algorithms, adaptive MOEA/D (AMOEA/D) and, adaptive NSGA-II to solve the MWTA problem. When comparing the efficiency of the proposed algorithms on MWTA instances, the adaptive NSGA-II was found better than the adaptive MOEA/D algorithm. Juan *et al.* [56] employed NSGA-II to solve a multi-objective dynamic weapon-target assignment problem (DWTA) and compared it with Monte Carlo random sampling method on DWTA instances. Jie *et al.* [57] solved a multi-objective missile-target assignment problem using three multi-objective optimization methods MOEA/D, DMOEA-εC, and NSGA-II. The computational experiments are performed, and the results claimed that DMOEA-εC and NSGA-II could find more non-dominated solutions.

Lin & Yehwas [62] used NSGA-II in integration with the Technique for order of preference by similarity to ideal solution (TOPSIS) to optimally assign transmission lines to computer/communication networks with minimum cost and maximum network reliability. The uniform and simple mutations principles and SPX were used for the proposed NSGA-II. Martínez-Vargas *et al.* [64] proposed NSGA-II for efficient bandwidth distribution to the spectrum sharing network. Four-point binary crossover, Laplace crossover, and non-uniform mutation were used as NSGA-II genetic operators. The proposed algorithm was compared with the weighted sum approach (WSA) and parallel cell coordinate system adaptive multi-objective PSO (pccsAMOPSO) using different SA cases where NSGA-II outperformed all the comparative algorithms.

Cao *et al.* [60] suggested NSGA-II for the spatial optimization problem of optimal land-use allocation. The single parent crossover and two mutation operators, mutation of patch cells, and mutation by constraint steering were used as genetic operators of NSGA-II.

Goyal *et al.* [61] proposed a two-phase decision framework for optimal configuration selection for the reconfigurable manufacturing system (RMS). In the first phase, NSGA-II was used with a two-point crossover (TPX) to obtain the Pareto optimal solutions, and in the second phase, the entropy weight method and TOPSIS were used to rank the Pareto optimal solutions. The apparent trade-off obtained using the above procedure helped in enhancing the decision quality in the RMS.

Azadeh *et al.* [47] used NSGA-II and MOPSO to solve a newly proposed model for cell formation and worker assignment problem in the field of dynamic cellular manufacturing systems. Test problems were randomly generated for the validation and verification of the proposed model and solution methods. The performance metrics such as the quantity of non-dominated points, CPU time, spacing & diversity metrics were used to compare the algorithms. Based on the comparison results, the authors claimed to use NSGA-II to provide

TABLE 7. Summary of reviewed papers using modified NSGA-II for MOCOPs.

Ref.	Problem	k	Test problems	Compared Algorithms/Other Algorithms
[63]	Assignment Problem	2	Randomly Generated	Branch & bound technique
[55]		2	MWTA instances	AMOEA/D
[62]		2	Three real computer networks: ARPA, OCT & TANET	SPGA-II
[64]		2	Cases defined for Spectral assignment problem	WSA & pccsAMOPSO
[61]		3	-	-
[60]		3	-	-
[47]		3	Randomly Generated	MOPSO & WSM
[52]		3	-	-
[46]		2	GAP Benchmark instances[2]	NSGA-II
[56]		3	DWTA instances	Monte Carlo method
[57]		2	Simulation Example	MOEA/D, DMOEA-εC & a rule based assignment
[89]	Allocation problem	3	Semi Hypothetical Dataset	NSGA-II
[76]		2	Created from existing single-objective RAP, benchmark systems lev-4 & lev-5	NSGA-II
[74]		2	Randomly Generated	MOPSO, MOHS
[67]		3	-	-
[66]		3	-	-
[90]		3	-	-
[73]		2	Test scenarios	FEM, SPEA II
[68]		3	Synthetic workload, driven from real-world references	NSGA-II, MOPSO, SPEA-II & PAES
[81]		2	Thirty RMMRAP test instances	ECM
[70]		2	WS-Dream, simulated datasets	NSGA-II with different mutation operators
[93]		2	From literature & randomly generated instances	NSGA-II, NSGA-III, GA-SF, GA-PF, ALNS & Branch & Bound method
[78]		2	Test Problem from literature	Solutions from previous literature
[77]		2	-	-
[79]		2	Test problems from literature	GA
[91]		2	-	FTCA model, the Reliability model
[69]		2	-	-
[82]		2	Two parallel-series systems as benchmark problems	Single objective K-Y & R-M algorithms
[71]		3	-	-
[84]		2	-	-
[75]		2	-	-
[85]		2	A numerical example with 10 k-out-of-n subsystems in series	Three GAs based on NSGA-II
[86]		2	Benchmarks: series system, series-parallel system & complex (bridge) system	Compared with results in the literature
[123]	VRP	2	Solomon Examples[1]	NSGA-II
[117]		5 to 3	Artificial instance	Random Method
[116]		5	Artificial instance	SPEA-II
[124]		2	Build a test case using data from a trade company	-
[113]		2	-	-
[112]		2	Benchmark data sets[3]	Crisp & type-1 fuzzy set based NSGA-II
[115]		4	-	-
[114]		2	Real-world Instance	NSGA-II & SPEA-II
[106]	TSP	2	Mutilple TSP Benchmarks from Literature[4]	P-ACO,MACS,PMX-X, g-MinMaxACS, CPLEX MinMax SD-MTSP,CPLEX MinMax SD-MTSP
[192]	Scheduling Problem	2	-	NSGA-II
[150]		2	Real-world TTSP Experiment & a TTSP for 2 units under test UUTs	GA, Genetic simulated annealing algorithm (GASA)
[141]		2	iMOPSE Benchmark Dataset[5]	DEGR, NSGA-II
[136]		2	Standard benchmark instances[6]	NSGA-II

[2] http://people.brunel.ac.uk/~mastjjb/jeb/info.html
[3] http://www.apollo.management.soton.ac.uk/prplib.htm
[4] https://profs.info.uaic.ro/~mtsplib/
[5] http://imopse.ii.pwr.wroc.pl/download.html
[6] http://www.ie.osakafu-u.ac.jp/~hisaoi/ci_lab_e/index.html

TABLE 7. *(Continued.)* **Summary of reviewed papers using modified NSGA-II for MOCOPs.**

[139]		3	Problem instances from (PSPLIB)[7]	AUGMECON2, MOPSO
[151]		2	Experiment	NSGA-II, NSPSO
[177]		3	Test Instances generated through RaGEN software	ECM
[126]		2	Randomly Generated	AUGMECON
[181]		2	-	NSGA-II
[155]		3	Experiment conducted through randomly generated data	NSGA-II & SPEA-II
[184]		2	Simulation Scenario	RANDOM, FIRMM
[189]		2	Experimental test	NSGA-II
[144]		2	-	-
[127]		2	Modified Deterministic FJSPs into Stochastic Problems	NRGA
[188]		2	Randomly Generated	Controlled elitist NSGA, NSGA-II
[125]		3	Test Problems	SPEA-II, MOPSO & AUGMECON
[178]		3	-	-
[159]		2	Randomly Generated	AUGMECON, Constructive Heuristic Method
[160]		2	New Test Cases	MOGA, PSO
[143]		2	Real agricultural example	-
[164]		4	-	GA & Greedy Algorithm
[165]		2	-	-
[170]		2	-	WSM (Reference set)
[176]		3	-	-
[146]		2	Sample network case	Enumeration Method
[180]		2	-	GA
[187]		3	-	-
[169]		2	-	Normal GA + periodic, Right shift
[149]		2	Numerical & Real-world Examples	Crisp and type-1 fuzzy set based NSGA-II
[193]		2	-	-
[147]		3	Randomly Generated Numerical example	MOPSO
[191]		2	Randomly Generated	-
[183]		5	-	GA
[161]		2	Randomly generated instances for unrelated parallel machine	-
[145]		2	Benchmark instances[8]	-
[104]	Knapsack Problem	2	Schaffer function	WSM, NSCSA, & NSHCSA
[94]		2	Real-world RALIC project & Random Datasets	NSGA-II, Archive-Based NSGA-II
[102]		2-10	Multi-objective 500-item 0/1 knapsack problems[9]	NSGA-II
[103]		2	Multi-objective 500-item 0/1 knapsack problems[9]	Modified NSGA-II
[95]		2	Testbed of Mobile Device	Branch & Bound Technique
[96]		3	-	Meshgi's method, Zhao's method
[99]		2-10	500-item 0/1 knapsack problems with 2, 4, 6, 8, 10 objectives	NSGA-II
[100]		8	Generated eight-objective knapsack problems with 500 items	NSGA-II
[205]	Miscellaneous	2	-	Binary NSGA-II, Binary MOEA/D, Non dominated sorting binary DE (NSBDE)
[195]		3	-	-
[212]		2	Randomly Generated	SPEA
[203]		2	Sample test problems	ECM
[202]		2	Sample test problems	MOPSO
[200]		3	Randomly Generated	NSDE
[204]		2	Randomly Generated	Greedy Method, ISA, ISA-LOCAL
[196]		3	CAB & AP datasets[10]	AUGMECON
[209]		2	-	-
[206]		2	Randomly Generated	Weighted Metric Approach
[207]		2	-	ECM, Multi-objective simulated annealing (MOSA)
[198]		2	Randomly Generated	SSPMO, WSM & ECM

[7] http://www.om-db.wi.tum.de/psplib/main.html
[8] http://www.om-db.wi.tum.de/psplib/getdata_sm.html
[9] https://sop.tik.ee.ethz.ch/download/supplementary/testProblemSuite/
[10] http://people.brunel.ac.uk/~mastjjb/jeb/orlib/phubinfo.html

a better quality of non-dominated solutions for large-sized problems.

In [46], an integer enhanced NSGA-II was proposed to solve the newly formulated multi-objective generalized assignment problem (GAP) with the additional objective of equilibrium. The proposed algorithm outperformed NSGA-II on six instances of the OR-Library. In [52], the authors utilized NSGA-II to solve the platform-assignment problem.

b: ALLOCATION PROBLEM

Song & Chen [89] developed a modified NSGA-II for the multi-objective land allocation problem. NSGA-II was modified with knowledge-informed initial population, crossover, and mutation operators and compared with classical NSGA-II. The results claimed that the knowledge-informed NSGA-II produced better solutions than conventional NSGA-II in terms of proximity to the Pareto front and computational time.

Sun *et al.* [76] implemented a modified NSGA-II on the ReAP in a multi-state series-parallel system under epistemic uncertainty to maximize the extremum of system availability under cost constraint. A repair operator was used in the crossover operation, and a local search operator was used in the mutation operation. The proposed algorithm was compared to the standard NSGA-II for the established benchmark instances and exceeded it in terms of performance measures. Ghorabee *et al.* [85] considered a bi-objective ReAP with k-out-of-n systems and solved it using NSGA-II based algorithm. Based on modifications related to diversity preservation and constraint handling, four methods were developed, and among them, the algorithms with modified crowding distance and modified constraint handling methods provided the best results. In [74], Alikar *et al.* proposed a new inventory ReAP with two objectives, i.e., minimizing overall costs and maximizing overall system reliability. Three multi-objective algorithms, NSGA-II, MOPSO, and MOHS, were used to solve the above-mentioned problem. Since there are no benchmarks available in the literature, comparisons between algorithms were made on randomly generated numerical examples, and NSGA-II was found to be better than the other algorithms. Madjid *et al.* [81] developed customized NSGA-II for a newly proposed multi-objective model on repairable multi-state ReAPs. The constraints are handled using a combination of modification strategy and penalty strategy. The proposed approach was compared with the ECM using 30 RMMRAP test instances of three different sizes, small, medium, and large. NSGA-II outperformed ECM for all the instances, and the results of ECM for large-sized instances were not even acceptable. Ardakan *et al.* [77] used NSGA-II to address the bi-objective ReAP with a new mixed redundancy strategy. Here, the TPX and a modified version of the max-min crossover and max-min mutation were used as genetic operators for the proposed algorithm. Safari *et al.* [79] introduced NSGA-II to solve the multi-objective ReAP. The proposed approach was compared with GA on a numerical example taken from literature. The uniform crossover (UX), modified UX, and max-min mutation were used for NSGA-II. The robustness of the proposed algorithm was evaluated using the ANOM technique. Solutions obtained using the proposed algorithm dominates the solution obtained by GA. Kayedpour *et al.* [84] applied NSGA-II to the multi-objective ReAP considering designing systems. The SPX and TPX were used as crossover operators, and bit-inversion, bit-reversal and random permutation mutation operators were used as mutation operators. Wang *et al.* [82] proposed NSGA-II for a multi-objective ReAP in Parallel-series systems. The SPX and bitwise mutation operators were used as genetic operators for NSGA-II. The proposed approach performed better than the two single-objective algorithms, K-Y and R-M algorithms, on the parallel-series system' benchmark problems. In [78], NSGA-II was developed to solve the ReAP with non-homogeneous components. The TPX and max-min crossover were used randomly for the selected parents, and then the general mutation and max-min mutation were also randomized. Here, all the best solutions found in previous studies are dominated by the solutions obtained using NSGA-II. In [75], a ReAP was addressed in which NSGA-II was implemented along with the k-means clustering algorithm to prune the size of the Pareto optimal solutions to ease the decision-making process.

Tian *et al.* [67] suggested a multi-objective terminal area RAP and optimized it using NSGA-II. Linear recombination crossover operator and stochastic mutation operator were used in the proposed algorithm. In order to handle the complexities of RAP, Datta *et al.* [66] proposed a problem independent NSGA-II–RAP algorithm similar to the conventional NSGA-II. They implemented it to real instances of IIT Kanpur class timetabling and land uses allocation in the landscape, located in Baixo Alentejo, Portugal. NSGA-II-RAP algorithm has a block-based crossover operator and PLM as genetic operators. The authors claimed that the developed algorithm has a tendency of multiple allocations to some resources in both instances. Afrin *et al.* [68] addressed the multi-objective RAP for robotic workflow in a smart factory. Here, NSGA-II was modified in terms of the initial population, chromosome representation, and mutation operator. The proposed algorithm outperformed the benchmark NSGA-II, MOPSO, SPEA-II and PAES by at least 18 % in optimizing the objective functions of various synthetic and real-world scenarios. In [69], NSGA-II was used to solve the multi-objective RAP in multiple input multiple output orthogonal frequency division multiple access systems. The SPX and bitwise mutation operators were used as genetic operators for NSGA-II. Zheng *et al.* [71] implemented NSGA-II to solve energy-aware RAPs in a cloud manufacturing environment. The best optimal solution was then achieved using TOPSIS. The TPX operator and mutation operator based on the concepts of simple mutation and uniform mutation were used as genetic operators. The effectiveness of the proposed approach was validated using a case study of supply chain service of a high-speed train in cloud manufacturing.

To optimize cloud resource usages, Tan *et al.* [70] developed genetic operators for NSGA-II to solve web service RAP in the cloud environment. The suggested approach did not include any crossover operator. The results of the proposed algorithm outperformed the results obtained from different variants of the algorithm.

In [86], the authors formulated a reliability-redundancy allocation problem with a cold-standby strategy and solved it using NSGA-II with modified genetic operators and penalty function method for constraint handling. The solution obtaining using the proposed method outperformed the best solution available in the literature.

Ji [93] modified the elite preservation strategy of NSGA-II and designed an archive for bias search in the direction of a feasible solution to solve the continuous berth allocation problem. The proposed algorithm outperformed NSGA-II, NSGA-III, GA with the suitability of feasibility (GA-SF), GA with penalty functions (GA-PF), adaptive large neighbourhood search (ALNS), and Branch and Bound on both randomly generated instances and instances taken from literature.

In [207], the nursing home location and allocation problem was explored using NSGA-II with designed crossover and mutation operators. The proposed NSGA-II was compared to an enhanced and designed SPEA-II algorithm. The findings of a case study based on two data sets showed that for small-scale problems, ECM was superior, but for large-scale problems, NSGA-II better approximate Pareto optimal solutions than SPEA-II.

Habib *et al.* [73] proposed design optimization of repairable k-out-of-n subsystems using NSGA-II with two different constrained handling techniques, penalty method and constraint domination principle (CDP). These two approaches were compared with the SPEA-II algorithm, and also the full enumeration method (FEM) was used for obtaining the true Pareto front. The simulation results showed that NSGA-II had all the exact non-dominated solutions for small and moderate instances. However, for large-sized instances, NSGA-II with penalty function provided better quality solutions in less computational time, and NSGA-II with CDP provided better uniform spread in comparison to SPEA-II

In [91], NSGA-II was used for multi-objective channel allocation problem to mobile hosts in a mobile computing network. The SPX and bitwise mutation operators were used as genetic operators for NSGA-II. Based on the results, NSGA-II provided better objective-values than the two existing models, the FTCA model, and the reliability model.

Shahryari *et al.* [90] suggested NSGA-II for allocating D-STATCOM in distribution systems and used fuzzy decision-making to obtain the best compromise solution. Here, arithmetic crossover and uniform mutation were used as genetic operators for the proposed algorithm.

c: VEHICLE ROUTING PROBLEM

Shamshirband *et al.* [123] proposed a new multi-objective VRP model with contradictory goals of reducing travel costs and optimizing demand coverage. Two approaches based on NSGA-II were developed using two different neighbourhood structures for mutation operators. In the first method, the 2-Opt structure was used as a mutation operator, and in the second method, three neighbourhood structures of 2-Opt, 2-Opt∗, and Or-Opt∗ were used as a mutation operator. The second method was dominant over the first method (in terms of spread and set coverage metrics) on typically created examples. Xu *et al.* [124] established a two-layered model for the VRP in which the first layer is a multi-objective model, which was handled using fast NSGA-II with a TPX and swap mutation operator.

Li *et al.* [113] presented NSGA-II for multi-objective ship weather routing problem to obtain Pareto optimal routes sets. The arithmetic crossover and mixed mutation combining the uniform mutation and Gaussian mutation were used as genetic operators for NSGA-II. The demonstration of the proposed algorithm was conducted using simulation experiments.

The VRP with demand responsive transport (VRPDRT) was proposed in [116], which was solved using NSGA-II and SPEA-II algorithms. Here, the TPX and 2-shuffle mutation were used as genetic operators for NSGA-II. The use of hypervolume performance measure and the statistical test showed that NSGA-II has greater convergence as compared to SPEA-II. Mendes *et al.* [117] addressed VRPDRT systems. Initially, they transformed the five-objective optimization problem into a three-objective optimization problem using objective functions aggregation. The random method and NSGA-II were then compared to solve the above three objective optimization problems using the set coverage metric. The results showed that the proposed NSGA-II exceeded the random method in obtaining a set of non-dominated solutions to the given problem.

Shukla *et al.* [112] used NSGA-II to solve a fuzzy pollution routing problem with high order uncertainty. Here, the partially mapped crossover (PMX) and swap mutation were used as genetic operators for NSGA-II. Simulation experiments were conducted in which type-2 fuzzy set based NSGA-II was more efficient than the crisp and type-1 fuzzy set based NSGA-II.

Liu *et al.* [115] proposed a four-objective dynamic routing planning problem in which a novel objective was considered for simpler routing and better user experience. NSGA-II was designed and used a node-based crossover operator to solve the proposed model to obtain a trade-off among the four objectives.

Miguel *et al.* [114] addressed a multi-depot time-dependent capacitated VRP with time windows problem in urban freight transport planning. A hybrid variant of NSGA-II was developed that incorporated the knowledge information of the problem in the chromosomes and used a newly designed ERX-MD recombination operator. A g-dominance strategy was also used to introduce the preference of the decision-makers. This proposed variant was compared with NSGA-II and SPEA-II using the hypervolume measure on real-world problem instances. The results claimed that the proposed algorithm outperformed the other algorithms.

d: TRAVELLING SALESMAN PROBLEM

Shuai *et al.* [106] proposed an NSGA-II based algorithm for multi-objective multiple TSP (MTSP) in which a novel crossover operator, called combined HGA and two mutation operators were designed to improve the global and local search capability of the algorithm. In addition, to demonstrate the effectiveness of the proposed algorithm, benchmark instances are used to compare it with five state-of-the-art algorithms from the literature. The proposed modified NSGA-II performed better than those five algorithms, out of which four algorithms are based on ant colony optimization (ACO), i.e., MoACO/D-ACS, MACS, g-MinMaxACS, and MoACO/D-ACS, and one algorithm is CPLEX MinMax SD-MTSP from CPLEX solver.

e: SCHEDULING PROBLEM

Lu *et al.* [150] proposed chaotic NSGA-II (CNGA) for automatic test task scheduling problem (TTSP) to improve the quality of solutions and also to avoid the problem of falling in local optima. Because chaotic maps were embedded as number generators instead of random number generators, chaotic variables were used instead of random variables. The proposed algorithm was tested on a real-world TTSP Experiment & a TTSP for two units under test. The proposed CNSGA algorithm has better local search capability than NSGA-II due to the ergodicity and pseudo-randomness of chaos. Salimi *et al.* [151] used fuzzy adaptive operators in NSGA-II to solve the task scheduling problem in computational grids. Classical NSGA-II and NSPSO algorithms were used for comparison with the proposed NSGA-II, and the results showed that the proposed approach outperformed the other algorithms in terms of convergences speed and quality of Pareto optimal solutions. Shukla *et al.* [149] implemented NSGA-II for the energy-efficient multi-objective task scheduling of the industrial system. The PMX and swap mutation were used as genetic operators for NSGA-II.

Vanucci *et al.* [144] studied multi-mode RCPSP (MRCPSP) and found its solutions using the modified NSGA-II. NSGA-II was modified using a problem-specific crossover and mutation operator and well as an encoding/decoding scheme used for problem representation.

Laszczyk & Myszkowski [141] proposed three modifications in the NSGA-II selection method for optimizing multi-objective multi-skilled RCPSP (MS-RCSP). Firstly, they increased the population size for tournament selection and eliminated the non-dominated sorting procedure; Secondly, they use a clone prevention method to replace the crowded distance operator to monitor the population for clones; and thirdly, they use a rank comparison operator. The proposed algorithm was compared to multiple runs of single-objective hybrid differential evolution with the greedy algorithm (DEGR) and proved useful for MS-RCSP. Wang *et al.* [143] suggested NSGA-II for RCPSP with multiple activity performance modes that were tested using an agricultural example. Damak *et al.* [145] designed NSGA-II to solve bi-objective multi-mode RCPSP with two objectives of minimizing makespan and non-renewable resource cost.

Habibi *et al.* [139] used arithmetic crossover and Gaussian mutation for population generation in NSGA-II to handle the integrated framework of project scheduling and material ordering problems with sustainability considerations. The modified NSGA-II was compared with the second version of the augmented ECM (AUGMECON2) for small problems and the modified MOPSO algorithm for large problems. The authors' results stated that the proposed NSGA-II outperformed the MOPSO algorithm in most performance metrics for all problem sizes.

Chang *et al.* [136] integrated NSGA-II with an artificial chromosome generation method to solve the multi-objective FSP. The proposed approach has better convergence and solution quality as compared to the classical NSGA-II.

In [127], the researchers solved a multi-objective flexible JSSP for random machine breakdown. NSGA-II and non-dominated ranking genetic algorithm (NRGA) were compared to solve the problem in which NRGA was better in terms of diversity metric and time, and NSGA-II was better in terms of spacing metric, MMID, and the number of Pareto optimal solutions. The genetic operators selected for this study are precedence preserving order-based crossover, modified position-based mutation, and machine-based mutation. According to Li *et al.* [160], NSGA-II was found better than the multi-objective GA (MOGA) and PSO for energy-conscious production in flexible machining job shops considering dynamic job arrivals and machine breakdowns. The operation-based order crossover (OX), job position mutation, and process plan mutation were used as genetic operators for the proposed NSGA-II.

Azadeh *et al.* [126] introduced a new bi-objective mixed-integer open shop scheduling problem and solved it using an extended NSGA-II in which the initial population was generated differently to improve algorithm speed, simulated annealing crossover operators, and variable neighbourhood search (VNS) mutation operator were used. To validate the proposed algorithm's efficiency, small, moderate, and large-sized instances were randomly generated, and augmented ECM (AUGMECON) was used for the comparison. The results showed that the proposed NSGA-II has high efficiency. Sheikhalishahi *et al.* [125] suggested an open shop scheduling problem model, considering human error and preventive maintenance that explicitly relates human error to open shop scheduling. NSGA-II, MOPSO, and SPEA-II were compared to solve the model on large-sized test instances, and the AUGMECON was used for small instances to validate the model. The genetic operators used for NSGA-II were SPX, arithmetic crossover, and swap mutation. For large instances, NSGA-II performed better than MOPSO and SPEA-II. Also, a real case study was used to find the preferred set of solutions.

Bandyopadhyay & Bhattacharya [155] formulated a three-objective parallel machine scheduling problem. and for its solution, they introduced a new mutation algorithm in NSGA-II, in which the mutation was applied to the entire population. This modified NSGA-II was compared to conventional NSGA-II and SPEA-II, and the results showed that the proposed algorithm outperformed the other algorithms. In [161], the authors investigated the conjecture that it could be worthy of using geometric-based operators in NSGA-II for solving scheduling problems in parallel machines (both identical and parallel).

Dou *et al.* [193] used NSGA-II with SBX operator and order mutation to solve a scheduling problem in RMS.

The researchers in [181] proposed a solution algorithm enhancing NSGA-II to solve the multi-objective contraflow scheduling problem. This solution algorithm incorporated preliminary results as prior information and included a meta-model as an alternative to objective evaluation through simulation. The proposed enhanced NSGA-II outperformed the original NSGA-II both in terms of convergence and diversity metrics.

Sun *et al.* [184] used NSGA-II with an improved crowding distance operator for fog computing resource scheduling. The proposed NSGA-II outperformed the random scheme and fog-based IOT resource management model (FIRMM).

In [188], the controlled elitist NSGA-II improved the multi-objective process planning and scheduling in manufacturing systems to consider the problem's computational intractability. The proposed algorithm was compared to the controlled elitist NSGA-II and NSGA-II for test cases, and the results indicated that the proposed algorithm provided more optimal and robust solutions.

Ruiming [192] suggested an improved NSGA-II that improves the solution diversity and convergence for multi-objective dynamic scheduling problem in an integrated energy system. An interactive strategy using an external archive to update the solution helped prevent local optimization. The authors used the traditional NSGA-II to compare the non-dominated solutions with the proposed algorithm and found that the improved NSGA-II has a better exploration ability and uniform spread of solutions.

In [189], Xu *et al.* investigated cross-trained workers scheduling problem for field service. An improved NSGA-II with dynamic crowding distance, multiple sorting principles, and adaptive tournament selection proved better than NSGA-II on an experimental test using performance metrics. In [147], a new multi-objective model was proposed for cross-docking scheduling problems in the supply chain. NSGA-II and MOPSO were implemented to solve the model and compared using a numerical example. The authors claimed that NSGA-II was found to be superior to the other algorithm.

Ghoddousi *et al.* [176] introduced a multi-mode resource-constrained discrete time cost resource optimization model and used NSGA-II to obtain the Pareto optimal solutions. The SPX crossover and a designed mutation operator were used to deal with the problem. In [178], an integrated framework of the MCDM methodology and multi-objective approach was proposed to obtain a single Pareto optimal solution for discrete-time-cost-quality trade-off problems (DTCQTPs). The Pareto optimal solutions obtained from NSGA-II were ranked using elective reasoning utilizing the weights obtained by the entropy weight method. This decision provided a better solution compared to the existing result. Here, TPX and swap mutation were used as the genetic operators for NSGA-II. A new multi-objective multi-mode model for DTCQTPs was proposed in [177], and a dynamic self-adaptive NSGA-II was implemented to solve the proposed model compared to an efficient ECM.

Mohapatra *et al.* [187] dealt with the optimization of adaptive setup plan in manufacturing system concerning the makespan, machining cost, and utilization of the machine. NSGA-II obtained the best compromise solution for the problem using SPX and bitwise mutation operators.

Niu *et al.* [164] suggested the NSGA-II algorithm for satellite scheduling of large areal tasks. TPX and single-point mutation operators were used as genetic operators. The proposed NSGA-II outperformed the two state-of-the-art approaches, the GA and the greedy algorithm, in finding the best compromised optimal schedules.

Kaushik & Vidyarthi [180] proposed a multi-objective resource allocation model for computational grid scheduling using a dynamic resource allocation scheme. Further, NSGA-II used to optimize this model proved better than GA as it offered alternative trade-off solutions instead of a single best compromise solution. Here, UX and random BFM were used as the genetic operators for NSGA-II

Wang *et al.* [169] suggested a real-time energy efficiency optimization method based on NSGA-II for energy-intensive manufacturing enterprises. Here, a multi-point crossover operator is used to schedule the production plans in an energy-efficient manner to achieve real-time key performance indicators relevant to enterprise information systems' energy.

Wang *et al.* [159] proposed NSGA-II for optimal production scheduling with designed initialization, crossover, and three mutation operators. The proposed algorithm was compared with AUGMECON for small-sized instances and with the constructive heuristic method for medium and large-sized instances. The conducted experiment showed that for medium and large-sized instances, NSGA-II performed better than the constructive heuristic method in terms of the number of non-dominated solutions and D_R metric.

Malik *et al.* [165] suggested NSGA-II having a multi-point crossover operator for solving the MOOP of elective surgeries scheduling of the operating room to minimize the number of patients waiting for elective surgery and the associated costs.

Wu *et al.* [146] proposed a new multi-objective model to re-synchronize the bus timetable for the bus transit company. A problem-designed NSGA-II was used to find the Pareto optimal front and compared it with the classical FEM. In terms of solution quality and convergence speed, the proposed NSGA-II was found better than the FEM.

The researchers in [170] used NSGA-II to schedule short-term incentive-based demand resource programs in retail electricity markets. Here, arithmetic crossover, Gaussian mutation, and binary mutation were used as genetic operators for NSGA-II.

In [191], a novel bi-objective optimization model was proposed for workforce scheduling in the seru production system (SPS). Here, improved ECM and NSGA-II were used to provide Pareto optimal solutions for small-sized and large-sized problem instances, respectively.

Souier *et al.* [183] developed a decision support system for the best solution to the multi-objective problem of selecting multiple routing for a flexible manufacturing system in an uncertain environment. NSGA-II has better performance than the GA in obtaining the trade-off solutions to the problem.

f: KNAPSACK PROBLEM

Zhang *et al.* [94] introduced a repair method based on NSGA-II for requirements interaction management based selection and optimization method. The proposed method was compared with conventional NSGA-II and archive-based NSGA-II on RALIC data sets and 27 combination random data sets using convergence and diversity performance measures and Kruskal–Wallis test. The results demonstrated that NSGA-II performed better than the other two methods.

Changdar *et al.* [104] proposed a modification in the refinement operation of NSGA-II for a multi-objective vegetable wholesaling problem. The authors claimed that the proposed algorithm was better than WSM, non-dominated sorting cuckoo search algorithm (NSCSA), and non-dominated sorting hybrid cuckoo search algorithm (NSHCSA) using benchmark instances.

In [103], the authors studied that the performance of NSGA-II was better using the non-geometric binary crossover with the geometric standard UX. The experiments were performed on a bi-objective 500-item 0/1 knapsack problem. Ishibuchi *et al.* [99] used the weighted sum fitness functions for parent selection and generation update of NSGA-II. The researchers investigated that the method mentioned above helped introduce additional selection pressure towards the Pareto front and improved the scalability of NSGA-II for many-objective 0/1 knapsack problems. Tanigaki *et al.* [102] used a preference-based mechanism instead of crowding distance for selection and population updates in NSGA-II. The modified NSGA-II experimented with benchmarked instances for many-objective knapsack problems and performed better than the traditional NSGA-II.

Murata & Taki [100] examined the effect of objective reduction technique using correlation-based WSM on many-objective knapsack problems. The eight objectives were divided into two groups, and the objectives of individual groups were aggregated using the WSA, and then NSGA-II was used to obtain the non-dominated solutions. The NSGA-II results on the aggregated problem were compared with its results on the problem with eight objectives which showed that after aggregating the objectives into two groups, the average value of objectives improved.

A new multi-objective resource allocation model on mobile cloud computing is presented in [95], including minimizing task completion time and the energy consumption of all participating mobile devices. A two-stage decision framework was developed in which NSGA-II was implemented in the first stage, and the second was based on TOPSIS, and entropy weight. The UX operator and the PLM operator were used as genetic operators for the proposed NSGA-II. The reference Pareto optimal solutions obtained using branch and bound algorithm were used to test the proposed algorithm' efficiency.

The researchers of [96] exploited NSGA-II to solve the multi-objective resource management problem of a device to device (D2D) multicasting, a knapsack problem concerned with the channel/power allocation to D2D links in such a way that the spectrum and energy efficiency are optimized. The outer layer crossover and designed mutation were used as genetic operators for NSGA-II. The simulation experiment results in the superior performance of NSGA-II as compared to other methods.

g: MISCELLANEOUS

Liu *et al.* [195] developed a new multi-objective resource allocation and activity scheduling model for fourth-party logistics. An improved NSGA-II developed using the improved precedence operation and multi-point preservative crossovers, and insertion and replace mutations were used to solve the proposed model.

Rashidnejad *et al.* [203] proposed an integrated vehicle routing and maintenance scheduling problem. The authors suggested an advanced NSGA-II in which a heuristic was used to produce the initial population, a novel route insertion crossover operator and three new mutation operators (rows swap, partially rows swap and exchange routing) were proposed for the offspring generation. The proposed approach was compared with ECM, and the results are admissible in terms of convergence and diversity metrics.

In [202], NSGA-II and MOPSO were proposed to solve a new bi-objective model for location-routing-problem in waste collection management. These proposed algorithms were compared using sample test problems in which NSGA-II outperformed the MOPSO algorithm.

Ji *et al.* [205] proposed a new multi-objective lock and water–land transshipment co-scheduling problem, which was decomposed into two sub-problems, lock scheduling and berth allocation. A hybrid heuristic method was proposed in which the main problem was solved using modified binary NSGA-II, and specific heuristics solved the two sub-problems. The modified NSGA-II replaces the crossover and mutation operators of binary NSGA-II with modified TPX and swap mutation operators. The feasibility of the problem model and hybrid heuristic superiority was demonstrated using instances extracted from historical data.

Li *et al.* [212] proposed PD-NSGA-II embedded with properties of non-dominated solutions provided by scheduling experts to solve the multi-objective production-distribution scheduling problem with a single machine for production and multiple vehicles for the delivery of products. The PD-NSGA-II outperformed the SPEA algorithm on various sized test problems.

The study in [200] proposed a new multi-objective location-routing model for disaster relief distribution in post-earthquake, including the location of distribution centres, vehicle routing, and scheduling. NSGA-II proposed to solve the problem has TPX and reverse sequence mutation in place of standard genetic operators. Out of the two algorithms, NSGA-II and Non-dominated sorting differential algorithm (NSDE) algorithms used to solve this problem, NSGA-II outperformed NSDE in most cases. In [198], a new transportation location-routing problem was formulated, and the methods named scatter tabu search procedure for non-linear multi-objective optimization (SSPMO), NSGA-II, WSM, and ECM were implemented to achieve a trade-off between the two conflicting objectives, cost and route balance. Computational experiments on randomly generated instances showed that NSGA-II provides efficient solutions for large instances compared to other approaches.

Pilato *et al.* [209] proposed NSGA-II for high-level synthesis (scheduling, resource allocation, and binding) of the field-programmable gate array. Here, the authors used binary crossover and unary mutation in the proposed algorithm.

Blank *et al.* [204] proposed NSGA-II for a complex bi-objective travelling thief problem, a combination of a TSP and a knapsack problem. The genetic operators used are SPX and bit-flip mutation (BFM). The proposed NSGA-II performed better than a greedy algorithm, an independent sub-problem algorithm (ISA), and ISA-local on randomly generated test instances.

In the field of system protection, Khanduzi *et al.* [206] applied the NSGA-II and Weighted metric method to solve a new integrated assignment allocation model with two objectives that maximize the sum of the efficiency of DMUs and minimize the total distance between customers and facilities. The genetic operators used in NSGA-II are TPX, single and inversion mutations. Both the above methods were compared on 48 randomly generated test instances using two performance measures, CPU time and dominance criteria, and as a result, NSGA-II outperformed the exact method in terms of computational time.

In [196], NSGA-II performed better than the improved ECM on large-sized instances for the location-scheduling problem in the perishable food supply chain. The proposed NSGA-II has SPX and shift and exchange mutation for performing genetic operations.

3) HYBRID NSGA-II FOR MOCOPS

NSGA-II is good at solving problems with large search spaces but traditionally requires substantial computational effort to find the true Pareto front. Therefore, other search methods are combined with conventional NSGA-II/ modified NSGA-II to push the non-dominated solutions towards the real Pareto optimal solutions with an acceptable computational cost. This section presents a detailed study of hybrid NSGA-II implementations to solve MOCOPs. The summary of the related literature is shown in Table 8.

a: ASSIGNMENT PROBLEM

In [48], Niakan *et al.* proposed a novel multi-objective dynamic cell formation problem considering worker's assignment, social, economic, and environmental aspects. The authors developed a hybrid algorithm combining NSGA-II with MOSA involving the standard crossover and single, multi, and inversion mutations and used randomly generated test instances and performance metrics to compare it with NSGA-II and MOSA. The obtained results showed the superiority of the proposed approach over the other compared algorithms.

In [59], Medaglia *et al.* developed a new facility location problem model and proposed two multi-objective evolutionary algorithms to obtain the set of Pareto optimal solutions. The first algorithm GA-GAH combines NSGA-II with a fast greedy fitness assignment heuristic, and the second algorithm GA-MIP combines it with a mixed-integer program (MIP) heuristic. The authors tested these two approaches on data from Boyacá's hospital waste management network. The GA-MIP was found better than GA-GAH in terms of the SSC metric. The proposed GA-MIP again compares with the non-inferior set estimation (NISE) method on publicly available instances. The GA-MIP scaled better than the NISE method on large instances and can also find non-supported solutions along with supported solutions.

Cococcioni *et al.* [50] proposed a multi-objective model for worker's risk perception and caution to improve workers' occupational safety at the workplace. They presented a modified version of NSGA-II based on mutation operator only and used semi-supervised learning to generate initial populations. After that, the best Pareto optimal solution was obtained using the TOPSIS method. Finally, the validation of the proposed methodology was carried out using data collected from small manufacturing enterprises.

Segredo *et al.* [54] suggested ways to deal with the frequency assignment problem (FAP) in designing a global system for mobile communications networks, known as automatic frequency planning and channel assignment problem. Several multi-objectivization methods integrated with NSGA-II and a novel non-destructive crossover operator (to avoid premature convergence) were proposed for the mono-objective FAP and compared with the best up-to-date sequential method on two US cities instances: Seattle and Denver. The results indicate that the proposed method has better quality and speed than other methods.

b: ALLOCATION PROBLEM

Guo *et al.* [88] merged NSGA-II with a tabu search based local improvement procedure and a self-adaptive population size adjustment process to solve a multi-objective order allocation problem. The modified mutation based on uniform mutation and fitness-based scanning crossover were used as genetic operators. The suggested approach performed better than the conventional NSGA-II and the industrial method on the performed experiment.

Su *et al.* [87] also integrated NSGA-II with tabu search (TS-NSGA-II) for the buffer allocation problem of remanufacturing systems. This TS-NSGA-II performed better than the traditional NSGA-II.

Britto *et al.* [92] proposed a hybrid approach based on NSGA-II and Mamdani fuzzy inference systems to address a team allocation problem in an agile software development project. The Mamdani fuzzy inference system was used to estimate the developer productivity.

In [83], NSGA-II was hybridized with an adaptive population-based simulated annealing (APBSA) to solve a bi-objective ReAP for systems reliability. The proposed approach was compared with three commonly known methods, MOGA, NRGA, and NSGA-II, on randomly generated test instances using four performance measures, i.e., mean ideal distance, spread, coverage metric, and data envelopment analysis. The developed hybrid algorithm outperformed the other algorithms for the last three performance measures, but NSGA-II has the best mean ideal distance. Zhang *et al.* [72] developed an NSGA-II-TRA algorithm in which a novel heuristic was used for constraint handling in NSGA-II to solve the optimal testing RAP. Also, the Z-score-based Euclidean distance is adopted to estimate the difference between solutions. The proposed algorithm was compared with two existing MOEAs, i.e., multi-objective differential evolution based on weighted normalized sum (WNSMODE) and harmonic distance-based non-dominated sorting genetic algorithm-II (HaD-MOEA), and was found better based on capacity, coverage, and pure diversity values.

c: VEHICLE ROUTING PROBLEM

Rauniyar *et al.* [111] incorporated a new paradigm of multi-factorial optimization into NSGA-II to handle the multi-objective pollution routing problem. Experiments were performed based on benchmark task sets. The proposed algorithm was compared with SPEA-II and conventional NSGA-II using performance measures to investigate the proposed approach' efficiency. Simulation results showed that the proposed method was more efficient than the other methods with faster convergence.

In [118], a mathematical formulation is devised for multi-objective VRP with the time windows model. Xu *et al.* suggested a hybrid NSGA-II in which the Or-opt heuristic was hybrid with NSGA-II to improve the quality of the solutions. The above heuristic was used in the initialization phase and also to generate mutants. This new hybrid algorithm outperformed NSGA-II on both the 30-customer and 498-customer cases. Wang *et al.* [119] designed a collaborative multi-depot VRP with time window assignment to reduce the time uncertainty, which causes operation challenges and extra cost to the logistics service provider. The authors presented a hybrid heuristic combining K-means clustering, Clarke–Wright (CW) saving algorithm, and an extended non-dominated sorting genetic algorithm-II (E-NSGA-II) for solutions to the model. E-NSGA-II combined NSGA-II with PMX, relocation, 2-opt∗ exchange, and swap mutation and compared with NSGA-II and MOPSO for its validation in which found superior to both approaches.

Wang *et al.* [120] introduced a new multi-objective model for collaborative multiple centres VRP with simultaneous delivery and pickup to minimize the operating costs and the number of vehicles in the network. They proposed a hybrid algorithm HNSGA-II combining NSGA-II with the K-means algorithm and used PMX and swap mutation operators. According to experimented results, HNSGA-II outperformed NSGA-II by 5.5% and MOPSO by 11.9% in terms of cost objective on modified Solomon benchmarks. HNSGA-II also has a high performance on a real case study in Chongqing city.

Mandal *et al.* [121] developed a memetic algorithm integrating NSGA-II with a dominance-based local search procedure (DBLSP) and a clone management principle (CMP) for a bi-objective mixed capacitated general routing problem (MCGRP). Also, three well-known crossover operators (X-set), i.e., PMX, OX, and edge recombination crossover (ERX), were used to explore the different parts of the search space. The proposed approach outperformed

XNSGA-II (NSGA-II with only X-set and CMP) on the experimental tests performed on standard MCGRP instances.

d: TRAVELLING SALESMAN PROBLEM

Chen *et al.* [110] suggested pNSGA-II, a hybrid NSGA-II, to overcome the limitations of multi-objective optimization algorithms based on GA, such as premature convergence and non-uniformly distributed solutions for bi-objective TSP (BTSP). In their work, NSGA-II was embedded with the Physarum-inspired computational model (PCM) in the initialization phase and the hill-climbing method. The proposed approach was compared with eight algorithms, including a typical GA based method HYGA, the multiple ant colony systems (MACS), Pareto ACO (PACO), three enhanced algorithms of PACO, i.e., pPACO, pMACS, and pBIANT, the bicriterion ant algorithm (BIANT) and NSGA-II. The benchmark instances were constructed using two single objective TSP instances available in the literature. The proposed algorithm pNSGA-II was found superior to the other algorithms using benchmark instances, performance measures, and statistical analysis. In [45], Moraes *et al.* proposed a subpopulation-based multi-objective approach MOEA/NSM for BTSP. This method integrated NSGA-II, SPEA-II, MOEA/D, and 2-opt local search technique was compared with NSGA-II, SPEA-II, and MOEA/D on BTSP datasets. The results showed that MOEA/NSM outperformed the other algorithms.

Li *et al.* [108] performed a comparison among NSGA-II, MOEA/D, and their variants NSGA-II-ACO and

TABLE 8. Summary of reviewed papers using hybrid NSGA-II for MOCOPs.

Ref.	Problem	*k*	Algorithms Used For Hybrid	Test Problems	Compared Algorithms
[48]	Assignment Problem	2	MOSA	Randomly Generated	MOSA, NSGA-II
[59]		2	Mixed integer programming (MIP) assignment heuristic	-	GA-GAH, NISE
[54]		2	Learning process based on a mono-objective hill-climbing local search procedure	US cities instances: Seattle & Denver	Best up to date Sequential approach
[50]		2	Semi-supervised learning	Real-World Data	-
[87]	Allocation Problem	2	Tabu Search	Five workstation line as an example	NSGA-II
[88]		3	Tabu Search	Experiments using Real-life production data from industrial practice	NSGA-II, industrial method
[92]		2	Mamdani Fuzzy Inference Systems	-	-
[83]		2	APBSA	Randomly generated test problems	MOGA, NRGA, & NSGA-II
[72]		3	Heuristic for constraint handling	Randomly generated test instances	HaD-MOEA & WNS-MODE
[118]	VRP	3	Or-opt heuristic	30-customer sample & the whole 498 customer case	NSGA-II
[121]		2	DBLSP & CMP	Benchmark MCGRP instances[11]	XNSGA-II(NSGA-II with only X-set & CMP)
[119]		2	K -means clustering & Clarke–Wright (CW) saving algorithm	Solomon datasets[1]	NSGA-II & MOPSO
[111]		2	Multi-Factorial Optimization	UK_10_01 dataset[3]	NSGA-II, SPEA-II
[120]		2	K-means algorithm	Modified Solomon datasets	MOPSO, NSGA-II
[110]	TSP	2	Physarum-inspired computational model (PCM) (initialization) & Hill climbing method (HC)(local search)	Benchmark constructed from two single objective TSP instances	HYGA, pPACO, pMACS, pBIANT, MACS, PACO, BIANT, NSGA-II
[107]		2	Heuristic principle in the initialization phase	Randomly Generated	NSGA-II
[108]		2	ACO	Benchmark constructed from two single objective TSP instances	NSGA-II, MOEA/D, MOEA/D-ACO
[109]		2	IVF	Real-world scenarios	NSGA-II, SPEA-II
[105]		2	Modified 2-opt local search & repair strategy	Modified Benchmark Instances	-
[45]		2	SPEA-II, MOEA/D & 2-opt local search	Datasets for TSP[12]	NSGA-II, SPEA-II & MOEA/D.
[131]	Scheduling Problem	3	GPHH	Test Scenarios are Designed	SPEA-II-based GPHH, WSM
[162]		2	Learning Mechanism	Constructed test cases for multiple satellites & multiple ground stations.	NSGAII, MOEA/D, multi-objective evolutionary algorithm based on dominance & decomposition (MOEA/DD) & multi-objective memetic algorithm based on decomposition (MOMA/D)
[163]		2	SVM	Randomly Generated	NSGA- II, IBEA, MOEA/D & SaMOEA/D
[134]		2	NEH	Taillard's Datasets[13]	23 ALGORITHMS
[156]		2	Multi-layer Perceptron Neural Networks	JSSP Benchmarks	Fast Pareto GA (FastPGA), Generalized Differential Evolution 3 (GDE3), Pareto Archived Evolution Strategy (PAES), improved variant of PAES (PESA-II) & SPEA-II.
[167]		2	Heuristic Local Search Operator	Spatial forest planning problem	GA
[168]		2	Tabu Search	Three instances	NSGA-II
[157]		2	Quantum Computing	Numerical Experiment	NSGA-II
[158]		2	Problem Specific Heuristic	Randomly Generated	Other problem-specific Approaches
[128]		2	Tabu Search	Benchmark instances	NSGA-II
[142]		2	Electromagnetism (EM) Heuristic	Benchmark datasets[14]	NSGA-II, hybrid SPEA-II, hybrid MOEA/D
[152]		2	Simple neighbourhood search (Local search)	Randomly generated & real-life numerical application task graphs	NSGA-II, SPEA-II, Weighted sum GA & their hybrid versions

[11] https://www.sintef.no/nearp
[12] https://eden.dei.uc.pt/~paquete/tsp/#Exp2
[13] http://mistic.heig-vd.ch/taillard/problemes.dir/ordonnancement.dir/ordonnancement.html
[14] http://www.om-db.wi.tum.de/psplib/getdata_sm.html

TABLE 8. *(Continued.)* **Summary of reviewed papers using hybrid NSGA-II for MOCOPs.**

[179]		2	Heuristic criterion for generation of initial population & Heuristic crossover operator	Sample Problems	NSGA-II, MOPSO, Hybrid chaotic MOPSO (HCMOPSO),, NSGA-III & ACO.
[129]		2	Mapping Method (5 Mapping hybridizations)	Randomly Generated	NSGA-II With Local search (Simple hill climbing)
[137]		3	NEH Adaptive heuristic	Instances based on Benchmarks	NSGA-II, SPEA-II
[182]		3	Decoding heuristic (DH) & NSCM	Randomly Generated	HYBRID SPEA-II
[175]		2	DE mutation, High-quality initial solutions & Approximation heuristic strategy	Randomly Generated	NSGA-II, NSGA-II/DE, NSGA-II/DE+POSQ, & NSGAII/DE+POSQ+AHS [POSQ-Pareto optimal solution quality AHS- Approximation Heuristic Strategy]
[133]		2	ERT (Earliest release time) - ECT (Earliest completion time) heuristic	Randomly Generated + Benchmarks	Simple NSGA-II (simNSGA-II) & modified NSGA-II (modNSGA-II)
[140]		2	Tabu Search	MRCPSP instances[15]	ECM, Tabu Search, Enumeration-based method & single-layer NSGA-II.
[130]		3	Local search based on the critical path	Constructed MO-FJSPW Benchmarks Instances based on FJSP	NSGA-II, NNIA & NNIA integrated with local search
[172]		2	MOPSO	-	Current fixed voyage generation scheduling methods
[153]		2	ANN	Sample problem consists of five resources & three task	NSGA-II
[148]		3	Scheduling based heuristic	Office from E3S Benchmark Suit[16]	Related Heuristic Methods from literature
[135]		3	Tabu search, Job Merge strategy	-	NSGA-II, NSGA-II + Tabu search
[186]		2	GSA	Amazon EC2 Instances	NSGA-II, SPEA-II
[173]		3	Effective production process simulator	-	-
[213]		2	EPANET	Two different sizes of water distribution networks	MOEA/D
[166]		5	Initialization using semi-random procedure	Random instances generated from real data	-
[138]		4	4 variants of NEH(for initialization), EDA	Randomly generated	NSGA-II, DHS & TA
[132]		3	Variable neighbourhood local search	Benchmark instances	Modified NSGA-II without local search & MOGA
[190]		2	Greedy local search strategy	10 Problem sets generated randomly	Greedy Algorithm & Enumeration method
[101]	Knapsack Problem	10,40	MOGLS	Multi-objective 0/1 knapsack problems	SPEA, NSGA-II, MPAES & MOGLS
[98]		2,3	Migration method	BNH, ZDT1	Conventional NSGA-II on a single CPU, parallel NSGA-II without migration method & DNSGA-II
[210]	Miscellaneous	3	Monte Carlo simulation	Randomly Generated	Hybrid simulation-analytical modelling approach
[201]		2	Local search technique	Randomly Generated	NSGAII, NSGA-II+LS Hybrid (NSGA-II + MOLAHC), Hybrid + LS
[211]		2	GA-MDF	Randomly Generated	WSM
[194]		2	VNS	Randomly Generated	NSGA-II
[208]		2	Differential Evolution	Higher-order simulated instances	MOHPSO

[15] http://www.om-db.wi.tum.de/psplib/getdata_mm.html
[16] http://ziyang.eecs.umich.edu/~dickrp/e3s/

MOEA/D-ACO for solving the multi-objective TSP using a pheromone trail based probabilistic representation. The benchmark instances were constructed using two single-objective instances given in the literature. Results showed that the proposed variants performed better than corresponding traditional algorithms. However, NSGA-II performed better than MOEA/D-ACO.

The researchers in [109] proposed a new model TSP model that aims to extend and combine different TSP variants to generate vendor routes in a sales territory. The authors introduced a new permutation representation and evaluated three different algorithms, i.e., NSGA-II, SPEA-II, and IVF/NSGA-II, on real scenarios. The results claimed that IVF/NSGA-II outperformed the other algorithms in most cases. Also, the obtained solution routes reduce the route distance by 35% and increase the overall performance by 60%.

Li *et al.* [107] proposed a hybrid algorithm HNSGA-II to solve a target mission planning model of GEO satellites. The suggested algorithm based on NSGA-II used a heuristic during initialization and mutation, embedded with TSP optimization, and performed better than NSGA-II on randomly generated instances using the hypervolume measure. The authors in [105] formulated a bi-objective selective pickup and delivery problem. They proposed a memetic algorithm based on NSGA-II along with a repair strategy for constraint handling.

e: SCHEDULING PROBLEM

Abdi & Zarandi [148] proposed a task scheduling method for the design optimization of heterogeneous multiprocessor embedded systems. In the optimization procedure, the authors used NSGA-II as a powerful design exploration engine. Half of the initial population was generated randomly for diversity preservation. The remaining half of the population was generated using a list scheduling-based heuristic to find solutions relatively close to the optimal solutions. Chitra *et al.* [152] also considered the multi-objective task scheduling problem on heterogeneous systems. Here, NSGA-II was hybridized with a local search method called the simple neighbourhood search method. This proposed algorithm provided better results than conventional NSGA-II, conventional SPEA-II, and hybrid SPEA-II on random task graphs. In [153], the authors presented a multi-objective model for task scheduling in cloud computing with two conflicting objectives makespan and energy consumption. NSGA-II was implemented with ANN support and without ANN support to obtain the Pareto optimal solutions. According to the authors, NSGA-II with ANN support provided better solutions as compared to NSGA-II. Vilcot & Billaut [128] considered a general JSSP with objectives to minimize the makespan and the maximum lateness. The authors proposed two methods based on the NSGA-II framework with different initialization phases. One of the methods used randomly generated initial population, and the other method used initial population partially generated using tabu search. According to the performance comparison results, NSGA-II with tabu search performed better in terms of solution quality and computational time.

In [131], NSGA-II was integrated with genetic programming hyper-heuristic (GPHH) to handle multi-objective dynamic flexible JSSP. The proposed algorithm performed better than two methods, i.e., SPEA-II based GPHH and WSM. Gong *et al.* [130] presented a multi-objective flexible JSSP with worker flexibility. Here, NSGA-II was integrated with a local search operator, a designed coding/encoding method, and adaptive genetic operators. The proposed algorithm was compared with NSGA-II, non-dominated neighbour immune algorithm (NNIA), and NNIA + LOCAL on instances constructed from traditional instances using convergence and diversity measures. The simulation results showed that the proposed memetic algorithm performed better than the other compared algorithms. Autuori *et al.* [129] claimed that for solving the flexible JSSP, the hybridization of the mapping method with NSGA-II was more efficient than the hybridization of simple hill-climbing local search method with NSGA-II in terms of hypervolume and set coverage metric. Wang *et al.* [132] proposed hybrid NSGA-II for multi-objective fuzzy flexible JSSP. In the proposed NSGA-II, the initial population was generated using machine assignment and operation sequencing rules, and a well-designed greedy chromosome algorithm was used along with two effective genetic operators. Further, the non-dominated sorting procedure was improved using a modified crowding distance measure. Also, VNS was used as a local search operator to enhance the exploitation ability of NSGA-II. The performance of the proposed algorithm was validated using benchmark instances available in the literature.

In [179], NSGA-II was hybrid with a heuristic for population initialization and a heuristic crossover operator to solve a new bi-objective production-distribution supply chain scheduling model in a flowshop environment. Cai *et al.* [137] proposed a novel mixed-integer linear programming model for a distributed permutation FSP with transportation conditions. NSGA-II was modified in terms of population initialization, i.e., a heuristic was used to initialize the population for each objective function. The improved NSGA-II outperformed the conventional NSGA-II and SPEA-II algorithms. Zeng *et al.* [135] proposed a hybrid algorithm integrating NSGA-II with tabu search and a job merging strategy for a multi-objective flexible batch processing FSP in manufacturing industries. For multi-objective permutation FSP, Chiang *et al.* [134] developed an efficient algorithm combining NSGA-II with a problem-specific local search procedure NEH and several adaptations, including acceptance criterion and ordering strategy. Wang *et al.* [133] proposed a memetic algorithm based on NSGA-II to solve the multi-objective parallel FSP that includes an order encoding scheme, a heuristic for population initialization, and an embedded local search operator. Han *et al.* [138] improved NSGA-II to solve multi-objective lot-streaming FSP. The traditional genetic operators of NSGA-II were replaced by the estimation of distributed algorithm (EDA) (crossover) and swap and insertion mutations. Also, a restarting strategy was performed on the population when the population diversity was less than the given threshold. The proposed modified NSGA-II outperformed NSGA-II, discrete harmony search (DHS) & threshold accepting (TA) on a series of random experiments

Vidal *et al.* [156] suggested a neuro-evolutionary algorithm integrating NSGA-II with a multi-layer perceptron neural network (for processing time estimations) to solve a complex machine scheduling problem in the custom furniture industry. The proposed approach was compared with five state-of-the-art algorithms on JSSP benchmark instances using a set coverage metric. The authors conclude that the proposed method was better than other methods in most of the test instances. Also, the estimated time obtained through multi-layer perceptron has better accuracy than the other regression techniques used for time estimations.

Liu *et al.* [157] studied machine scheduling under disruption to minimize weighted discounted total completion time and deviation from the initial schedule. A quantum-inspired hybrid algorithm was employed to solve the problem in which NSGA-II was hybrid with quantum computing considering qubit representation. Here, the near-optimal schedules obtained by the proposed algorithm were more effective than the conventional NSGA-II. Ramacher & Mönch [158] hybridized NSGA-II with a problem-specific heuristic to solve a machine scheduling problem with interfering job sets.

Song *et al.* [162] proposed learning guided NSGA-II for a multi-objective satellite range scheduling problem. The algorithm contained NSGA-II and a learning mechanism to speed up the convergence. Zhang *et al.* [163] presented a multi-objective model for a large-scale satellite-data transmission scheduling problem. NSGA-II integrated with support vector machine (SVM) classification was proposed and compared with dominance-based NSGA-II, indicator-based evolutionary algorithm (IBEA), decomposition-based evolutionary algorithm (MOEA/D), and self-adaptive MOEA/D (SaMOEA/D) for large scale problems. The results showed that NSGA-II with SVM found more efficient solutions for large-scale problems in a reasonable amount of time.

Zeng *et al.* [168] used NSGA-II with tabu search for energy-efficiency scheduling in paper mills to save energy. The proposed algorithm performed better than NSGA-II. Huang *et al.* [172] merged NSGA-II with MOPSO for joint voyage scheduling and economic dispatch for energy-efficient scheduling in all-electric ships with virtual energy storage.

Xiao *et al.* [142] proposed three hybrid algorithms for the RCPSP, each combining the electromagnetism heuristic with NSGA-II, MOEA/D, and SPEA-II, respectively. According to this study, the integration of electromagnetism was best suitable for NSGA-II. Tao & Dong [140] suggested integrating NSGA-II with tabu search for a newly proposed multi-mode RCPSP with alternative project structures.

Guo *et al.* [173] combined NSGA-II based multi-objective framework with an effective production process simulator to handle the order scheduling problems in production planning. Here, NSGA-II was modified in terms of chromosome representation, genetic operators and embedded with heuristic pruning and decision-making method to find a single solution from a set of Pareto optimal solutions.

In [182], the authors integrated NSGA-II with a decoding heuristic and a non-dominated solution construction method (NSCM) to obtain efficient Pareto optimal solutions for multi-objective production scheduling with release time in steel plants.

Wang *et al.* [175] solved an integrated problem of preventive maintenance and rescheduling problem for the arrival of a new job in a single machine layout using an improved The traditional gene NSGA-II. The exploration and exploitation of NSGA-II were balanced using the mutation operator of differential evolution, high-quality initial solutions, and approximation heuristic strategy (AHS).

Naik *et al.* [186] introduced the adaptive multi-objective resource selection model for selecting the resources inside the hybrid cloud environment. In this model, NSGA-II was hybrid with gravitational search algorithm (GSA) to find the near-optimal schedule for the cloud users.

Hu & Yan [213] proposed NSGA-II coupled with an EPANET simulator to solve a new multi-objective model for scheduling valves and hydrants to improve the response of drinking water contamination event. The proposed model and methodology were validated using two water distribution networks and studied the impact of different parameters on the proposed algorithm.

To solve the spatial combinatorial problem in forest planning, Fotakis *et al.* [167] introduced a spatial operator, a local search operator, or the second kind of mutation in NSGA-II.

In [166], the authors proposed a five-objective mixed-integer linear programming model for complex decision-making regarding the planning and scheduling of operation theatres in hospitals. The authors utilized NSGA-II with a semi-random procedure for initialization to reduce computational time.

Guo *et al*. [190] proposed NSGA-II with a novel greedy local search to accelerate its convergence speed to solve a multi-dock cross-docking scheduling problem. The proposed algorithm outperformed the greedy strategy and approximated the enumeration algorithm for a small-size problem. For a large-size problem, the proposed algorithm was found more efficient than the enumeration algorithm.

f: KNAPSACK PROBLEM

Sato *et al.* [98] proposed a distributed parallelized NSGA-II with a migration method (e-DNSGA-II) for constrained multi-objective knapsack problems. The proposed approach was compared with conventional single CPU NSGA-II, parallel NSGA-II without migration method, and DNSGA-II using two constrained test problems. Results showed that e-DNSGA-II achieved higher hypervolume, enabled high-speed operation, improved diversity, and has an increased number of non-dominated solutions for both The traditional gene problems.

Ishibuchi & Narukawa [101] proposed S-MOGLS, the hybrid algorithm of NSGA-II with the local search method, for many-objective knapsack problems. The authors explained the framework of S-MOGLS and examined its four variants based on genetic search and local search method (Weighted scalar or Pareto ranking). These four versions of S-MOGLS performed better than SPEA, NSGA-II, memetic Pareto archived evolution strategy (MPAES), and the MOGLS algorithm on many-objective test problems, especially in terms of D_{1R} measure.

g: MISCELLANEOUS

Leesutthipornchai *et al.* [211] solved a routing and wavelength assignment problem in wavelength division multiplexing optical networks using a multi-objective evolutionary approach. The authors hybridized NSGA-II with an algorithm named GA for routing allocation with minimum degree first for wavelength assignment (GA-MDF) to obtain the non-dominated solutions for the problem and compared it with WSM. According to the authors, although NSGA-II was computationally expensive, its solutions were more diverse than WSM.

Rabbani *et al.* [210] studied waste management in the industrial sector and extended a deterministic industrial waste location-routing model capable of covering inventory decisions in waste treatment, considered a multi-period planning horizon, and was a stochastic model. Along with this novelty in the model, the authors integrated NSGA-II and Monte-Carlo simulation, which provide high-quality solutions in less computational time than the hybrid simulation-analytical modeling approach on randomly generated problem instances.

Amini *et al.* [201] studied a location-arc routing problem, a combination of location problem and arc routing problem. A mathematical model was developed to minimize the two objectives, makespan and total costs. Two metaheuristics: NSGA-II and multi-objective late acceptance hill-climbing (MOLAHC) algorithm, were considered. The hybridization of NSGA-II and MOLAHC with local search (hybrid + LS) and hybridization of NSGA-II with local search (NSGA-II + LS) were found better when compared with the same algorithms without using the local search. Out of these two algorithms, NSGA-II + LS was more efficient, and hybrid + LS took less computational time.

The researchers in [194] proposed a new mathematical model integrating two problems: supply chain scheduling and VRP to minimize the resources and energy consumption and penalty for total tardiness. Here, NSGA-II integrated with VNS outperformed NSGA-II in obtaining the Pareto optimal solutions for the given problem

Doolun *et al.* [208] integrated NSGA-II with five different variants of the differential evolution algorithm to solve a multi-objective location-allocation problem in a multi-echelon green supply chain network. The problem was to find the location of manufacturing plants and warehouses and then allocating resources to the various stages of the supply chain. The proposed algorithms (NSDEA) was compared with the existing multi-objective hybrid PSO (MOHPSO) algorithm and outperformed it in evaluating Pareto optimal solutions

B. PERFORMANCE ASSESSMENT

This section discusses the test instances, case studies, performance measures, and statistical tests used by the researchers to validate the effectiveness of the NSGA-II algorithms to solve MOCOPs.

1) TEST INSTANCES

The researchers used test instances to validate their proposed model and algorithms. Typically, the test instances are of three sizes, small-sized, medium-sized, and large-sized instances. The performances of NSGA-II based algorithms for small-sized instances are mostly close to the exact algorithms. However, for medium and large-sized instances, exact algorithms generally fail to provide solutions in a reasonable time because of the NP-hard nature of most of the MOCOPs. Therefore, an intelligent algorithm like NSGA-II is proposed to obtain near-optimal solutions to such problems in less computational time.

The test instances are generally taken from standard benchmarks/datasets available in the literature. However, for many newly proposed models of MOCOP, benchmarks are not available in the literature. The validation of such models is done through randomly generated test instances. The test instances used in the studied literature are given in Table 6–8. Link sources for some of the test instances are provided in the footnotes below the respective tables.

2) CASE STUDIES

The researchers performed case studies to demonstrate the effectiveness of the NSGA-II based algorithms and their application in practice. The conducted case studies in the literature are given in Table 9.

3) PERFORMANCE MEASURES

In the studied literature, a comparison with other state-of-the-art algorithms quantifies the proposed NSGA-II algorithms' effectiveness. Single-objective optimization algorithms can be easily compared using objective-values or computational times. In multi-objective optimization algorithms also, if all the objective-values of one algorithm are better than the corresponding objective-values of the other, then they can be compared using their objectives-values. However, it is difficult to compare the non-dominated sets of near-optimal solutions obtained using the multi-objective optimization algorithms. Thus, many metrics have been developed to evaluate the performance of such algorithms. They are used to compare the sets of solutions obtained by the algorithms in terms of convergence and diversity [214]. Researchers have used different performance metrics to compare their proposed NSGA-II with exact methods, random methods, single-objective and multi-objective optimization algorithms, and many other methods, as illustrated in Table 6-8.

The researchers also considered computational time to compare the efficiency of two or more algorithms. Therefore, in this study, the objective function values and computational time are also treated as performance metrics. The most used performance metrics in the studied literature are given in Table 10. The other rarely used performance metrics are maximum sum of the objective-values (MaxSum) [102], [99], maximum distance Dmax [175], [157], epsilon indicator [45], [134], average quality [157], [175], average hypervolume [105], [121], width measure (M2 metric) [147], system performance [148], solution quality [54], size of reference set [62], relative percentage difference between objective-values [210], relative and absolute quality [59], overall non-dominated vector generation (ONVG) [175], number of unscheduled tasks [163], number of generations [68], number of channel reuses, user level fairness, and

TABLE 9. Case studies.

Ref.	Problem	Case study
[60]	Assignment Problem	Land use allocation in Tongzhou new town, China
[65]		Rescue teams' assignment based on 2008 Wenchuan earthquake
[59]		Boyacá's hospital waste management network design
[51]		Dynamic load balancing of IIT PATNA college network traffic
[71]	Allocation Problem	Supply chain service of a high-speed train in cloud manufacturing environment
[67]		Terminal airspace operation with environmental considerartion of Shanghai terminal area which serves ZSPD (Pudong International Airport) and ZSSS (Hongqiao International Airport)
[66]		Classtimetabling of IIT-Kanpur, India, and allocation of land uses in a land-scape, located in Baixo Alentejo, Portugal.
[87]		Buffer allocation for a remanufacturing system
[119]	Vehicle Routing Problem	Collaborative multi-depot logistics network design with time window assignment in Chongqing city, China
[120]		Collaborative multiple centers vehicle routing problem with simultaneous delivery and pickup in Chongqing city, China
[125]	Scheduling Problem	Automobile spare parts manufacturer
[146]		Re-planning of bus network timetable of transit company of Shenyang, China
[164]		2008 Wenchuan earthquake is revisited in terms of satellite image acquisition in the context of emergency response.
[135]		Flexible FSP with batch process real tissue paper mill industry, China
[168]		Process optimization with energy-efficient scheduling for real tissue paper mill industry, China
[170]		Scheduling of short-term incentive-based demand response programs: IEEE 24 bus reliability test system
[172]		Joint voyage scheduling and economic dispatch for 4-DG penetrated AES
[173]		Order scheduling problem in apparel manufacturing company producing outerwear and sportswear in mainland China.
[139]		Project scheduling and material ordering: Track bed construction project of Mianeh-Bostanabad-Tabriz Railway in Iran
[176]		Warehouse construction resource-constrained discrete-time-project scheduling
[178]		Highway construction project: Time-cost-quality trade-off problems
[159]		Real-world scheduling problem in an automobile stamping die manufacturing shop floor
[193]		Configuration generation and scheduling for RMSs
[181]		Contraflow shop scheduling problem for a study site, which is an approximately 140-mile Contraflow section of I-65 in Alabama between Exit 30 and Exit 170 identified by the Alabama Department of Transportation
[182]		Practical scheduling with release times for steel plants in Chongqing Iron and Steel Corporation, China, and Panzhihua Iron and Steel Corporation, China
[169]		Energy-intensive manufacturing for tire production by a collaborative company in China
[144]		Task assignment in some sub-projects related to the design of the facilities of a new mining plant located in the northern Brazilian territory
[166]		Operating room planning and scheduling for the Surgical Department of the General Hospital of Cosenza, Italy
[165]		Aggregate capacity planning for elective surgeries using real data from a European public hospital[17]
[95]	Knapsack Problem	A Face detection application for context-aware resource allocation in mobile cloud
[97]		Optimal selection of safety measures in Gas wellhead and surface facilities
[104]		Vegetable wholesale problem in Gate Bazaar in Midnapore Town, West Bengal, India
[200]	Miscellaneous	Optimized relief distribution for Great Sichuan Earthquake in China
[195]		Resource allocation and activity scheduling for the Logistics market in Wuhani
[209]		High-level synthesis of two steps of the baseline JPEG compression algorithm with Huffman encoding for a Xilinx MicroBlaze System-on-Chip Architecture implemented on a Virtex II-PRO XC2VP4 FPGA device
[203]		Monitoring and maintaining ATMs of Melli Bank (one of the greatest banks in Iran) with preventive maintenance approach
[205]		Lock scheduling and birth allocation using historical data of traffic at Three Gorges Dam
[207]		Nursing home location and allocation for Kongjiang road in Shanghai using two datasets containing information about locations and communities of elderly people
[208]		Optimization of an automotive electronic parts supply chain in Malaysia

[17] https://data.oecd.org/

stability of the communication mode of the D2D users [96], norm based pure diversity metric [72], modified mean ideal distance measure [127], maximum Pareto front error [201], M1,M2,M3 [110], k-distance [198], hole-relative size metric, μ distance metric [73], error, ratio, distance based measure, fairness [158], empirical attainment function [45], data envelopment analysis [83], data dependency threshold [68], convex hull of the approximated efficient frontier [59], convergent metric [140], capacity measure [72], average rank index, average crowding distance and the mapping pattern of solutions [89], convergent rate metric [85], infeasibility metric [85], ratio of non-dominated solutions [138], rate of achievement to two objectives simultaneously [190], and area under linear regression curves [190].

4) STATISTICAL ANALYSIS

In some papers, to investigate the effectiveness of the proposed optimization model, the researchers conducted a series of experiments using available or randomly generated test instances or datasets. They performed statistical tests on the performance metrics values obtained from the compared algorithms to show the statistical significance of the

TABLE 10. Performance metrics.

Performance Metrics	Papers
Objective function values	[49], [64], [178], [200], [197], [196], [112], [180], [100], [163], [137], [172], [153], [186], [164], [170], [122], [149], [155], [184], [188], [106], [63], [212], [118], [121], [119], [111], [120], [183], [206], [89], [104], [192], [151], [148], [181], [96], [160], [91], [82], [88], [208], [68], [78], [70], [93], [86], [46], [53]
CPU time/Run time /computational time /execution time	[206], [89], [74], [47], [160], [199], [198], [196], [200], [65], [127], [95], [73], [55], [150], [146], [188], [127], [203], [211], [54], [118], [119], [120], [98], [163], [128], [179], [194], [140], [210], [147], [160], [81], [93], [53]
Number of Pareto optimal solutions, /Quantity metric/ Pareto front size	[74], [47], [62], [64], [95], [125], [159], [198], [191], [73], [94], [76], [139], [177], [126], [189], [127], [80], [207], [202], [157], [179], [137], [182], [201], [194], [199], [141], [81], [138]
Hypervolume (Size of the space covered (SSC))	[116], [204], [171], [102], [103], [141], [198], [205], [59], [131], [107], [109], [111], [114], [99], [98], [162], [167], [168], [129], [135], [201], [134], [175], [132], [161], [53]
Set coverage (C-Metric)/ Zitzler measure/Coverage Rate (CR)/Purity measure	[117], [154], [198], [191], [55], [123], [150], [205], [136], [156], [157], [142], [129], [133], [130], [175], [73], [182], [141], [134], [83], [72], [57], [132]
Spacing / Tan's spacing	[47], [125], [127], [147], [73], [141], [177], [126], [127], [202], [48], [179], [137], [201], [210], [157], [159], [80], [207], [81]
D1$_R$ metric (D$_R$ measure, Inverted generational distance (IGD))/Average distance	[191], [136], [159], [55], [103], [131], [108], [109], [111], [101], [152], [133], [130], [201], [175], [95], [62], [157], [207], [56], [57], [138]
Ratio of non-dominated individuals (RNI)/ Quality metric	[154], [55], [141], [118], [121], [152], [62], [139], [189], [48], [128], [179], [137], [194], [140], [210], [57]
Mean Ideal Distance Measure (MIDM)(Generational distance (GD)/ Euclidean distance/ Average distance	[147], [139], [203], [177], [94], [150], [141], [101], [179], [201], [194], [142], [80], [83], [81], [53], [190]
Spread (Δ)	[47], [191], [123], [94], [150], [202], [111], [101], [133], [201], [159], [83], [85], [138], [190]
Maximum spread/Range	[154], [157], [182], [201], [127], [102], [103], [108], [99]
Diversification metric	[177], [189], [48], [179], [140], [80]
Schott spacing/Relative distance	[199], [150], [202], [182]
Error ratio/ Error rate	[73], [201], [177], [81], [53]
Diversity metrics	[125], [199], [126], [82]
Extreme values of Pareto front, Boundaries of objective functions	[167], [76], [105]

experimental results. Therefore, similar to performance metrics, statistical analysis is also used to measure the algorithms' performance. The various statistical tests used in the studied literature are given in Table 11.

C. POST-PARETO OPTIMALITY ANALYSIS

A population-based algorithm like NSGA-II provides a set of compromised optimal solutions after solving a MOOP. The choice of the best-compromised solution among the set of all compromised solutions is made by decision-makers using the preference information. Many techniques based on MCDM, data clustering, fuzzy logic, and some other criteria that are applied to find the best-compromised solution in the studied literature is given in Table 12.

V. ANALYSIS OF MODIFICATIONS IN NSGA-II

Researchers modified NSGA-II mainly in terms of crossover operator (113 papers), mutation operator (119 papers), initialization procedure (27 papers), parent selection (17 papers), and constraint handling technique (7 papers) to improve its convergence and diversity. The other modifications (24 papers) are related to crowding distance calculation, external archive, non-dominated sorting algorithm, adaptive parameter, correlation-based weighted-sum fitness, parallel processing, refinement operation, elite preservation strategy, controlled elitism, and dominance relation, as illustrated in Table 13.

The authors mostly modified crossover and mutation operators because these operators depend on the type of COP. In other words, the selection or design of these operators

TABLE 11. Statistical tests.

Statistical Tests	References
ANOVA	[201], [136], [139], [49], [183], [54]
t-test	[127], [45], [199], [133], [117], [50]
Wilcoxon sign rank test	[141], [168], [109], [208], [93]
Wilcoxon rank-sum test	[201], [114], [205], [80]
Statistical hypothesis tests	[159], [47], [107], [194]
Kruskal-Wallis test	[201], [94], [54]
Friedman test	[184], [110], [208]
Wilcoxon paired test	[137], [45]
Shapiro–Wilk statistical hypothesis test	[45], [54]
ANOM test	[79], [85]
Sign test, Permutation test, Bonferroni/Dunn's test, Welch test, Levene test, Kolmogorov-Smirnov (K-S) test, Post-hoc test	[137], [116], [110], [54], [54], [80], [208]

depends on the chromosome representation of the problem. The chromosome representation is used to represent the potential solution to a problem. The common chromosome representations for GA are binary coding (e.g., 1101101), integer coding (e.g., 1,2,5,7,8), real coding (e.g., 0.235, 0.43, 0.53, 8.5) and permutation representation (e.g.., (1 2 3), (1 3 2)). The chromosome representation is selected according to the nature of the problem. The conventional NSGA-II crossover and mutation cannot be applied to all types of COPs. Also, the inappropriate representation may result in poor performance of the algorithm. Therefore, other crossover operators, such as TPX, UX (binary coding), arithmetic crossover (real coding), PMX, OX (integer coding),

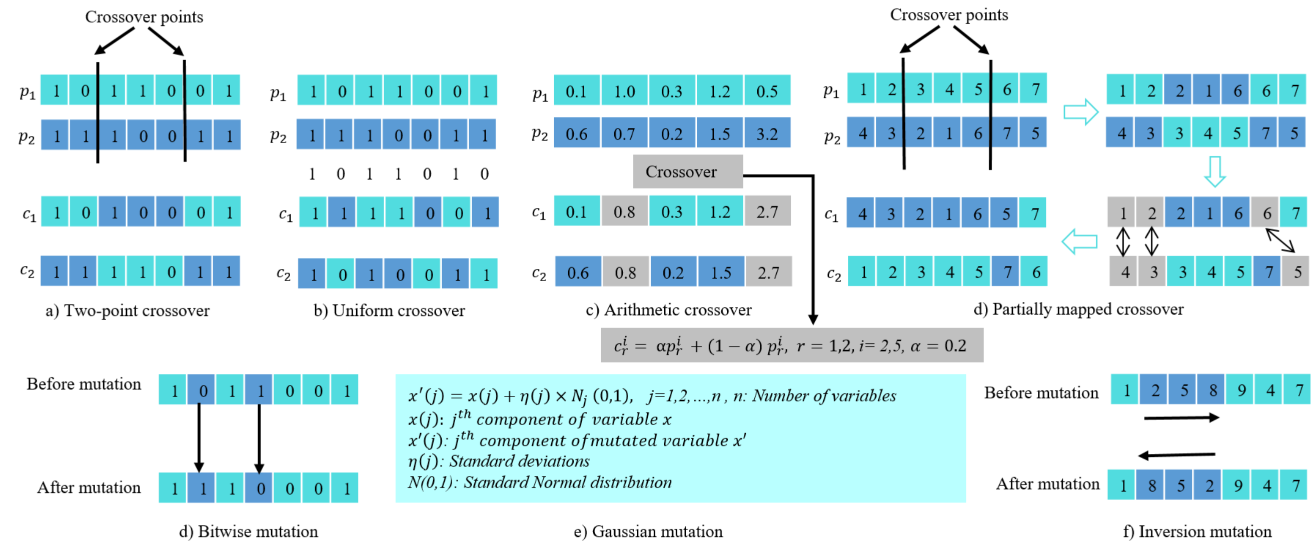

FIGURE 4. Crossover and mutation operators.

TABLE 12. Post-Pareto optimality techniques.

Post-Pareto optimality techniques	References
The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	[62], [61], [96], [183], [50], [71]
Entropy Weight technique	[95], [178], [61]
Analytic hierarchy process (AHP)	[89]
Fuzzy based Mechanism	[187], [65], [90]
Preference-based methods (Reference Value Method & Ranking Objective Method)	[122]
Data Clustering Approach	[75]
Knee point selection technique	[194]
L2 Norm	[79]

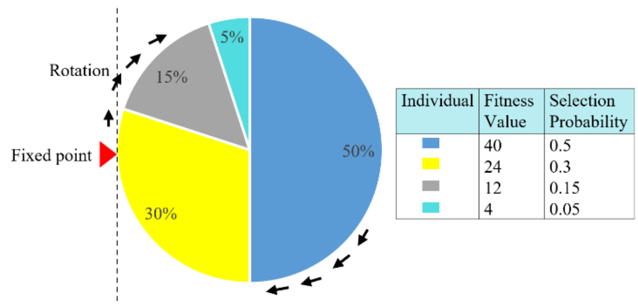

FIGURE 5. Roulette wheel selection.

and mutation operators such as bit-wise mutation, bit-flip mutation (binary coding), Gaussian mutation (real coding) and inversion mutation (integer coding) are used according to the chromosome representation. The most used crossover and mutation operators are shown in Fig. 4.

The modifications in the parent selection mechanism are done to improve the convergence rate of the algorithm. The modifications are related to the increase in tournament size or using the other techniques. Roulette wheel selection is the most used (5 out of 17 papers) technique among all the parent selection modifications. In this selection, a wheel is rotated, and the fixed point on the wheel's circumference chooses a parent among all individuals, and the individual with a greater pie has a greater probability of becoming a parent, as shown in Fig. 5.

Further, in conventional NSGA-II, the initial population is randomly generated. The researchers modified this procedure by generating the initial population using heuristic or problem information for rapid convergence and high-quality solutions.

The researchers used CDP (used in conventional NSGA-II), penalty function strategy, and repair method for handling constraints. In the penalty function method, infeasible solutions' fitness is reduced in proportion to the number of violated constraints. On the other hand, the repair mechanism modifies the infeasible solutions so that the violated constraints get satisfied.

Further, researchers also hybrid other local search methods with NSGA-II to explore the solutions in a solution' neighbourhood. These local search methods include methods such as machine learning techniques, heuristics, and other meta-heuristics. The hybrid methods used in the studied literature are given in Table 8. These methods are embedded mainly in the initialization procedure and before parent selection to improve the local search or exploitation ability of NSGA-II.

VI. BIBLIOMETRIC ANALYSIS

The scheduling problem (42%) is the most exploited MOCOP using NSGA-II, followed by allocation problem (17%), miscellaneous (11%), assignment problem (11%), VRP (8%), knapsack problem (7%), and TSP (4%) as shown in Fig. 6. The modified NSGA-II algorithms (58%) are the most applied algorithms, followed by hybrid NSGA-II (34%) and conventional NSGA-II (8%), as shown in Fig. 7.

Fig. 8 shows the distribution of papers based on the number of objective functions. Bi-objective problems, the most considered problems in the studied literature, comprise 72% of the total papers reviewed, followed by tri-objective problems (21%) and many-objective problems (6%).

Further, the authors in [98] consider both bi-objective and tri-objective problems, and the authors in [117] reduced a 5-objective problem to a 3-objective problem.

The benchmarking of an algorithm (using different test instances) studies the best practices of its implementation to

TABLE 13. Modifications in NSGA-II.

	Modifications
Mutation	Bitwise mutation (or BFM) [91], [69], [82], [187], [94], [181], [105], [180], [102], [100], [99], [103], [204]; Gaussian mutation [170], [139], [157], [148], [175]; Inversion mutation [48], [121], [109], [105], [206], [210]; Random mutations [52], [90], [209], [115], [183], [129], [143], [156], [56]; Insertion mutation [114], [126], [195], [202], [83]; Mutation using heuristic [118], [107], [179]; Uniform mutation [62], [46], [153]; Modified uniform mutation [88], [79], [88], [144], [173]; Max-min mutation [78], [79], [86]; Reverse mutation [126], [133], [202]; Exchange mutation [190], [196]; Single mutation [206]; Insert mutation [138], [133]; Seru swap mutation [63]; Simple mutation [62], [86]; Non-uniform mutation [64], [54]; Mutation of patch cells [60]; Mutation by constraint steering [60]; Neighbour-based Mutation [54]; GAP Mutation [46]; Patch-based-mutation & constraint-edge-mutation[89]; Stochastic mutation[67]; Modified mutation [145]; Roulette wheel mutation [70], [137]; Mutation with greedy algorithm [70]; 2-Opt, 2-Opt* & Or-Opt* mutations[123]; 2-shuffle mutation [117], [116]; Modified inversion mutation [147]; Simple inversion mutation [109]; Relocation [119]; 2-opt* exchange [119]; Fuzzy mutation [151]; Modified position-based & machine based mutations [127]; Order mutation [193]; Intra-segment & inter-segment mutation [162]; Load balancing mutation [156]; Spatial operator for mutation [167]; Sequence mutation [168]; Sequence mutation using gene exchange operator [189]; Mutation based on the local search [128]; Reciprocal exchange mutation [182]; DE mutation [175]; Process mutation, worker mutation & machine mutation [130]; Greedy mutation [161]; Non-geometric binary crossover as mutation [103]; Shift mutation [196]; Replace mutation [195]; Rows swap mutation, partially rows swap mutation & exchange routing mutation [203]; Reverse sequence mutation [200]; Reversion [83]; Binary mutation [170]; Regeneration, complement, mirror & replacement [201]; One-bit mutation [211]; Scramble mutation [194]; Multi-mutation [48]; Mixed mutation combining uniform & Gaussian mutation [113]; Mutation operator based on simple & uniform mutations [71]; Adaptive mutation with a learning time [165]; Bit-inversion, bit-reversal & random permutation [84]; Other modified mutations [76], [73], [81], [77], [87], [188], [159], [213], [146], [207], [128], [132], [212], [152], [176]
Crossover	TPX [55], [61], [48], [57], [81], [78], [77], [71], [85], [86], [117], [116], [124], [204], [200], [205], [137], [130], [156], [163], [164], [178], [189], [126], [201], [206], [200], [84], [160]; Four-point crossover [64]; 5-point crossover [155]; Multi-point crossover [169], [165]; UX [54], [209], [102], [95], [99], [100], [153], [173], [180], [132], [103], [170], [73], [83], [79], [107]; Arithmetic crossover [74], [90], [113], [170], [139], [125], [148]; PMX [112], [121], [119], [111], [120], [109], [149], [190]; OX [121], [105], [45], [202]; Seru swap crossover [63]; Linear order TPX [134]; SPX with roulette wheel sampling [196] ; Modified SPX [191]; Laplace crossover [64]; Single parent crossover [60]; Parametrized UX [158]; Interference-based Crossover[54]; Inversion crossover [56]; Knowledge informed crossover(edge-crossover) [89]; Linear recombination [67];Block-based crossover [66];Fitness-based scanning crossover[88];Max-min crossover [86]; Modified Max-min crossover[77]; Node-based crossover [115]; ERX-MD crossover [114]; Hybrid TPX /EM; crossover [142]; ERX [204], [121]; HGA crossover [106]; Fuzzy variance based crossover operator [151]; Precedence preserving order-based crossover [127]; Intra-segment & inter-segment crossover [162];Crossover (based on the local search) [128]; Hybrid TPX /EM crossover [142]; Heuristic crossover [179]; Gene exchange rule in linear OX [182]; Intermediate crossover [175]; Job-based crossover [168], [130]; Distance-based crossovers [161]; Simple point crossover [145]; EDA for crossover [138]; POX crossover [132]; Outer layer crossover [96]; Improved precedence operator crossover & multi-point preservative operator [195]; route insertion crossover [203]; Crossover using Combination solutions method [198]; Weighted mean crossover [201]; Other modified crossover [76], [87], [118], [159], [213], [146], [52], [207], [128], [133], [212], [152]
Selection	Roulette wheel selection [116], [117], [162], [118], [129]; Adaptive tournament selection [189]; Stochastic universal sampling [161]; Random parent selection [103]; 2/4-replacement selection [134]; Other [47], [68], [131], [182], [94], [141]; Weighted sum fitness [99]
Initialization	Using Problem-based initialization operator (PBIO) [60]; Semi-supervised learning [50], PFIH (Push Forward Insertion Heuristic) [123], CW [119], Ini-PopGen heuristic [127], ERT-ECT heuristic [133], 4 variants of NEH heuristics [138], k-means algorithms [120], partially by Tabu search & partially by greedy algorithm [128], Problem information [66], Prior knowledge of Physarum-inspired computational model (PCM) [110], using semi-random procedure [166], Ramped-half-and-half method [131], Constructive algorithm [198]; Knowledge informed initial population [89]; Initialization using heuristic; Chaotic initial population [150]; Other [118], [107], [159], [164], [170], [129], [137], [203], [132]
Constraint handling techniques	Penalty function method [46], [74], [73], [77], [86]; Modified CDP [85]; Repair strategy [105]
Others	Crowding distance calculation [85], [163], [132], [102], [155], [184], [189]; External archive [138], [134], [192], [89], [47] Non-dominated soring algorithm [212]; Adaptive parameters [55], [54]; Correlation-Based Weighted-Sum fitness [100]; Parallel processing [98]; Modification in refinement operation [104]; Repair [55]; Elite preservation strategy [188], [93]; Controlled elitism [75]; Fuzzy Pareto dominance [132]; g-dominance [114]

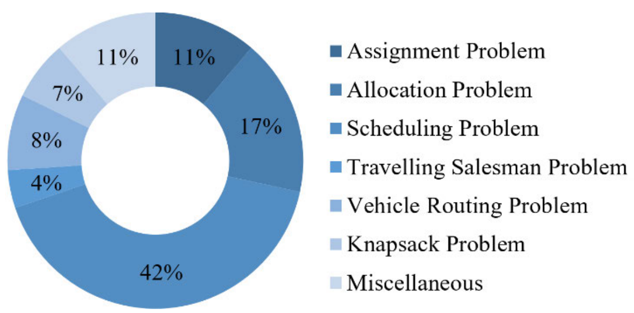

FIGURE 6. Problem-based distribution of the reviewed papers.

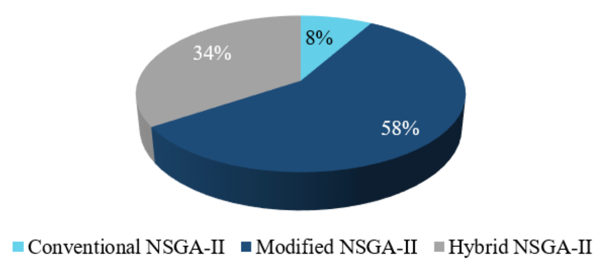

FIGURE 7. Algorithm-based distribution of the reviewed papers based on statistical tests.

a specific problem rather than using them as an optimization tool. The number of papers that performed benchmarking is shown in Fig. 9. Around 79% of papers in the studied literature performed benchmarking. Further, 9/14 (i.e., 9 out of 14), 71/97, and 53/58 papers are from conventional NSGA-II, modified NSGA-II, and hybrid NSGA-II algorithms, respectively.

The researchers compared NSGA-II with algorithms based on NSGA-II, SPEA-II, MOPSO, MOEA/D, GA, WSM, ECM, ACO, AUGMECON, and others. It can be seen from

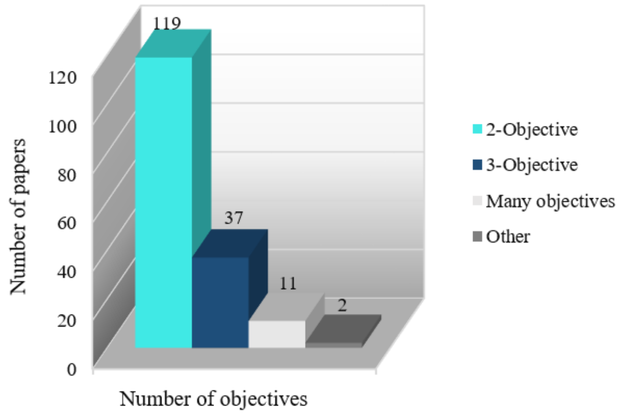

FIGURE 8. **Distribution of the reviewed papers based on the number of objectives.**

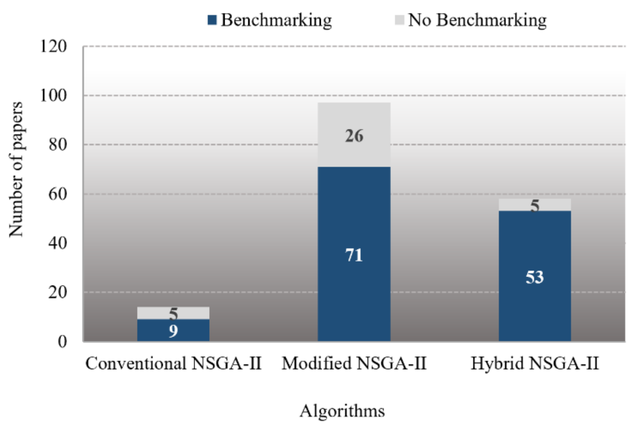

FIGURE 9. **Distribution of the reviewed papers based on benchmarking.**

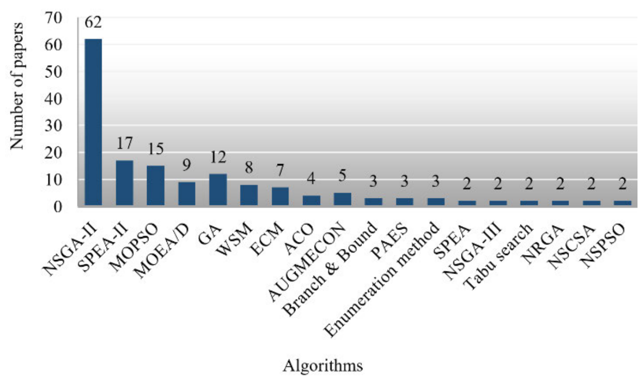

FIGURE 10. **Distribution of the reviewed papers based on compared algorithms.**

Fig. 10 that NSGA-II based algorithms (62 papers) are mostly considered for comparison, followed by SPEA-II based algorithms (17 papers) and MOPSO based algorithms (15 papers).

Fig. 11 shows the performance metrics used in the papers studied. The objective function values (50 papers) and time (36 papers) are the most used criteria by the researchers for comparing NSGA-II with other algorithms. The other commonly used performance metrics are NPS (30 papers), hypervolume (27 papers), set coverage

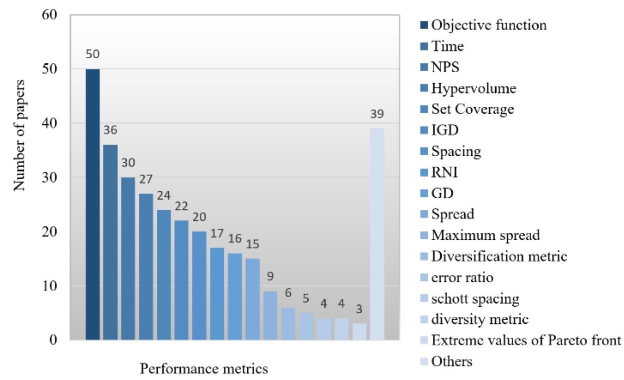

FIGURE 11. **Distribution of the reviewed papers based on performance metrics.**

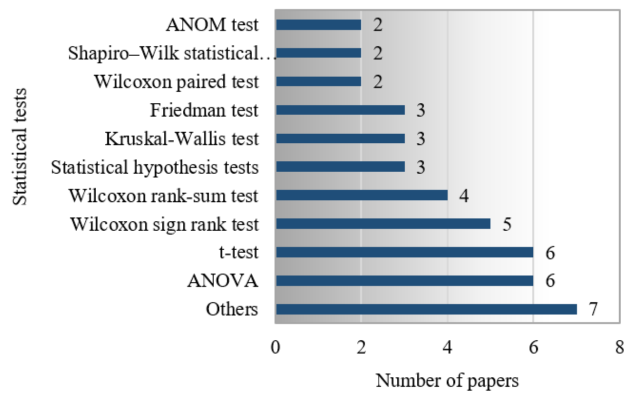

FIGURE 12. **Distribution of the reviewed papers based on statistical tests.**

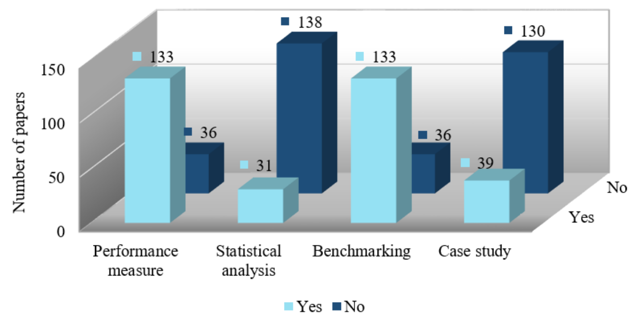

FIGURE 13. **Performance assessment analysis of the reviewed papers.**

(24 papers), IGD (22 papers), spacing (20 papers), RNI (17 papers), GD (16 papers), spread (15 papers), maximum spread (9 papers) and rest are rarely used performance metrics (discussed in not more than 6 papers).

The details about the usage of statistical tests for comparing the algorithms are shown in Fig. 12, from where it can be observed that the three tests most frequently applied tests for statistical analysis of NSGA-II based algorithms are ANOVA, t-test, and Wilcoxon sign rank test.

The performance assessment has been done in many papers to validate the efficiency of the algorithm. Out of total studies done for this article, 77% of studies performed benchmarking and used performance metrics. Contrary to that, only 23% of studies considered a case study to demonstrate the

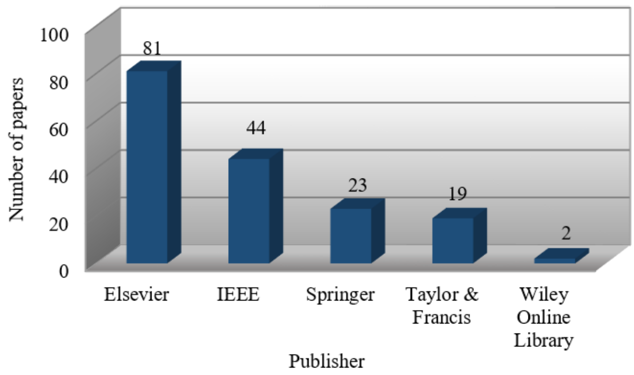

FIGURE 14. Statistics based on differential publishers.

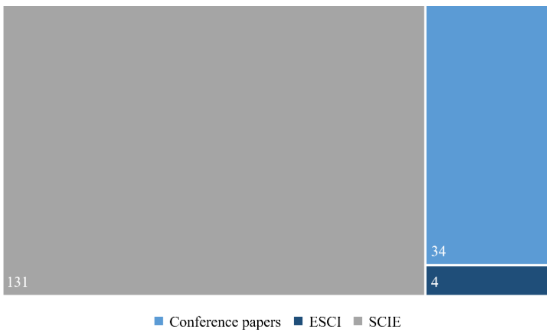

FIGURE 15. Distribution of the reviewed papers based on journals index.

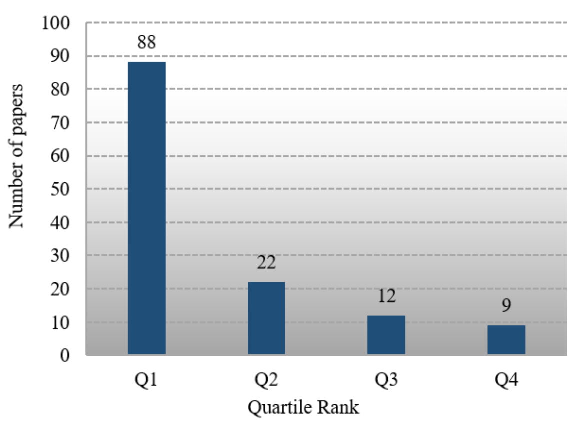

FIGURE 16. Quantitative analysis of JCR Quartile Ranking of reviewed papers.

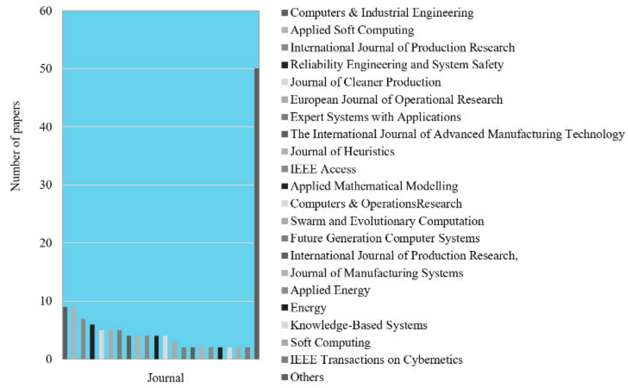

FIGURE 17. Distribution of the reviewed papers based on journals.

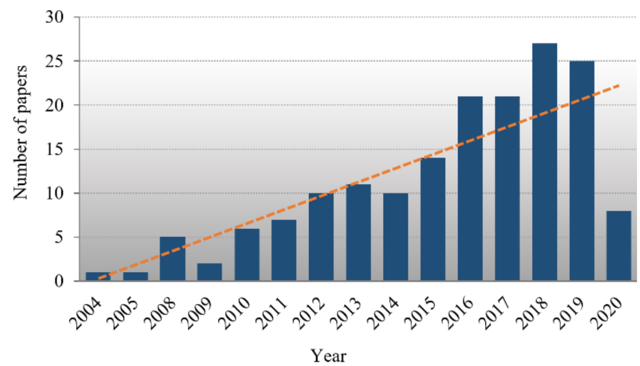

FIGURE 18. Year-wise distribution of the reviewed papers.

FIGURE 19. Visualization map for the origin of researchers.

effectiveness of the developed model or the effectiveness of NSGA-II for solving real-world problems, and 18% used statistical tests for comparing NSGA-II or its variant with other algorithms, as shown in Fig. 13.

The methods used for post-Pareto optimality analysis are shown in Table 10. Approximately 10% of the total papers used decision-making methods for selecting a solution from a set of Pareto optimal solutions. TOPSIS is the most applied method, followed by fuzzy-based mechanism and entropy weight technique.

The number of papers based on different publishing houses is shown in Fig. 14. The maximum number of papers are from Elsevier, whereas the least are from Wiley Online Library.

Out of the total reviewed papers, 135 are journal papers (131 from SCIE and four from ESCI indexed journals, respectively), and the rest 34 are conference papers, as shown in Fig. 15.

The distribution of journal papers indexed in SCIE based on JCR ranking is shown in Fig. 16. The ranking of papers is categorized as per their quartile score using Incites (https://incites.clarivate.com/). The maximum number of papers (88 papers, more than 50 % of total papers) are of Q1 ranking.

The distribution of published papers based on journals is shown in Fig. 17. The maximum number of research articles

(9 papers) are from two journals: applied soft computing and computer & industrial engineering. There are another 50 journals with one paper only are included in the other category. The top six journals are in the Q1 category.

The year-wise distribution of reviewed papers is shown in Fig. 18. It can be seen from the figure that in the last five-six years, the interest in solving MOCOPs using NSGA-II is continuously growing among researchers.

The Bubble chart in Fig. 19 shows the origin of the researchers of the reviewed papers (origin of first authors). The maximum number of researchers are from China, followed by Iran and India.

VII. CONCLUSION AND FUTURE SCOPE

This article presented an extensive review of the implementation of NSGA-II to MOCOPs, such as assignment problem, allocation problem, scheduling problem, TSP, VRP, knapsack problem, and their combinations. The primary aspect considered in the evaluation of each paper is the implementation of NSGA-II to MOCOPs. Based on these implementations, three categories of algorithms are identified: conventional NSGA-II, modified NSGA-II, and hybrid NSGA-II. The analysis of the modifications related to the initialization, genetic operators, constraint handling techniques, etc., is done to study the development of NSGA-II for MOCOPs. The other aspects, such as the use of various test problems, algorithms used for comparison with NSGA-II, performance measures and statistical tests for performance assessment, number of objective functions, and post-Pareto optimality techniques, are also analyzed.

The study can be concluded with the following points-

- The practice of using NSGA-II for solving MOCOPs is increasing, especially over the last five-six years.
- Most of the studied papers are based on scheduling problems. In other words, scheduling problems are the most popular MOCOPs among the selected problems solved using NSGA-II algorithms.
- Most of the studied MOCOPs are bi-objective optimization problems.
- Among the three categories of NSGA-II, the modified NSGA-II is the most applied algorithm on selected MOCOPs.
- The tabu search is the most frequently used algorithm to be hybridized with NSGA-II.
- Most researchers performed benchmarking and measured the efficiency of their NSGA-II based algorithm using various performance metrics.
- Only a few studies performed case studies, statistical analysis, and post-Pareto optimality analysis.
- The modified and hybrid NSGA-II algorithms discussed in this paper can be treated as a benchmark as these algorithms have already been compared with NSGA-II and other algorithms. This can be beneficial for the researchers to initiate their work in this area as they will have an initial idea about the working and performance of different algorithms. Moreover, the efficiency of these algorithms can further be analyzed by comparing them with recent algorithms.
- The bibliometric analysis provided in the paper can help the authors in identifying the areas that need attention. It can also help the authors in identifying the relevant journals and publications.

Future directions-

- Besides GA, there are several other metaheuristics like PSO, DE, ACO, ABC, etc., for which the multi-objective variants have been developed and tested. For example: MOPSO [215], MODE [216], [217], MOACO [218] and MOABC [219], MOGWO [220], MOEA\D [221]. A study highlighting the features of different multi-objective algorithms is likely to be quite interesting.
- Besides the six MOCOPs discussed in the paper, there are other areas as well that can be considered for a detailed study, for example, network design problem [222], subset sum problem [223], and constraint satisfaction problem [224].
- Metaheuristics like GA are parallel in nature; therefore, more focus can be laid on developing the parallel variants of NSGA-II as in [68] to improve their efficiency in solving different MOCOPs.
- In literature, very few studies have used statistical tests. However, it is essential to ensure that the improvements in an algorithm's results are not due to stochastic differences in runs during algorithms' comparison. The researchers working in this area are suggested to compare the results statistically; it will clarify the statistical significance of the performance gaps found among the compared algorithms.
- More research is needed to include decision-makers (human experts)' preference in the multi-objective optimization process to produce the most suitable solution from the set of Pareto optimal solutions.
- At present, the scalable test instances for most of the MOCOPs are not available. Therefore, it is not easy to compare the performances of the algorithms. A detailed study of the methods to generate the test instances will help explore the new problems in this area.
- Use dynamic parameters to develop more robust NSGA-II based algorithms.
- NSGA-II based algorithms can be used in the following area, such as complex scheduling environment of hybrid FSP, other realistic situations modelled as parallel scheduling problem (such as non-identical machines, sequence and machine-dependent setup times, and job-dependent energy consumption), and pollution routing problem with real-time transportation information (such as road condition and parking space' availability).

The authors would finish the paper with the remark that though they have tried to include all the relevant references, there is a possibility that an important reference has been missed for which the authors express their apology.

REFERENCES

[1] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, "A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II," in *Parallel Problem Solving From Nature PPSN VI* (Lecture Notes in Computer Science), vol. 1917. Berlin, Germany: Springer, 2000, pp. 849–858, doi: 10.1007/3-540-45356-3_83.

[2] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.

[3] M. Ehrgott, "Approximation algorithms for combinatorial multicriteria optimization problems," *Int. Trans. Oper. Res.*, vol. 7, no. 1, pp. 5–31, Jan. 2000, doi: 10.1016/s0969-6016(99)00024-6.

[4] H. Mühlenbein, M. Gorges-Schleuter, and O. Krämer, "Evolution algorithms in combinatorial optimization," *Parallel Comput.*, vol. 7, no. 1, pp. 65–85, Apr. 1988, doi: 10.1016/0167-8191(88)90098-1.

[5] E. L. Ulungu and J. Teghem, "Multi-objective combinatorial optimization problems: A survey," *J. Multi-Criteria Decis. Anal.*, vol. 3, no. 2, pp. 83–104, 1994, doi: 10.1002/mcda.4020030204.

[6] C. A. C. Coello, C. Dhaenens, and L. Jourdan, "Multi-objective combinatorial optimization: Problematic and context," *Stud. Comput. Intell.*, vol. 272, pp. 1–21, 2010, doi: 10.1007/978-3-642-11218-8_1.

[7] M. Ehrgott and X. Gandibleux, "Hybrid metaheuristics for multi-objective combinatorial optimization," *Stud. Comput. Intell.*, vol. 114, pp. 221–259, 2008, doi: 10.1007/978-3-540-78295-7_8.

[8] X. Gandibleux and M. Ehrgott, "1984-2004–20 years of multiobjective metaheuristics. But what about the solution of combinatorial problems with multiple objectives?" in *Evolutionary Multi-Criterion Optimization* (Lecture Notes in Computer Science), vol. 3410. Berlin, Germany: Springer-Verlag, 2005, pp. 33–46, doi: 10.1007/978-3-540-31880-4_3.

[9] Q. Liu, X. Li, H. Liu, and Z. Guo, "Multi-objective metaheuristics for discrete optimization problems: A review of the state-of-the-art," *Appl. Soft Comput.*, vol. 93, Aug. 2020, Art. no. 106382, doi: 10.1016/j.asoc.2020.106382.

[10] H. H. Miyata and M. S. Nagano, "The blocking flow shop scheduling problem: A comprehensive and conceptual review," *Expert Syst. Appl.*, vol. 137, pp. 130–156, Dec. 2019, doi: 10.1016/j.eswa.2019.06.069.

[11] M. M. Yenisey and B. Yagmahan, "Multi-objective permutation flow shop scheduling problem: Literature review, classification and current trends," *Omega*, vol. 45, pp. 119–135, Jun. 2014, doi: 10.1016/j.omega.2013.07.004.

[12] D. A. Rossit, F. Tohmé, and M. Frutos, "The non-permutation flow-shop scheduling problem: A literature review," *Omega*, vol. 77, pp. 143–153, Jun. 2018, doi: 10.1016/j.omega.2017.05.010.

[13] A. Kaim, A. F. Cord, and M. Volk, "A review of multi-criteria optimization techniques for agricultural land use allocation," *Environ. Model. Softw.*, vol. 105, pp. 79–93, Jul. 2018, doi: 10.1016/j.envsoft.2018.03.031.

[14] R. Z. Farahani, M. Steadieseifi, and N. Asgari, "Multiple criteria facility location problems: A survey," *Appl. Math. Model.*, vol. 34, no. 7, pp. 1689–1709, Jul. 2010, doi: 10.1016/j.apm.2009.10.005.

[15] H. Hu, J. He, X. He, W. Yang, J. Nie, and B. Ran, "Emergency material scheduling optimization model and algorithms: A review," *J. Traffic Transp. Eng.*, vol. 6, no. 5, pp. 441–454, Oct. 2019, doi: 10.1016/j.jtte.2019.07.001.

[16] M. Pesaran H. A, P. D. Huy, and V. K. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms," *Renew. Sustain. Energy Rev.*, vol. 75, pp. 293–312, Aug. 2017, doi: 10.1016/j.rser.2016.10.071.

[17] C. Prodhon and C. Prins, "A survey of recent research on location-routing problems," *Eur. J. Oper. Res.*, vol. 238, no. 1, pp. 1–17, Oct. 2014, doi: 10.1016/j.ejor.2014.01.005.

[18] W. Ejaz, S. K. Sharma, S. Saadat, M. Naeem, A. Anpalagan, and N. A. Chughtai, "A comprehensive survey on resource allocation for CRAN in 5G and beyond networks," *J. Netw. Comput. Appl.*, vol. 160, Jun. 2020, Art. no. 102638, doi: 10.1016/j.jnca.2020.102638.

[19] N. Jozefowiez, F. Semet, and E.-G. Talbi, "Multi-objective vehicle routing problems," *Eur. J. Oper. Res.*, vol. 189, no. 2, pp. 293–309, Sep. 2008, doi: 10.1016/j.ejor.2007.05.055.

[20] G. Papaioannou and J. M. Wilson, "The evolution of cell formation problem methodologies based on recent studies (1997–2008): Review and directions for future research," *Eur. J. Oper. Res.*, vol. 206, no. 3, pp. 509–521, Nov. 2010, doi: 10.1016/j.ejor.2009.10.020.

[21] N. Srinivas and K. Deb, "Multiobjective optimization using nondominated sorting in genetic algorithms," *Evol. Comput.*, vol. 2, no. 3, pp. 221–248, Dec. 1994, doi: 10.1162/evco.1994.2.3.221.

[22] X. Li and S. Ma, "Multiobjective discrete artificial bee colony algorithm for multiobjective permutation flow shop scheduling problem with sequence dependent setup times," *IEEE Trans. Eng. Manag.*, vol. 64, no. 2, pp. 149–165, May 2017, doi: 10.1109/TEM.2016.2645790.

[23] J.-Q. Li, Q.-K. Pan, and M. F. Tasgetiren, "A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities," *Appl. Math. Model.*, vol. 38, no. 3, pp. 1111–1132, Feb. 2014, doi: 10.1016/j.apm.2013.07.038.

[24] R. H. Caldeira, A. Gnanavelbabu, and J. J. Solomon, "Solving the flexible job shop scheduling problem using a hybrid artificial bee colony algorithm," in *Trends in Manufacturing and Engineering Management* (Lecture Notes in Mechanical Engineering). Singapore: Springer, 2021, pp. 833–843, doi: 10.1007/978-981-15-4745-4_72.

[25] J.-Q. Li, Q.-K. Pan, and P.-Y. Duan, "An improved artificial bee colony algorithm for solving hybrid flexible flowshop with dynamic operation skipping," *IEEE Trans. Cybern.*, vol. 46, no. 6, pp. 1311–1324, Jun. 2016, doi: 10.1109/TCYB.2015.2444383.

[26] S. Samanta, D. Philip, and S. Chakraborty, "Bi-objective dependent location quadratic assignment problem: Formulation and solution using a modified artificial bee colony algorithm," *Comput. Ind. Eng.*, vol. 121, pp. 8–26, Jul. 2018, doi: 10.1016/j.cie.2018.05.018.

[27] D. Gong, Y. Han, and J. Sun, "A novel hybrid multi-objective artificial bee colony algorithm for blocking lot-streaming flow shop scheduling problems," *Knowl.-Based Syst.*, vol. 148, pp. 115–130, May 2018, doi: 10.1016/j.knosys.2018.02.029.

[28] J. Liu and J. Liu, "Applying multi-objective ant colony optimization algorithm for solving the unequal area facility layout problems," *Appl. Soft Comput.*, vol. 74, pp. 167–189, Jan. 2019, doi: 10.1016/j.asoc.2018.10.012.

[29] J. Li, Z.-M. Liu, C. Li, and Z. Zheng, "Improved artificial immune system algorithm for type-2 fuzzy flexible job shop scheduling problem," *IEEE Trans. Fuzzy Syst.*, early access, Aug. 12, 2020, doi: 10.1109/tfuzz.2020.3016225.

[30] J.-Q. Li, X.-R. Tao, B.-X. Jia, Y.-Y. Han, C. Liu, P. Duan, Z.-X. Zheng, and H.-Y. Sang, "Efficient multi-objective algorithm for the lot-streaming hybrid flowshop with variable sub-lots," *Swarm Evol. Comput.*, vol. 52, Feb. 2020, Art. no. 100600, doi: 10.1016/j.swevo.2019.100600.

[31] X. Li and S. Ma, "Multi-objective memetic search algorithm for multi-objective permutation flow shop scheduling problem," *IEEE Access*, vol. 4, pp. 2154–2165, 2016, doi: 10.1109/ACCESS.2016.2565622.

[32] X. Wang and L. Tang, "A machine-learning based memetic algorithm for the multi-objective permutation flowshop scheduling problem," *Comput. Oper. Res.*, vol. 79, pp. 60–77, Mar. 2017, doi: 10.1016/j.cor.2016.10.003.

[33] C. Sanhueza, F. Jimenez, R. Berretta, and P. Moscato, "PasMoQAP: A parallel asynchronous memetic algorithm for solving the multi-objective quadratic assignment problem," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 1103–1110, doi: 10.1109/CEC.2017.7969430.

[34] J. M. Colmenar, R. Martí, and A. Duarte, "Multi-objective memetic optimization for the bi-objective obnoxious *p*-median problem," *Knowl.-Based Syst.*, vol. 144, pp. 88–101, Mar. 2018, doi: 10.1016/j.knosys.2017.12.028.

[35] Y.-J. Zheng, X.-Q. Lu, Y.-C. Du, Y. Xue, and W.-G. Sheng, "Water wave optimization for combinatorial optimization: Design strategies and applications," *Appl. Soft Comput.*, vol. 83, Oct. 2019, Art. no. 105611, doi: 10.1016/j.asoc.2019.105611.

[36] X. Yu, W.-N. Chen, T. Gu, H. Zhang, H. Yuan, S. Kwong, and J. Zhang, "Set-based discrete particle swarm optimization based on decomposition for permutation-based multiobjective combinatorial optimization problems," *IEEE Trans. Cybern.*, vol. 48, no. 7, pp. 2139–2153, Jul. 2018, doi: 10.1109/TCYB.2017.2728120.

[37] W. Deng, H. Zhao, X. Yang, J. Xiong, M. Sun, and B. Li, "Study on an improved adaptive PSO algorithm for solving multi-objective gate assignment," *Appl. Soft Comput.*, vol. 59, pp. 288–302, Oct. 2017, doi: 10.1016/j.asoc.2017.06.004.

[38] F. Benbouzid-SiTayeb, M. Bessedik, M. R. Keddar, and A. E. Kiouche, "An effective multi-objective hybrid immune algorithm for the frequency assignment problem," *Appl. Soft Comput.*, vol. 85, Dec. 2019, Art. no. 105797, doi: 10.1016/j.asoc.2019.105797.

[39] O. Kabadurmus, M. F. Tasgetiren, H. Oztop, and M. S. Erdogan, "Solving 0-1 bi-objective multi-dimensional knapsack problems using binary genetic algorithm," in *Heuristics for Optimization and Learning*, vol. 906. Cham, Switzerland: Springer, 2021, pp. 51–67, doi: 10.1007/978-3-030-58930-1_4.

[40] T. Jiang and C. Zhang, "Application of grey wolf optimization for solving combinatorial problems: Job shop and flexible job shop scheduling cases," *IEEE Access*, vol. 6, pp. 26231–26240, 2018, doi: 10.1109/ACCESS.2018.2833552.

[41] D. Zouache, A. Moussaoui, and F. Ben Abdelaziz, "A cooperative swarm intelligence algorithm for multi-objective discrete optimization with application to the knapsack problem," *Eur. J. Oper. Res.*, vol. 264, no. 1, pp. 74–88, Jan. 2018, doi: 10.1016/j.ejor.2017.06.058.

[42] L. Wang and X.-L. Zheng, "A knowledge-guided multi-objective fruit fly optimization algorithm for the multi-skill resource constrained project scheduling problem," *Swarm Evol. Comput.*, vol. 38, pp. 54–63, Feb. 2018, doi: 10.1016/j.swevo.2017.06.001.

[43] C. Lu, X. Li, L. Gao, W. Liao, and J. Yi, "An effective multi-objective discrete virus optimization algorithm for flexible job-shop scheduling problem with controllable processing times," *Comput. Ind. Eng.*, vol. 104, pp. 156–174, Feb. 2017, doi: 10.1016/j.cie.2016.12.020.

[44] J. Alcaraz, M. Landete, J. F. Monge, and J. L. Sainz-Pardo, "Multi-objective evolutionary algorithms for a reliability location problem," *Eur. J. Oper. Res.*, vol. 283, no. 1, pp. 83–93, May 2020, doi: 10.1016/j.ejor.2019.10.043.

[45] D. H. Moraes, D. S. Sanches, J. da Silva Rocha, J. M. C. Garbelini, and M. F. Castoldi, "A novel multi-objective evolutionary algorithm based on subpopulations for the bi-objective traveling salesman problem," *Soft Comput.*, vol. 23, no. 15, pp. 6157–6168, Aug. 2019, doi: 10.1007/s00500-018-3269-8.

[46] R. F. Subtil, E. G. Carrano, M. J. F. Souza, and R. H. C. Takahashi, "Using an enhanced integer NSGA-II for solving the multiobjective generalized assignment problem," in *Proc. IEEE Congr. Evol. Comput. (WCCI)*, Jul. 2010, pp. 1–7, doi: 10.1109/CEC.2010.5586086.

[47] A. Azadeh, M. Ravanbakhsh, M. Rezaei-Malek, M. Sheikhalishahi, and A. Taheri-Moghaddam, "Unique NSGA-II and MOPSO algorithms for improved dynamic cellular manufacturing systems considering human factors," *Appl. Math. Model.*, vol. 48, pp. 655–672, Aug. 2017, doi: 10.1016/j.apm.2017.02.026.

[48] F. Niakan, A. Baboli, T. Moyaux, and V. Botta-Genoulaz, "A bi-objective model in sustainable dynamic cell formation problem with skill-based worker assignment," *J. Manuf. Syst.*, vol. 38, pp. 46–62, Jan. 2016, doi: 10.1016/j.jmsy.2015.11.001.

[49] A. Azadeh, S. Pashapour, and S. A. Zadeh, "Designing a cellular manufacturing system considering decision style, skill and job security by NSGA-II and response surface methodology," *Int. J. Prod. Res.*, vol. 54, no. 22, pp. 6825–6847, May 2016, doi: 10.1080/00207543.2016.1178407.

[50] M. Cococcioni, B. Lazzerini, and F. Pistolesi, "A semi-supervised learning-aided evolutionary approach to occupational safety improvement," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2016, pp. 3695–3701, doi: 10.1109/CEC.2016.7744257.

[51] A. S. Sairam, S. Saha, A. Ekbal, and G. R. T. Reddy, "Improved multobjective algorithm for dynamic load balancing of network traffic," in *Proc. Annu. IEEE India Conf. (INDICON)*, Dec. 2013, pp. 1–6, doi: 10.1109/INDCON.2013.6725850.

[52] M. Mazurek and S. Wesolkowski, "Minimizing risk on a fleet mix problem with a multiobjective evolutionary algorithm," in *Proc. IEEE Symp. Comput. Intell. Secur. Defense Appl.*, Jul. 2009, pp. 1–7, doi: 10.1109/CISDA.2009.5356525.

[53] M. V. O. Camara, G. M. Ribeiro, and M. D. C. R. Tosta, "A Pareto optimal study for the multi-objective oil platform location problem with NSGA-II," *J. Petroleum Sci. Eng.*, vol. 169, pp. 258–268, Oct. 2018, doi: 10.1016/j.petrol.2018.05.037.

[54] E. Segredo, C. Segura, C. Le, and S. Francisco, "A multiobjectivised memetic algorithm for the frequency assignment problem," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2011, pp. 1132–1139, doi: 10.1109/CEC.2011.5949744.

[55] J. Li, J. Chen, B. Xin, and L. Dou, "Solving multi-objective multi-stage weapon target assignment problem via adaptive NSGA-II and adaptive MOEA/D: A comparison study," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, May 2015, pp. 3132–3139, doi: 10.1109/CEC.2015.7257280.

[56] L. Juan, C. Jie, and X. Bin, "Efficiently solving multi-objective dynamic weapon-target assignment problems by NSGA-II," in *Proc. 34th Chin. Control Conf. (CCC)*, Jul. 2015, pp. 2556–2561, doi: 10.1109/ChiCC.2015.7260033.

[57] J. Zeng, L. Dou, and B. Xin, "Multi-objective cooperative salvo attack against group target," *J. Syst. Sci. Complex.*, vol. 31, no. 1, pp. 244–261, Feb. 2018, doi: 10.1007/s11424-018-7437-9.

[58] R. Bhattacharya and S. Bandyopadhyay, "Solving conflicting bi-objective facility location problem by NSGA II evolutionary algorithm," *Int. J. Adv. Manuf. Technol.*, vol. 51, nos. 1–4, pp. 397–414, Apr. 2010, doi: 10.1007/s00170-010-2622-6.

[59] A. L. Medaglia, J. G. Villegas, and D. M. Rodríguez-Coca, "Hybrid biobjective evolutionary algorithms for the design of a hospital waste management network," *J. Heuristics*, vol. 15, no. 2, pp. 153–176, Apr. 2009, doi: 10.1007/s10732-008-9070-6.

[60] K. Cao, M. Batty, B. Huang, Y. Liu, L. Yu, and J. Chen, "Spatial multi-objective land use optimization: Extensions to the non-dominated sorting genetic algorithm-II," *Int. J. Geographical Inf. Sci.*, vol. 25, no. 12, pp. 1949–1969, Dec. 2011, doi: 10.1080/13658816.2011.570269.

[61] K. K. Goyal, P. K. Jain, and M. Jain, "Optimal configuration selection for reconfigurable manufacturing system using NSGA II and TOPSIS," *Int. J. Prod. Res.*, vol. 50, no. 15, pp. 4175–4191, Aug. 2012, doi: 10.1080/00207543.2011.599345.

[62] Y.-K. Lin and C.-T. Yeh, "Multi-objective optimization for stochastic computer networks using NSGA-II and TOPSIS," *Eur. J. Oper. Res.*, vol. 218, no. 3, pp. 735–746, May 2012, doi: 10.1016/j.ejor.2011.11.028.

[63] J. Lian, C. Liu, W. Li, and Y. Yin, "A multi-skilled worker assignment problem in seru production systems considering the worker heterogeneity," *Comput. Ind. Eng.*, vol. 118, pp. 366–382, Apr. 2018, doi: 10.1016/j.cie.2018.02.035.

[64] A. Martínez-Vargas, J. Domínguez-Guerrero, Á. G. Andrade, R. Sepúlveda, and O. Montiel-Ross, "Application of NSGA-II algorithm to the spectrum assignment problem in spectrum sharing networks," *Appl. Soft Comput.*, vol. 39, pp. 188–198, Feb. 2016, doi: 10.1016/j.asoc.2015.11.010.

[65] S. Zhang, H. Guo, K. Zhu, S. Yu, and J. Li, "Multistage assignment optimization for emergency rescue teams in the disaster chain," *Knowl.-Based Syst.*, vol. 137, pp. 123–137, Dec. 2017, doi: 10.1016/j.knosys.2017.09.024.

[66] D. Datta, C. M. Fonseca, and K. Deb, "A multi-objective evolutionary algorithm to exploit the similarities of resource allocation problems," *J. Scheduling*, vol. 11, pp. 405–419, Jul. 2008, doi: 10.1007/s10951-008-0073-9.

[67] Y. Tian, L. Wan, K. Han, and B. Ye, "Optimization of terminal airspace operation with environmental considerations," *Transp. Res. D, Transp. Environ.*, vol. 63, pp. 872–889, Aug. 2018, doi: 10.1016/j.trd.2018.06.018.

[68] M. Afrin, J. Jin, A. Rahman, Y. C. Tian, and A. Kulkarni, "Multi-objective resource allocation for edge cloud based robotic workflow in smart factory," *Futur. Gener. Comput. Syst.*, vol. 97, pp. 119–130, Aug. 2019, doi: 10.1016/j.future.2019.02.062.

[69] N. Sharma and K. R. Anupama, "On the use of NSGA-II for multi-objective resource allocation in MIMO-OFDMA systems," *Wirel. Netw.*, vol. 17, pp. 1191–1201, Apr. 2011, doi: 10.1007/s11276-011-0340-0.

[70] B. Tan, H. Ma, and Y. Mei, "A NSGA-II-based approach for service resource allocation in cloud," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2017, pp. 2574–2581, doi: 10.1109/CEC.2017.7969618.

[71] H. Zheng, Y. Feng, and J. Tan, "A hybrid energy-aware resource allocation approach in cloud manufacturing environment," *IEEE Access*, vol. 5, pp. 12648–12656, 2017, doi: 10.1109/ACCESS.2017.2715829.

[72] G. Zhang, Z. Su, M. Li, F. Yue, J. Jiang, and X. Yao, "Constraint handling in NSGA-II for solving optimal testing resource allocation problems," *IEEE Trans. Rel.*, vol. 66, no. 4, pp. 1193–1212, Dec. 2017, doi: 10.1109/TR.2017.2738660.

[73] M. Habib, F. Yalaoui, H. Chehade, I. Jarkass, and N. Chebbo, "Multi-objective design optimisation of repairable k-out-of-*n* subsystems in series with redundant dependency," *Int. J. Prod. Res.*, vol. 55, no. 23, pp. 7000–7021, Jul. 2017, doi: 10.1080/00207543.2017.1346319.

[74] N. Alikar, S. M. Mousavi, R. A. R. Ghazilla, M. Tavana, and E. U. Olugu, "Application of the NSGA-II algorithm to a multi-period inventory-redundancy allocation problem in a series-parallel system," *Rel. Eng. Syst. Saf.*, vol. 160, pp. 1–10, Apr. 2017, doi: 10.1016/j.ress.2016.10.023.

[75] H. A. Taboada and D. W. Coit, "Data clustering of solutions for multiple objective system reliability optimization problems," *Qual. Technol. Quantum Manag.*, vol. 4, no. 2, pp. 191–210, Feb. 2007, doi: 10.1080/16843703.2007.11673145.

[76] M. Sun, Y. Li, and E. Zio, "On the optimal redundancy allocation for multi-state series–parallel systems under epistemic uncertainty," *Reliab. Eng. Syst. Saf.*, vol. 192, Dec. 2019, Art. no. 106019, doi: 10.1016/j.ress.2017.11.025.

[77] M. A. Ardakan, A. Z. Hamadani, and M. Alinaghian, "Optimizing bi-objective redundancy allocation problem with a mixed redundancy strategy," *ISA Trans.*, vol. 55, pp. 116–128, Mar. 2015, doi: 10.1016/j.isatra.2014.10.002.

[78] A. E. Jahromi and M. Feizabadi, "Optimization of multi-objective redundancy allocation problem with non-homogeneous components," *Comput. Ind. Eng.*, vol. 108, pp. 111–123, Jun. 2017, doi: 10.1016/j.cie.2017.04.009.

[79] J. Safari, "Multi-objective reliability optimization of series-parallel systems with a choice of redundancy strategies," *Rel. Eng. Syst. Saf.*, vol. 108, pp. 10–20, Dec. 2012, doi: 10.1016/j.ress.2012.06.001.

[80] A. Attar, S. Raissi, and K. Khalili-Damghani, "A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems," *Rel. Eng. Syst. Saf.*, vol. 157, pp. 177–191, Jan. 2017, doi: 10.1016/j.ress.2016.09.006.

[81] M. Tavana, K. Khalili-Damghani, D. Di Caprio, and Z. Oveisi, "An evolutionary computation approach to solving repairable multi-state multi-objective redundancy allocation problems," *Neural Comput. Appl.*, vol. 30, no. 1, pp. 127–139, Jul. 2018, doi: 10.1007/s00521-016-2676-y.
[82] Z. Wang, T. Chen, K. Tang, and X. Yao, "A multi-objective approach to redundancy allocation problem in parallel-series systems," in *Proc. IEEE Congr. Evol. Comput.*, May 2009, pp. 582–589, doi: 10.1109/CEC.2009.4982998.
[83] K. Govindan, A. Jafarian, M. E. Azbari, and T.-M. Choi, "Optimal bi-objective redundancy allocation for systems reliability and risk management," *IEEE Trans. Cybern.*, vol. 46, no. 8, pp. 1735–1748, Aug. 2016, doi: 10.1109/TCYB.2014.2382666.
[84] F. Kayedpour, M. Amiri, M. Rafizadeh, and A. S. Nia, "Multi-objective redundancy allocation problem for a system with repairable components considering instantaneous availability and strategy selection," *Rel. Eng. Syst. Saf.*, vol. 160, pp. 11–20, Apr. 2017, doi: 10.1016/j.ress.2016.10.009.
[85] M. K. Ghorabaee, M. Amiri, and P. Azimi, "Genetic algorithm for solving bi-objective redundancy allocation problem with k-out-of-n subsystems," *Appl. Math. Model.*, vol. 39, no. 20, pp. 6396–6409, Oct. 2015, doi: 10.1016/j.apm.2015.01.070.
[86] M. A. Ardakan and M. T. Rezvan, "Multi-objective optimization of reliability–redundancy allocation problem with cold-standby strategy using NSGA-II," *Reliab. Eng. Syst. Saf.*, vol. 172, pp. 225–238, Apr. 2018, doi: 10.1016/j.ress.2017.12.019.
[87] C. Su, Y. Shi, and J. Dou, "Multi-objective optimization of buffer allocation for remanufacturing system based on TS-NSGAII hybrid algorithm," *J. Clean. Prod.*, vol. 166, pp. 756–770, Nov. 2017, doi: 10.1016/j.jclepro.2017.08.064.
[88] Z. X. Guo, W. K. Wong, and S. Y. S. Leung, "A hybrid intelligent model for order allocation planning in make-to-order manufacturing," *Appl. Soft Comput. J.*, vol. 13, no. 3, pp. 1376–1390, Mar. 2013, doi: 10.1016/j.asoc.2012.07.019.
[89] M. Song and D. Chen, "An improved knowledge-informed NSGA-II for multi-objective land allocation (MOLA)," *Geo-Spatial Inf. Sci.*, vol. 21, no. 4, pp. 273–287, Jul. 2018, doi: 10.1080/10095020.2018.1489576.
[90] E. Shahryari, H. Shayeghi, and M. Moradzadeh, "Probabilistic and multi-objective placement of D-STATCOM in distribution systems considering load uncertainty," *Electr. Power Compon. Syst.*, vol. 46, no. 1, pp. 27–42, Mar. 2018, doi: 10.1080/15325008.2018.1431819.
[91] D. Vidyarthi and L. Khanbary, "Multi-objective optimization for channel allocation in mobile computing using NSGA-II," *Int. J. Netw. Manage.*, vol. 21, no. 3, pp. 247–266, May 2011, doi: 10.1002/nem.763.
[92] R. Britto, P. S. Neto, R. Rabelo, W. Ayala, and T. Soares, "A hybrid approach to solve the agile team allocation problem," in *Proc. IEEE Congr. Evol. Comput.*, Jun. 2012, pp. 1–8, doi: 10.1109/CEC.2012.6252999.
[93] B. Ji, X. Yuan, and Y. Yuan, "Modified NSGA-II for solving continuous berth allocation problem: Using multiobjective constraint-handling strategy," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2885–2895, Sep. 2017, doi: 10.1109/TCYB.2017.2669334.
[94] Y. Zhang, M. Harman, and S. L. Lim, "Empirical evaluation of search based requirements interaction management," *Inf. Softw. Technol.*, vol. 55, no. 1, pp. 126–152, Jan. 2013, doi: 10.1016/j.infsof.2012.03.007.
[95] S. Ghasemi-Falavarjani, M. Nematbakhsh, and B. S. Ghahfarokhi, "Context-aware multi-objective resource allocation in mobile cloud," *Comput. Electr. Eng.*, vol. 44, pp. 218–240, May 2015, doi: 10.1016/j.compeleceng.2015.02.006.
[96] B. S. Ghahfarokhi, M. Azadmanesh, and S. K. Khorasani, "Energy and spectrum efficient mobility-aware resource management for D2D multicasting," *Comput. Netw.*, vol. 146, pp. 47–64, Dec. 2018, doi: 10.1016/j.comnet.2018.09.013.
[97] A. E. Baladeh, M. Cheraghi, and N. Khakzad, "A multi-objective model to optimal selection of safety measures in oil and gas facilities," *Process Saf. Environ. Protection*, vol. 125, pp. 71–82, May 2019, doi: 10.1016/j.psep.2019.02.024.
[98] Y. Sato, M. Sato, H. Goto, and M. Miyakawa, "Distributed NSGA-II sharing extreme non-dominated solutions for constrained knapsack problems," in *Proc. Int. Conf. Control, Artif. Intell., Robot. Optim. (ICCAIRO)*, May 2018, pp. 197–202, doi: 10.1109/ICCAIRO.2018.00040.
[99] H. Ishibuchi, N. Tsukamoto, and Y. Nojima, "Empirical analysis of using weighted sum fitness functions in NSGA-II for many-objective 0/1 knapsack problems," in *Proc. 11th Int. Conf. Comput. Modeling Simulation*, 2009, pp. 71–76, doi: 10.1109/UKSIM.2009.54.
[100] T. Murata and A. Taki, "Examination of the performance of objective reduction using correlation-based weighted-sum for many objective knapsack problems," in *Proc. 10th Int. Conf. Hybrid Intell. Syst.*, Aug. 2010, pp. 175–180, doi: 10.1109/HIS.2010.5600027.
[101] H. Ishibuchi, "Performance evaluation of simple multiobjective genetic local search algorithms on multiobjective 0/1 knapsack problems," in *Proc. Congr. Evol. Comput. (CEC)*, 2004, pp. 441–448, doi: 10.1109/cec.2004.1330890.
[102] Y. Tanigaki, K. Narukawa, Y. Nojima, and H. Ishibuch, "Preference-based NSGA-II for many-objective knapsack problems," in *Proc. Joint 7th Int. Conf. Soft Comput. Intell. Syst. (SCIS), 15th Int. Symp. Adv. Intell. Syst. (ISIS)*, Dec. 2014, pp. 637–642, doi: 10.1109/SCIS-ISIS.2014.7044821.
[103] H. I. I. Shibuchi, N. O. T. Sukamoto, and Y. U. N. Ojima, "Use of non-geometric binary crossover as mutation," in *Proc. World Automat. Congr.*, 2010, pp. 1–6.
[104] C. Changdar, R. Kumar, P. Ghanshaym, and S. Mahapatra, "A genetic algorithm based approach to solve multi-resource multi-objective knapsack problem for vegetable wholesalers in fuzzy environment," *Oper. Res.*, vol. 20, pp. 1321–1352, Mar. 2020, doi: 10.1007/s12351-018-0392-3.
[105] X.-L. Liao and C.-K. Ting, "Solving the biobjective selective pickup and delivery problem with memetic algorithm," in *Proc. IEEE Symp. Comput. Intell. Prod. Logistics Syst. (CIPLS)*, Apr. 2013, pp. 107–114, doi: 10.1109/CIPLS.2013.6595207.
[106] A. Open, A. Journal, Y. Shuai, S. Yunfeng, and Z. Kai, "An effective method for solving multiple travelling salesman problem based on NSGA-II," *Syst. Sci. Control Eng.*, vol. 7, no. 2, pp. 108–116, Oct. 2019, doi: 10.1080/21642583.2019.1674220.
[107] J. Li, S. Zhang, X. Liu, and R. He, "Multi-objective evolutionary optimization for geostationary orbit satellite mission planning," *J. Syst. Eng. Electron.*, vol. 28, no. 5, pp. 934–945, Dec. 2017, doi: 10.21629/JSEE.2017.05.11.
[108] H. Li, D. Landa-Silva, and X. Gandibleux, "Evolutionary multi-objective optimization algorithms with probabilistic representation based on pheromone trails," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2010, pp. 1–8, doi: 10.1109/CEC.2010.5585998.
[109] S. M. Sampaio, A. Dantas, and C. G. Camilo, Jr., "Routing sales territory by solving a multi-objective TSP variant with evolutionary algorithms," in *Proc. IEEE 31st Int. Conf. Tools Artif. Intell. (ICTAI)*, Nov. 2019, pp. 109–116, doi: 10.1109/ICTAI.2019.00024.
[110] X. Chen, Y. Liu, X. Li, Z. Wang, S. Wang, and C. Gao, "A new evolutionary multiobjective model for traveling salesman problem," *IEEE Access*, vol. 7, pp. 66964–66979, 2019, doi: 10.1109/ACCESS.2019.2917838.
[111] A. Rauniyar, R. Nath, and P. K. Muhuri, "Multi-factorial evolutionary algorithm based novel solution approach for multi-objective pollution-routing problem," *Comput. Ind. Eng.*, vol. 130, pp. 757–771, Apr. 2019, doi: 10.1016/j.cie.2019.02.031.
[112] A. K. Shukla, R. Nath, and P. K. Muhuri, "NSGA-II based multi-objective pollution routing problem with higher order uncertainty," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Jul. 2017, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2017.8015668.
[113] X. Li, H. Wang, and Q. Wu, "Multi-objective optimization in ship weather routing," in *Proc. Constructive Nonsmooth Anal. Rel. Topics, Dedicated Memory V. F. Demyanov (CNSA)*, 2017, pp. 1–4, doi: 10.1109/CNSA.2017.7973982.
[114] F. Miguel, M. Frutos, F. Tohmé, and M. M. Babey, "A decision support tool for urban freight transport planning based on a multi-objective evolutionary algorithm," *IEEE Access*, vol. 7, pp. 156707–156721, 2019, doi: 10.1109/ACCESS.2019.2949948.
[115] Y. Y. Liu, F. Enayatollahi, and P. Thulasiraman, "Traffic aware many-objective dynamic route planning," in *Proc. IEEE Symp. Ser. Comput. Intell. (SSCI)*, Dec. 2019, pp. 1241–1248, doi: 10.1109/SSCI44817.2019.9002725.
[116] R. S. Mendes, D. S. Miranda, E. F. Wanner, J. F. M. Sarubbi, and F. V. C. Martins, "Multiobjective approach to the vehicle routing problem with demand responsive transport," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2016, pp. 3761–3768, doi: 10.1109/CEC.2016.7744266.
[117] R. S. Mendes, E. F. Wanner, J. F. M. Sarubbi, and F. V. C. Martins, "Optimization of the vehicle routing problem with demand responsive transport using the NSGA-II algorithm," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 2657–2662, doi: 10.1109/ITSC.2016.7795983.
[118] H. Xu, W. Fan, T. Wei, and L. Yu, "An or-opt NSGA-II algorithm for multi-objective vehicle routing problem with time windows," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, Aug. 2008, pp. 309–314, doi: 10.1109/COASE.2008.4626505.
[119] Y. Wang, S. Zhang, X. Guan, S. Peng, H. Wang, Y. Liu, and M. Xu, "Collaborative multi-depot logistics network design with time window assignment," *Expert Syst. Appl.*, vol. 140, Feb. 2020, Art. no. 112910, doi: 10.1016/j.eswa.2019.112910.

[120] Y. Wang, J. Zhang, K. Assogba, Y. Liu, M. Xu, and Y. Wang, "Collaboration and transportation resource sharing in multiple centers vehicle routing optimization with delivery and pickup," *Knowl.-Based Syst.*, vol. 160, pp. 296–310, Nov. 2018, doi: 10.1016/j.knosys.2018.07.024.

[121] S. K. Mandal, D. Pacciarelli, A. Løkketangen, and G. Hasle, "A memetic NSGA-II for the bi-objective mixed capacitated general routing problem," *J. Heuristics*, vol. 21, no. 3, pp. 359–390, Jan. 2015, doi: 10.1007/s10732-015-9280-7.

[122] T. Sooktip and N. Wattanapongsakorn, "Identifying preferred solutions for multi-objective optimization: Application to capacitated vehicle routing problem," *Cluster Comput.*, vol. 18, no. 4, pp. 1435–1448, Sep. 2015, doi: 10.1007/s10586-015-0478-0.

[123] S. Shamshirband, M. Shojafar, A. A. R. Hosseinabadi, and A. Abraham, "A solution for multi-objective commodity vehicle routing problem by NSGA-II," in *Proc. 14th Int. Conf. Hybrid Intell. Syst.*, Dec. 2014, pp. 12–17, doi: 10.1109/HIS.2014.7086201.

[124] X. Xu, W. Fan, W. Wang, and H. Xu, "A two-layer model for vehicle routing problem based on genetic algorithm," in *Proc. IEEE Int. Conf. Service Oper. Logistics, Informat.*, Oct. 2008, pp. 2102–2106, doi: 10.1109/SOLI.2008.4682880.

[125] M. Sheikhalishahi, N. Eskandari, A. Mashayekhi, and A. Azadeh, "Multi-objective open shop scheduling by considering human error and preventive maintenance," *Appl. Math. Model.*, vol. 67, pp. 573–587, Mar. 2019, doi: 10.1016/j.apm.2018.11.015.

[126] A. Azadeh, S. Goldansaz, and A. Zahedi-Anaraki, "Solving and optimizing a bi-objective open shop scheduling problem by a modified genetic algorithm," *Int. J. Adv. Manuf. Technol.*, vol. 85, nos. 5–8, pp. 1603–1613, Jul. 2016, doi: 10.1007/s00170-015-8069-z.

[127] E. Ahmadi, M. Zandieh, M. Farrokh, and S. M. Emami, "A multi objective optimization approach for flexible job shop scheduling problem under random machine breakdown by evolutionary algorithms," *Comput. Oper. Res.*, vol. 73, pp. 56–66, Sep. 2016, doi: 10.1016/j.cor.2016.03.009.

[128] G. Vilcot and J.-C. Billaut, "A tabu search and a genetic algorithm for solving a bicriteria general job shop scheduling problem," *Eur. J. Oper. Res.*, vol. 190, no. 2, pp. 398–411, Oct. 2008, doi: 10.1016/j.ejor.2007.06.039.

[129] J. Autuori, F. Hnaien, and F. Yalaoui, "A mapping technique for better solution exploration: NSGA-II adaptation," *J. Heuristics*, vol. 22, no. 1, pp. 89–123, Feb. 2016, doi: 10.1007/s10732-015-9303-4.

[130] X. Gong, Q. Deng, G. Gong, W. Liu, and Q. Ren, "A memetic algorithm for multi-objective flexible job-shop problem with worker flexibility," *Int. J. Prod. Res.*, vol. 56, no. 7, pp. 2506–2522, Apr. 2018, doi: 10.1080/00207543.2017.1388933.

[131] F. Zhang, Y. Mei, and M. Zhang, "Evolving dispatching rules for multi-objective dynamic flexible job shop scheduling via genetic programming hyper-heuristics," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 1366–1373, doi: 10.1109/CEC.2019.8790112.

[132] C. Wang, N. Tian, Z. Ji, and Y. Wang, "Multi-objective fuzzy flexible job shop scheduling using memetic algorithm," *J. Stat. Comput. Simul.*, vol. 87, no. 14, pp. 2828–2846, Sep. 2017, doi: 10.1080/00949655.2017.1344846.

[133] H. Wang, Y. Fu, M. Huang, G. Q. Huang, and J. Wang, "A NSGA-II based memetic algorithm for multiobjective parallel flowshop scheduling problem," *Comput. Ind. Eng.*, vol. 113, pp. 185–194, Nov. 2017, doi: 10.1016/j.cie.2017.09.009.

[134] T.-C. Chiang, H.-C. Cheng, and L.-C. Fu, "NNMA: An effective memetic algorithm for solving multiobjective permutation flow shop scheduling problems," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 5986–5999, May 2011, doi: 10.1016/j.eswa.2010.11.022.

[135] Z. Zeng, M. Hong, Y. Man, J. Li, Y. Zhang, and H. Liu, "Multi-object optimization of flexible flow shop scheduling with batch process—Consideration total electricity consumption and material wastage," *J. Cleaner Prod.*, vol. 183, pp. 925–939, May 2018, doi: 10.1016/j.jclepro.2018.02.224.

[136] P.-C. Chang, S.-H. Chen, C.-Y. Fan, and C.-L. Chan, "Genetic algorithm integrated with artificial chromosomes for multi-objective flowshop scheduling problems," *Appl. Math. Comput.*, vol. 205, no. 2, pp. 550–561, Nov. 2008, doi: 10.1016/j.amc.2008.05.027.

[137] S. Cai, K. Yang, and K. Liu, "Multi-objective optimization of the distributed permutation flow shop scheduling problem with transportation and eligibility constraints," *J. Oper. Res. Soc. China*, vol. 6, no. 3, pp. 391–416, Sep. 2018, doi: 10.1007/s40305-017-0165-3.

[138] Y.-Y. Han, D.-W. Gong, X.-Y. Sun, and Q.-K. Pan, "An improved NSGA-II algorithm for multi-objective lot-streaming flow shop scheduling problem," *Int. J. Prod. Res.*, vol. 52, no. 8, pp. 2211–2231, Apr. 2014, doi: 10.1080/00207543.2013.848492.

[139] F. Habibi, F. Barzinpour, and S. J. Sadjadi, "A mathematical model for project scheduling and material ordering problem with sustainability considerations: A case study in Iran," *Comput. Ind. Eng.*, vol. 128, pp. 690–710, Feb. 2019, doi: 10.1016/j.cie.2019.01.007.

[140] S. Tao and Z. Sasha, "Multi-mode resource-constrained project scheduling problem with alternative project structures," *Comput. Ind. Eng.*, vol. 125, pp. 333–347, Nov. 2018, doi: 10.1016/j.cie.2018.08.027.

[141] M. Laszczyk and P. B. Myszkowski, "Improved selection in evolutionary multi–objective optimization of multi–skill resource–constrained project scheduling problem," *Inf. Sci.*, vol. 481, pp. 412–431, May 2019, doi: 10.1016/j.ins.2019.01.002.

[142] J. Xiao, Z. Wu, X. Hong, J. Tang, and Y. Tang, "Integration of electromagnetism with multi-objective evolutionary algorithms for RCPSP," *Eur. J. Oper. Res.*, vol. 251, no. 1, pp. 22–35, May 2016, doi: 10.1016/j.ejor.2015.10.059.

[143] H. Wang, D. A. N. Lin, and M. Li, "A competitive genetic algorithm for resource-constrained project scheduling problem," in *Proc. Int. Conf. Mach. Learn. Cybern.*, 2005, pp. 2945–2949, doi: 10.1002/(SICI)1520-6750(199810)45:7<733::AID-NAV5>3.0.CO;2-C.

[144] S. C. Vanucci, E. G. Carrano, R. Bicalho, and R. H. C. Takahashi, "A modified NSGA-II for the multiobjective multi-mode resource-constrained project scheduling problem," in *Proc. IEEE Congr. Evol. Comput.*, Jun. 2012, pp. 1–7, doi: 10.1109/CEC.2012.6256616.

[145] N. Damak, B. Jarboui, and T. Loukil, "Non-dominated sorting genetic algorithm-II to solve bi-objective multi-mode resource-constrained project scheduling problem," in *Proc. Int. Conf. Control, Decis. Inf. Technol. (CoDIT)*, 2013, pp. 842–846, doi: 10.1109/CoDIT.2013.6689652.

[146] Y. Wu, H. Yang, J. Tang, and Y. Yu, "Multi-objective re-synchronizing of bus timetable: Model, complexity and solution," *Transp. Res. C, Emerg. Technol.*, vol. 67, pp. 149–168, Jun. 2016, doi: 10.1016/j.trc.2016.02.007.

[147] A. Mohtashami, M. Tavana, F. J. Santos-Arteaga, and A. Fallahian-Najafabadi, "A novel multi-objective meta-heuristic model for solving cross-docking scheduling problems," *Appl. Soft Comput. J.*, vol. 31, pp. 30–47, Jun. 2015, doi: 10.1016/j.asoc.2015.02.030.

[148] A. Abdi and H. R. Zarandi, "A meta heuristic-based task scheduling and mapping method to optimize main design challenges of heterogeneous multiprocessor embedded systems," *Microelectron. J.*, vol. 87, pp. 1–11, May 2019, doi: 10.1016/j.mejo.2019.03.006.

[149] A. K. Shukla, R. Nath, P. K. Muhuri, and Q. M. D. Lohani, "Energy efficient multi-objective scheduling of tasks with interval type-2 fuzzy timing constraints in an Industry 4.0 ecosystem," *Eng. Appl. Artif. Intell.*, vol. 87, Jan. 2020, Art. no. 103257, doi: 10.1016/j.engappai.2019.103257.

[150] H. Lu, R. Niu, J. Liu, and Z. Zhu, "A chaotic non-dominated sorting genetic algorithm for the multi-objective automatic test task scheduling problem," *Appl. Soft Comput. J.*, vol. 13, no. 5, pp. 2790–2802, May 2013, doi: 10.1016/j.asoc.2012.10.001.

[151] J. P. D. Comput, R. Salimi, H. Motameni, and H. Omranpour, "Task scheduling using NSGA II with fuzzy adaptive operators for computational grids," *J. Parallel Distrib. Comput.*, vol. 74, no. 5, pp. 2333–2350, May 2014, doi: 10.1016/j.jpdc.2014.01.006.

[152] P. Chitra, R. Rajaram, and P. Venkatesh, "Application and comparison of hybrid evolutionary multiobjective optimization algorithms for solving task scheduling problem on heterogeneous systems," *Appl. Soft Comput. J.*, vol. 11, no. 2, pp. 2725–2734, Mar. 2011, doi: 10.1016/j.asoc.2010.11.003.

[153] A. S. Sofia and P. GaneshKumar, "Multi-objective task scheduling to minimize energy consumption and makespan of cloud computing using NSGA-II," *J. Netw. Syst. Manag.*, vol. 26, no. 2, pp. 463–485, Sep. 2018, doi: 10.1007/s10922-017-9425-0.

[154] G. Subashini and M. C. Bhuvaneswari, "Comparison of multi-objective evolutionary approaches for task scheduling in distributed computing systems," *Sadhana*, vol. 37, no. 6, pp. 675–694, Jan. 2012, doi: 10.1007/s12046-012-0102-4.

[155] S. Bandyopadhyay and R. Bhattacharya, "Solving multi-objective parallel machine scheduling problem by a modified NSGA-II," *Appl. Math. Model.*, vol. 37, nos. 10–11, pp. 6718–6729, Jun. 2013, doi: 10.1016/j.apm.2013.01.050.

[156] J. C. Vidal, M. Mucientes, A. Bugarín, and M. Lama, "Machine scheduling in custom furniture industry through neuro-evolutionary hybridization," *Appl. Soft Comput.*, vol. 11, no. 2, pp. 1600–1613, Mar. 2011, doi: 10.1016/j.asoc.2010.04.020.

[157] F. Liu, J.-J. Wang, and D.-L. Yang, "Solving single machine scheduling under disruption with discounted costs by quantum-inspired hybrid heuristics," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 715–723, Oct. 2013, doi: 10.1016/j.jmsy.2013.04.002.

[158] R. Ramacher and L. Mönch, "An automated negotiation approach to solve single machine scheduling problems with interfering job sets," *Comput. Ind. Eng.*, vol. 99, pp. 318–329, Sep. 2016, doi: 10.1016/j.cie.2016.01.013.
[159] S. Wang, X. Wang, J. Yu, S. Ma, and M. Liu, "Bi-objective identical parallel machine scheduling to minimize total energy consumption and makespan," *J. Cleaner Prod.*, vol. 193, pp. 424–440, Aug. 2018, doi: 10.1016/j.jclepro.2018.05.056.
[160] Y. Li, Y. He, Y. Wang, F. Tao, and J. W. Sutherland, "An optimization method for energy-conscious production in flexible machining job shops with dynamic job arrivals and machine breakdowns," *J. Cleaner Prod.*, vol. 254, May 2020, Art. no. 120009, doi: 10.1016/j.jclepro.2020.120009.
[161] A. C. M. A. Tepedino, R. H. C. Takahashi, and E. G. Carrano, "Distance based NSGA-II for earliness and tardiness minimization in parallel machine scheduling," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2013, pp. 317–324, doi: 10.1109/CEC.2013.6557586.
[162] Y.-J. Song, X. Ma, X.-J. Li, L.-N. Xing, and P. Wang, "Learning-guided nondominated sorting genetic algorithm II for multi-objective satellite range scheduling problem," *Swarm Evol. Comput.*, vol. 49, pp. 194–205, Sep. 2019, doi: 10.1016/j.swevo.2019.06.008.
[163] J. Zhang, L. Xing, G. Peng, F. Yao, and C. Chen, "A large-scale multiobjective satellite data transmission scheduling algorithm based on SVM+NSGA-II," *Swarm Evol. Comput.*, vol. 50, Nov. 2019, Art. no. 100560, doi: 10.1016/j.swevo.2019.100560.
[164] X. Niu, H. Tang, and L. Wu, "Satellite scheduling of large areal tasks for rapid response to natural disaster using a multi-objective genetic algorithm," *Int. J. Disaster Risk Reduction*, vol. 28, pp. 813–825, Jun. 2018, doi: 10.1016/j.ijdrr.2018.02.013.
[165] M. M. Malik, M. Khan, and S. Abdallah, "Aggregate capacity planning for elective surgeries: A bi-objective optimization approach to balance patients waiting with healthcare costs," *Oper. Res. Health Care*, vol. 7, pp. 3–13, Dec. 2015, doi: 10.1016/j.orhc.2015.09.009.
[166] R. Guido and D. Conforti, "A hybrid genetic approach for solving an integrated multi-objective operating room planning and scheduling problem," *Comput. Oper. Res.*, vol. 87, pp. 270–282, Nov. 2017, doi: 10.1016/j.cor.2016.11.009.
[167] D. G. Fotakis, E. Sidiropoulos, D. Myronidis, and K. Ioannou, "Spatial genetic algorithm for multi-objective forest planning," *Forest Policy Econ.*, vol. 21, pp. 12–19, Aug. 2012, doi: 10.1016/j.forpol.2012.04.002.
[168] Z. Zeng, M. Hong, J. Li, Y. Man, H. Liu, Z. Li, and H. Zhang, "Integrating process optimization with energy-efficiency scheduling to save energy for paper mills," *Appl. Energy*, vol. 225, pp. 542–558, Sep. 2018, doi: 10.1016/j.apenergy.2018.05.051.
[169] W. Wang, H. Yang, Y. Zhang, and J. Xu, "IoT-enabled real-time energy efficiency optimisation method for energy-intensive manufacturing enterprises," *Int. J. Comput. Integr. Manuf.*, vol. 31, nos. 4–5, pp. 362–379, Apr. 2018, doi: 10.1080/0951192X.2017.1337929.
[170] M. A. F. Ghazvini, J. Soares, N. Horta, R. Neves, R. Castro, and Z. Vale, "A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers," *Appl. Energy*, vol. 151, pp. 102–118, Aug. 2015, doi: 10.1016/j.apenergy.2015.04.067.
[171] T. Cortés-Arcos, J. L. Bernal-Agustín, R. Dufo-López, J. M. Lujano-Rojas, and J. Contreras, "Multi-objective demand response to real-time prices (RTP) using a task scheduling methodology," *Energy*, vol. 138, pp. 19–31, Nov. 2017, doi: 10.1016/j.energy.2017.07.056.
[172] Y. Huang, H. Lan, Y. Y. Hong, S. Wen, and S. Fang, "Joint voyage scheduling and economic dispatch for all-electric ships with virtual energy storage systems," *Energy*, vol. 190, Jan. 2020, Art. no. 116268, doi: 10.1016/j.energy.2019.116268.
[173] Z. X. Guo, W. K. Wong, Z. Li, and P. Ren, "Modeling and Pareto optimization of multi-objective order scheduling problems in production planning," *Comput. Ind. Eng.*, vol. 64, no. 4, pp. 972–986, Apr. 2013, doi: 10.1016/j.cie.2013.01.006.
[174] S. Zhong, A. A. Pantelous, M. Goh, and J. Zhou, "A reliability-and-cost-based fuzzy approach to optimize preventive maintenance scheduling for offshore wind farms," *Mech. Syst. Signal Process.*, vol. 124, pp. 643–663, Jul. 2019, doi: 10.1016/j.ymssp.2019.02.012.
[175] D.-J. Wang, F. Liu, J.-J. Wang, and Y.-Z. Wang, "Integrated rescheduling and preventive maintenance for arrival of new jobs through evolutionary multi-objective optimization," *Soft Comput.*, vol. 20, no. 4, pp. 1635–1652, Apr. 2016, doi: 10.1007/s00500-015-1615-7.
[176] P. Ghoddousi, E. Eshtehardian, S. Jooybanpour, and A. Javanmardi, "Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm," *Autom. Construct.*, vol. 30, pp. 216–227, Mar. 2013, doi: 10.1016/j.autcon.2012.11.014.
[177] M. Tavana, A. Abtahi, and K. Khalili-damghani, "A new multi-objective multi-mode model for solving preemptive time–cost–quality trade-off project scheduling problems," *Expert Syst. Appl.*, vol. 41, no. 4, pp. 1830–1846, Mar. 2014, doi: 10.1016/j.eswa.2013.08.081.
[178] S. Monghasemi, M. R. Nikoo, M. A. K. Fasaee, and J. Adamowski, "A novel multi criteria decision making model for optimizing time–cost–quality trade-off problems in construction projects," *Expert Syst. Appl.*, vol. 42, no. 6, pp. 3089–3104, Apr. 2015, doi: 10.1016/j.eswa.2014.11.032.
[179] A. Hassanzadeh, M. Rasti-Barzoki, and H. Khosroshahi, "Two new meta-heuristics for a bi-objective supply chain scheduling problem in flow-shop environment," *Appl. Soft Comput.*, vol. 49, pp. 335–351, Dec. 2016, doi: 10.1016/j.asoc.2016.08.019.
[180] A. Kaushik and D. P. Vidyarthi, "An energy-efficient reliable grid scheduling model using NSGA-II," *Eng. Comput.*, vol. 32, no. 3, pp. 355–376, Jul. 2016, doi: 10.1007/s00366-015-0419-9.
[181] P.-H. Li and Y.-Y. Lou, "An integer multi-objective optimization model and an enhanced non-dominated sorting genetic algorithm for contraflow scheduling problem," *J. Central South Univ.*, vol. 22, no. 6, pp. 2399–2405, Jun. 2015, doi: 10.1007/s11771-015-2766-5.
[182] J. Long, Z. Zheng, X. Gao, and P. M. Pardalos, "A hybrid multi-objective evolutionary algorithm based on NSGA-II for practical scheduling with release times in steel plants," *J. Oper. Res. Soc.*, vol. 67, no. 9, pp. 1184–1199, Sep. 2016, doi: 10.1057/jors.2016.17.
[183] M. Souier, M. Dahane, and F. Maliki, "An NSGA-II-based multiobjective approach for real-time routing selection in a flexible manufacturing system under uncertainty and reliability constraints," *Int. J. Adv. Manuf. Technol.*, vol. 100, nos. 9–12, pp. 2813–2829, Feb. 2019, doi: 10.1007/s00170-018-2897-6.
[184] Y. Sun, F. Lin, and H. Xu, "Multi-objective optimization of resource scheduling in fog computing using an improved NSGA-II," *Wireless Pers. Commun.*, vol. 102, no. 2, pp. 1369–1385, Jan. 2018, doi: 10.1007/s11277-017-5200-5.
[185] H. Choi, M.-H. Park, D.-M. Jeong, and J.-H. Kim, "Soil recycling among construction sites by optimizing schedule and costs for earth-moving," *J. Asian Archit. Building Eng.*, vol. 16, no. 2, pp. 439–446, May 2017, doi: 10.3130/jaabe.16.439.
[186] K. B. Naik, G. M. Gandhi, S. H. Patil, K. B. Naik, G. M. Gandhi, and S. H. Patil, "Pareto-based adaptive resources selection model in hybrid cloud environment," *IETE J. Res.*, pp. 1–13, Oct. 2018, doi: 10.1080/03772063.2018.1535919.
[187] P. Mohapatra, L. Benyoucef, and M. K. Tiwari, "Integration of process planning and scheduling through adaptive setup planning: A multi-objective approach," *Int. J. Prod. Res.*, vol. 51, nos. 23–24, pp. 7190–7208, Nov. 2013, doi: 10.1080/00207543.2013.853890.
[188] P. Mohapatra, A. Nayak, S. K. Kumar, and M. K. Tiwari, "Multi-objective process planning and scheduling using controlled elitist non-dominated sorting genetic algorithm," *Int. J. Prod. Res.*, vol. 53, no. 6, pp. 1712–1735, Sep. 2015, doi: 10.1080/00207543.2014.957872.
[189] Z. Xu, X. G. Ming, M. Zheng, M. Li, L. He, and W. Song, "Cross-trained workers scheduling for field service using improved NSGA-II," *Int. J. Prod. Res.*, vol. 53, no. 4, pp. 1255–1272, Sep. 2015, doi: 10.1080/00207543.2014.955923.
[190] Y. Guo, Z.-R. Chen, Y.-L. Ruan, and J. Zhang, "Application of NSGA-II with local search to multi-dock cross-docking sheduling problem," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2012, pp. 779–784, doi: 10.1109/ICSMC.2012.6377822.
[191] Ö. F. Yılmaz, "Operational strategies for seru production system: A bi-objective optimisation model and solution methods," *Int. J. Prod. Res.*, vol. 58, no. 11, pp. 3195–3219, Sep. 2020, doi: 10.1080/00207543.2019.1669841.
[192] F. Ruiming, "Multi-objective optimized operation of integrated energy system with hydrogen storage," *Int. J. Hydrogen Energy*, vol. 44, no. 56, pp. 29409–29417, Nov. 2019, doi: 10.1016/j.ijhydene.2019.02.168.
[193] J. Dou, J. Li, and C. Su, "Bi-objective optimization of integrating configuration generation and scheduling for reconfigurable flow lines using NSGA-II," *Int. J. Adv. Manuf. Technol.*, vol. 86, pp. 1945–1962, Jan. 2016, doi: 10.1007/s00170-015-8291-8.
[194] A. Hassanzadeh and M. Rasti-barzoki, "Minimizing total resource consumption and total tardiness penalty in a resource allocation supply chain scheduling and vehicle routing problem," *Appl. Soft Comput. J.*, vol. 58, pp. 307–323, Sep. 2017, doi: 10.1016/j.asoc.2017.05.010.
[195] Q. Liu, C. Zhang, K. Zhu, and Y. Rao, "Novel multi-objective resource allocation and activity scheduling for fourth party logistics," *Comput. Oper. Res.*, vol. 44, pp. 42–51, Apr. 2014, doi: 10.1016/j.cor.2013.10.010.

[196] M. Musavi and A. Bozorgi-Amiri, "A multi-objective sustainable hub location-scheduling problem for perishable food supply chain," *Comput. Ind. Eng.*, vol. 113, pp. 766–778, Nov. 2017, doi: 10.1016/j.cie.2017.07.039.

[197] A. De, A. Choudhary, and M. K. Tiwari, "Multiobjective approach for sustainable ship routing and scheduling with draft restrictions," *IEEE Trans. Eng. Manag.*, vol. 66, no. 1, pp. 35–51, Feb. 2019, doi: 10.1109/TEM.2017.2766443.

[198] I. A. Martínez-Salazar, J. Molina, F. Ángel-Bello, T. Gómez, and R. Caballero, "Solving a bi-objective transportation location routing problem by metaheuristic algorithms," *Eur. J. Oper. Res.*, vol. 234, no. 1, pp. 25–36, Apr. 2014, doi: 10.1016/j.ejor.2013.09.008.

[199] M. Rabbani, R. Heidari, H. Farrokhi-Asl, and N. Rahimi, "Using metaheuristic algorithms to solve a multi-objective industrial hazardous waste location-routing problem considering incompatible waste types," *J. Cleaner Prod.*, vol. 170, pp. 227–241, Jan. 2018, doi: 10.1016/j.jclepro.2017.09.029.

[200] H. Wang, L. Du, and S. Ma, "Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake," *Transp. Res. E, Logistics Transp. Rev.*, vol. 69, pp. 160–179, Sep. 2014, doi: 10.1016/j.tre.2014.06.006.

[201] A. Amini, R. Tavakkoli-Moghaddam, and S. Ebrahimnejad, "A bi-objective transportation-location arc routing problem," *Transp. Lett.*, vol. 12, no. 9, pp. 623–637, Oct. 2020, doi: 10.1080/19427867.2019.1679405.

[202] H. Farrokhi-Asl, R. Tavakkoli-Moghaddam, B. Asgarian, and E. Sangari, "Metaheuristics for a bi-objective location-routing-problem in waste collection management," *J. Ind. Prod. Eng.*, vol. 34, no. 4, pp. 239–252, May 2017, doi: 10.1080/21681015.2016.1253619.

[203] M. Rashidnejad, S. Ebrahimnejad, and J. Safari, "A bi-objective model of preventive maintenance planning in distributed systems considering vehicle routing problem," *Comput. Ind. Eng.*, vol. 120, pp. 360–381, Jun. 2018, doi: 10.1016/j.cie.2018.05.001.

[204] J. Blank, K. Deb, and S. Mostaghim, "Solving the bi-objective traveling thief problem with multi-objective evolutionary algorithms," in *Proc. Int. Conf. Evol. Multi-Criterion Optim. (EMO)*, vol. 10173, 2017, pp. 46–60, doi: 10.1007/978-3-319-54157-0_4.

[205] B. Ji, H. Sun, X. Yuan, Y. Yuan, and X. Wang, "Coordinated optimized scheduling of locks and transshipment in inland waterway transportation using binary NSGA-II," *Int. Trans. Oper. Res.*, vol. 27, no. 3, pp. 1501–1525, May 2020, doi: 10.1111/itor.12720.

[206] R. Khanduzi, M. R. Peyghami, and A. K. Sangaiah, "Data envelopment analysis and interdiction median problem with fortification for enabling IoT technologies to relieve potential attacks," *Futur. Gener. Comput. Syst.*, vol. 79, pp. 928–940, Feb. 2018, doi: 10.1016/j.future.2017.08.056.

[207] S. Wang and S. Ma, "Efficient methods for a bi-objective nursing home location and allocation problem: A case study," *Appl. Soft Comput.*, vol. 65, pp. 280–291, Apr. 2018, doi: 10.1016/j.asoc.2018.01.014.

[208] I. S. Doolun, S. G. Ponnambalam, N. Subramanian, and G. Kanagaraj, "Data driven hybrid evolutionary analytical approach for multi objective location allocation decisions: Automotive green supply chain empirical evidence," *Comput. Oper. Res.*, vol. 98, pp. 265–283, Oct. 2018, doi: 10.1016/j.cor.2018.01.008.

[209] C. Pilato, A. Tumeo, G. Palermo, F. Ferrandi, P. L. Lanzi, and D. Sciuto, "Improving evolutionary exploration to area-time optimization of FPGA designs," *J. Syst. Archit.*, vol. 54, no. 11, pp. 1046–1057, Nov. 2008, doi: 10.1016/j.sysarc.2008.04.010.

[210] M. Rabbani, R. Heidari, and R. Yazdanparast, "A stochastic multi-period industrial hazardous waste location-routing problem: Integrating NSGA-II and Monte Carlo simulation," *Eur. J. Oper. Res.*, vol. 272, no. 3, pp. 945–961, 2019, doi: 10.1016/j.ejor.2018.07.024.

[211] P. Leesutthipornchai, C. Charnsripinyo, and N. Wattanapongsakorn, "Solving multi-objective routing and wavelength assignment in WDM network using hybrid evolutionary computation approach," *Comput. Commun.*, vol. 33, no. 18, pp. 2246–2259, Dec. 2010, doi: 10.1016/j.comcom.2010.07.029.

[212] K. Li, C. Zhou, J. Y.-T. Leung, and Y. Ma, "Integrated production and delivery with single machine and multiple vehicles," *Expert Syst. Appl.*, vol. 57, pp. 12–20, Sep. 2016, doi: 10.1016/j.eswa.2016.02.033.

[213] C. Hu, X. Yan, W. Gong, X. Liu, L. Wang, and L. Gao, "Multi-objective based scheduling algorithm for sudden drinking water contamination incident," *Swarm Evol. Comput.*, vol. 55, Jun. 2020, Art. no. 100674, doi: 10.1016/j.swevo.2020.100674.

[214] J. Knowles and D. Corne, "On metrics for comparing nondominated sets," in *Proc. Congr. Evol. Comput. (CEC)*, Aug. 2002, vol. 1, no. 2, pp. 711–716, doi: 10.1109/CEC.2002.1007013.

[215] C. A. Coello Coello and M. S. Lechuga, "MOPSO: A proposal for multiple objective particle swarm optimization," in *Proc. Congr. Evol. Comput. (CEC)*, vol. 2, 2002, pp. 1051–1056, doi: 10.1109/CEC.2002.1004388.

[216] F. Xue, A. C. Sanderson, and R. J. Graves, "Multi-objective differential evolution-algorithm, convergence analysis, and applications," in *Proc. IEEE Congr. Evol. Comput.*, vol. 1, Sep. 2005, pp. 743–750, doi: 10.1109/cec.2005.1554757.

[217] M. Ayaz, A. Panwar, and M. Pant, "A brief review on multi-objective differential evolution," in *Proc. Adv. Intell. Syst. Comput.*, vol. 1053, 2020, pp. 1027–1040, doi: 10.1007/978-981-15-0751-9_95.

[218] I. Alaya, C. Solnon, and K. Ghedira, "Ant colony optimization for multi-objective optimization problems," in *Proc. 19th IEEE Int. Conf. Tools Artif. Intell. (ICTAI)*, vol. 1, Oct. 2007, pp. 450–457, doi: 10.1109/ICTAI.2007.108.

[219] R. Akbari, R. Hedayatzadeh, K. Ziarati, and B. Hassanizadeh, "A multi-objective artificial bee colony algorithm," *Swarm Evol. Comput.*, vol. 2, pp. 39–52, Feb. 2012, doi: 10.1016/j.swevo.2011.08.001.

[220] S. Mirjalili, S. Saremi, S. M. Mirjalili, and L. D. S. Coelho, "Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization," *Expert Syst. Appl.*, vol. 47, pp. 106–119, Apr. 2016, doi: 10.1016/j.eswa.2015.10.039.

[221] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Trans. Evol. Comput.*, vol. 11, no. 6, pp. 712–731, Dec. 2007, doi: 10.1109/TEVC.2007.892759.

[222] B. Korte and J. Vygen, "Network design problems," in *Combinatorial Optimization: Theory and Algorithms*, vol. 21. Berlin, Germany: Springer, 2008, pp. 491–525, doi: 10.1007/978-3-540-71844-4_20.

[223] P. Rohlfshagen and X. Yao, "Dynamic combinatorial optimisation problems: An analysis of the subset sum problem," *Soft Comput.*, vol. 15, no. 9, pp. 1723–1734, Sep. 2011, doi: 10.1007/s00500-010-0616-9.

[224] S. C. Brailsford, C. N. Potts, and B. M. Smith, "Constraint satisfaction problems: Algorithms and applications," *Eur. J. Oper. Res.*, vol. 119, no. 3, pp. 557–581, Dec. 1999, doi: 10.1016/S0377-2217(98)00364-6.

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