International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 20 (2017) pp. 9774-9793

Many-Objective Optimization: Problems and Evolutionary Algorithms – A Short Review

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Abstract

The many-objective optimization problems are special case of multi-objective optimization problems with more than three objectives. Many-objective optimization problem solving is challenging due to various properties associated with it. Since last decade, many researchers are working on development of evolutionary algorithms to solve many-objective optimization problems. This paper presents a short review about many-objective optimization problems, many-objective evolutionary algorithms and future research directions. The research papers are considered for this study from year 2005 to 2017.

Keywords: Many-objective Optimization; Many-objective Optimization Benchmark Problems; Many-objective Evolutionary Algorithms;

INTRODUCTION

The many-objective optimization problems (MaOPs) are special case of multi-objective optimization problems. The many-objective optimization problems contain four or more objective functions. The real world optimization problems found in science, engineering and other domains can be mathematically modeled as multi or many-objective optimization problems. In such problems, solutions are obtained after evaluation of multiple conflicting criterions [1-4]. The KanGAL report published by Saxena et al. have discussed various challenges and properties of many-objective optimization problems. The many-objective optimization problem solving is more challenging because of several reasons. The high computational cost due to increased evaluation of number of points required for Pareto front approximation, inability of existing evolutionary multi-objective algorithms to solve many-objective optimization problems, difficulty to visualize the Pareto front with more than four objectives. The many-objective optimization problems possess various properties or characteristics, which makes them more difficult for solving. The many-objective optimization problems consist of more than three objectives, the decision variables can be from several hundreds to thousands, the points required to decide Pareto front increases exponentially due to increase in number of objectives, the computational cost increases while increase in number of objectives, the visualization is difficult. The many-objective optimization problem handling becomes difficult due to different five classes, according to Ishibuchi et al. It includes difficulty in searching Pareto optimal solutions, huge number of solutions may be needed to estimate entire Pareto front, difficult to represent obtained solutions, difficult to choose single final solution, and evaluation of search strategies is difficult [5]. While solving the many-objective optimization problems, researchers have focused mainly on scalability of number of objectives, the less attention is paid on scalability of decision variables. The optimization problems with large number of objectives and decision variables are known as large scale many-objective optimization problems.

This paper presents a short review on many-objective optimization problems and algorithms used to solve it. It also presents the set of standard benchmark sets used to test the proposed algorithms as well as real time applications. The existing algorithms and specific algorithms designed to solve many-objective optimization problems are discussed. This paper also presents the future research directions from literature. This paper presents short review on the said topic by adding papers published after 2015 on many-objective optimization evolutionary algorithms (MaOEAs) and problems. The Table 1 presents number of paper published since 2005 related with many-objective optimization evolutionary algorithms and problems collected from Google Scholar's first page, searched using keyword "many objective optimization". The earlier reviews published about such problems and algorithms are also considered.

Table 1: Number of Papers Published in Major Conferences and Journals in Recent Years

Sr. No.	Year	No. of Multi/Many Objective Optimization Problems Related Papers Published	Reference
1.	2005	1	[1]
2.	2006	1	[2]
3.	2007	1	[3]
4.	2008	2	[4-5]
5.	2009	7	[6-12]
6.	2010	7	[13-19]
7.	2011	10	[20-29]
8.	2012	12	[30-41]
9.	2013	18	[42-60]
10.	2014	21	[61-81]
11.	2015	19	[82-100]
12.	2016	27	[101-127]
13.	2017	25	[128-152]

Earlier researchers have been presented a review on many-objective, multi-objective optimization problems and evolutionary algorithms to solve such problems in the year 2007 (22 papers), 2008 (55 papers), 2014 (112 papers), and 2015 (238 papers). Also the reviews presents comparison of different performance metrics, categories of standard benchmark suits and its development [2], [3], [5], [29], [81], [99], [100], [110], [116], [146], [149].

According to Zhang et al. the algorithms developed to solve many-objective optimization problems mainly focus on two issues, the first is improvement in convergence rate and second is improvement in diversity of solutions. The four different categories presented to address these issues viz., modify Pareto dominance, use of performance metrics as selection criterion, decomposition approach and conversion of many-objective optimization problem into multi-objective optimization problem [101]. In many-objective optimization problems, obtaining complete and exact set of Pareto optimal solutions is difficult task. As the number of objectives increased in multi-objective optimization problems, the convergence becomes difficult. Interaction among different objectives and increase in problem dimension makes many-objective optimization problems more difficult. The evolutionary methods developed to solve many-objective optimization problems are based on preference relations and transforming original problem into suitable one to be solved using existing multi-objective evolutionary algorithm. The multi-objective evolutionary algorithms need to modify so that it will be suitable for addressing many-objective optimization problems. [29], [81].

The many-objective optimization problems have attempted by researchers using existing evolutionary multi-objective optimization algorithms. Some of them are, NSGA-II, MOEA/D, SMS-EMOA, HypE, hyper-heuristic based MOPSO algorithm, etc. Also several decomposition-based approaches have been proposed by researchers to solve constrained standard as well as complex real world many objective optimization problems [71]. These algorithms have several limitations to solve many objective optimization problems. The various challenges need to be addressed like, scalability, solution representation and visualization, algorithm design, and metrics to evaluate presented algorithm. While solving many objective optimization problems using multi-objective optimization algorithms, the effect of preference relations or guided search and parameter settings need to be studied.

The rest of the paper is organized as; Section 2 presents overview of many-objective optimization problems, which includes both standard as well as real time applications. Section 3 presents the summary of existing multi-objective optimization algorithms used to solve many-objective optimization problems as well as the algorithms developed to solve many-objective optimization problems. Section 4 presents the future research directions to attempt many-objective optimization problems as well as to develop new algorithms. The conclusion of the study is presented in section 5.

MANY-OBJECTIVE OPTIMIZATION PROBLEMS

The optimization problems found in science, engineering and other business domain contains number of conflicting objectives need to fulfill simultaneously for obtaining satisfactory solution. The problems with more than one objective are known as multiobjective optimization problems. The earlier researchers in optimization field focused on problems with 2 to 3 objectives. Since last decades researchers attracted towards problems with more than 3 objectives, this class of problems is known as many objective optimization problems [1].

The multi-objective, many objective and large scale compute intensive optimization problems have attracted researchers from nature inspired computing community. The new algorithms developed or proposed to solve multi/many objective optimization and large scale optimization problems tested on different standard benchmark problems for performance evaluation purpose. The standard benchmark problems are of type constrained and unconstrained. There are several benchmark suits developed, found in literature. The widely used test suits are ZDT proposed by Zitzler, Deb, and Thiele and DTLZ proposed by Deb, Thiele, Laumanns, and Zitzler for multi-objective optimization algorithms. The ZDT test suit has limitations; some of them are, test problems are of two objectives, Pareto front is not degenerate, none of its problems are non-separable, only distance parameters are scalable, fitness landscape is without flat regions. The ZDT problems are concave and convex in geometry.

The DTLZ test problems are scalable, linear and concave in geometry. Also the DTLZ test suit has some limitations; the fitness landscape is without flat regions, problems are practically non-separable,

Van Veldhuizen's test suite is another multiobjective optimization problem set. The Van Veldhuizen's test suite is collection of 7 (MOP1-MOP7) test problems from literature. These problem set are also non-scalable from objective-wise, most of the problems are in adhoc nature so it makes them difficult for analyses. The review of ZDT, DTLZ, WFG, Knapsack and other multi-objective and other scalable test problems is presented in [2].

The WFG is another scalable objective wise many objective test suit. It contains WFG1-WFG9 test functions with different characteristics. The problems are with biased PF, deceptive fitness landscape, and non-separable fitness landscape. Also researchers have proposed other many objective test suits with specific features. In [2] authors have been cited such test functions. The proposed standard test suits are for only multi or many-objective type of problems. The problems related to large scale multi or many-objective optimization not reported largely in literature. Cheng et al. have been proposed a large scale multi and many objective test functions. It contains LSMOP1 – LSMOP9. These test problems have characteristics like, non-uniform distribution of decision variables in different groups, correlation between decision variables and objective functions, decision variables are mixed separable. Other properties include modality as unimodal, multimodal, and mixed, separability as fully separable, partially separable, and mixed [129]. The quadratic and DTLZ test problems used in [27] with objectives from 2 to 50. Hadka and Reed presented UF1-UF13 test problems with two to eight objectives [37]. The real time many-objective optimization problems are also found in literature from various domains addressed by many researchers. The real time multi-objective and many-objective optimization problems found in [40], [53], [57-59], [73-74], [80], [89], [96-97], [108], [125], [133], [137], [141-142], [144], [147].

The problems from automotive engineering, aerospace engineering, many-objective simplified nurse scheduling problem, optimization of air-foil design, the 5-objective water resource management problem and the 10-objective general aviation aircraft design problem, the many-objective space trajectory design problem, many-objective software refactoring, the hybrid car controller optimization problem with six objectives, Optimization of three centrifugal design problems having six to nine objectives, the many-objective 0/1 knapsack problem, Heuristic learning, TSP, Job shop scheduling, flight control system, supersonic wing design, six-objective design of a factory-shed truss, etc. found in [1], [5], [99].

In [99] Chand and Wagner have presented a quick start guide about many objective optimizations. Li et al. presented a survey on many objective optimization algorithms. They have surveyed about 238 papers from various databases, from year 2007 to year 2013. These papers have addressed many objective optimization problems with four or more than four objectives [100]. Authors have also listed real time and benchmark many objective optimization problems addressed in literature. Other survey presented in multi-objective and many-objective optimization algorithms and test suits are also found earlier in literature. Huband et al., in [2] presented rigorous analysis and review of multiobjective test problems as well as scalable test problem toolkit. Ishibuchi et al., in [5] has been listed benchmark and real time many-objective optimization problems. Christian et al. listed the many-objective benchmark problems used to test the various multi-objective optimization problems [81]. The DTLZ, WFG, 0-1 Knapsack and other real time many-objective optimization problems found in [99]. The researchers from China are also working on many-objective optimization problems. They have used ZDT and DTLZ test problems [116]. He and Yan presented comparison of visualization approaches in many-objective optimization problems. The authors have presented the DTLZ and ZDT problems [149].

From the literature, it is found that, researchers are using benchmark test suits to evaluate the performance of many-objective evolutionary algorithms. The widely used test suits are DTLZ, WFG and ZDT with different number of objectives. The DTLZ and WFG test suit are widely used by researchers to evaluate the performance of existing or modified multi-objective optimization problems with objectives from 2 to 50. Also other test problems are found in literature, used for evaluation purpose. The real time problems with 3 – 10 objectives are solved by researchers.

Table 2 present list of many-objective optimization problems (benchmark test suits as well as real time problems) used in literature to test and evaluate the recommended or newly designed and implemented many-objective optimization evolutionary algorithms from literature. The selected papers are published from 2005 to 2017, which have reported the objectives three or more, as per the best knowledge of the authors of this paper.

Table 2: List of Many-Objective Optimization Problems (Benchmark Test Suits As Well As Real Time Problems)

Sr. No.	Test/Real Time Problems	No. of Objectives	Ref.
1	Flight Control System Design	8 objectives	[1]
2	ZDT1-ZDT5, DTLZ1-DTLZ7, Van Veldhuizen's Test Suite, Knapsack, WFG1-WFG9, Other Test Problems	--	[2]

3	DTLZ1and DTLZ2	3 to 6 Objectives	[3]
4	DTLZ1, DTLZ2, and DTLZ6	3 to 9 Objectives	[4]
5	500-item Knapsack Problem	2 - 8 Objectives	[5]
6	DTLZ2	3 to 12 Objectives	[19]
7	1. Quadratic Test Problems, 2. DTLZ 1-6	2 to 50 Objectives	[27]
8	DTLZ2	6 to 20 Objectives	[28]
9	1. Scheduling heuristics 2. Data mining and rule extraction 3. Assignment and management 4. Circuits and communications 5. Bioinformatics 6. Control systems and robotics 7. Pattern recognition and image processing 8. Artificial neural networks (ANNs) and fuzzy systems 9. Manufacturing 10. Traffic engineering and transportation	--	[29]
10	DTLZ2, DTLZ5	5 to 20 Objectives	[36]
11	UF1-UF13, DTLZ 1-4, DTLZ7	2 to 8 Objectives	[37]
12	DTLZ2	2 to 20 Objectives	[38]
13	DTLZ2, DTLZ4 and DTLZ7	2 to 20 Objectives	[39]
14	1. Mechanical Engineering Problems (TMTD, GTD, MDCD, SD, WBD) 2. Circuit component sizing for the Alpha Pro pump		[40]
15	DTLZ2	3 to 9 Objectives	[41]
16	1. DTLZ 1-DTLZ7 2. MOTSP	1. 4 to 10 Objectives 2. 5, 10 Objectives	[50]
17	1. TNK 2. CTP1 3. CTP2 4. CTP3 5. DTLZ4 6. WFG1	--	[51]
18	1. ZDT1-ZDT3 2. ZDT4, ZDT6 3. DTLZ 1-DTLZ4 4. WFG 1-WFG4	1. 2 Objectives 2. 2 Objectives 3. 3 Objectives 4. 3 Objectives	[52]
19	1. DTLZ2 2. Water Resource Optimization Problem	1. 2 - 8 Objectives 2. 5 Objectives	[53]
20	1. ZDT1, ZDT2, ZDT3 and ZDT6 2. DTLZ 1-DTLZ4	1. 2 Objectives 2. 5, 10, 15 Objectives	[54]
21	1. UF1-UF13 2. DTLZ 1-DTLZ4, DTLZ7	1. 2 - 5 Objectives 2. 2 - 8 Objectives	[55]
22	WFG 2-WFG9	2, 4, 7, 10 Objectives	[56]
23	Space Trajectory Design Multi-Objective Problem	3 - 6 Objectives	[57]
24	1. DTLZ 1-DTLZ7 2. Airfoil 3. Pump	1. 3 - 7 Objectives 2. 6 Objectives 3. 8 Objectives	[58]
25	1. Modified ZDT1 2. Storm Drainage Problem 3. Car Side-Impact Problem	1. 3 Objectives 2. 5 Objectives 3. 11 Objectives	[59]
26	1. DTLZ 1- DTLZ 4, DTLZ 7 2. DTLZ5 2. WFG3	1. 5 -30 Objectives 2. 5- 50 Objectives 3. 5 -25 Objectives	[60]
27	DTLZ 1- DTLZ 7	2 to 20 Objectives	[70]
28	Rectangle problem: A Test Problem for Visual Investigation of High-Dimensional Multi-Objective Search	4 Objectives	[71]
29	1. DTLZ 1- DTLZ 4 2. WFG 6-WFG7	3 to 15 Objectives	[72]
30	1. C1DTLZ1, C1DTLZ 3 2. C2DTLZ2 3. C3DTLZ1, C3DTLZ 4 4. Car Side Impact Problem 5. Water Problem	1. 3 to 15 Objectives 2. 3 Objectives 3. 5 Objectives	[73]
31	ZDT1, DTLZ2, DTLZ8, DTLZ9	3 to 5 Objectives	[74]
32	1. DTLZ1, DTLZ2 2. Fixed Front Dataset 3. Cloud dataset	2 to 30 Objectives	[75]
33	DTLZ2, DTLZ7	2 to 10 Objectives	[76]
34	1. DTLZ1- DTLZ7 2. WFG 1-WFG2	5 to 20 Objectives	[77]
35	Apache Ant, ArgoUML, Gantt, etc.	15 Objectives	[78]
36	DTLZ1- DTLZ 6	4 to 10 objectives	[79]
37	45-story tall steel frame subject to 3D wind loads with two incident direction cases	4 Objectives	[80]
38	1. DTLZ 2. MNK Landscape 3. WFG 4. Knapsack	--	[81]
39	1. DTLZ1-DTLZ4 2. WFG1-WFG9 3. Car Side Impact Problem 4. Water Resource Management Problem 5. General Aviation Aircraft Design Problem	1. 3 to 15 Objectives 2. 3 to 15 Objectives 3. 3 Objectives 4. 5 Objectives 5. 10 Objectives	[89]
40	1. DTLZ1- DTLZ4 2. WFG 1-9	1. 3 to 15 Objectives 2. 3 to 10 Objectives	[90]
41	1. WFG 1-9 2. 0/1 Knapsack Problem 3. TSP Problem	1. 5 to 15 Objectives 2. 5 to 15 Objectives 3. 5 to 15 Objectives	[91]
42	DTLZ1- DTLZ4	3 Objectives	[92]
43	Numerical construction project - Time, Cost, Quality trade-off	60 Activities	[93]

44	1. DTLZ1- DTLZ4, DTLZ7 2. WFG2, WFG3, WFG5, WFG6, WFG8, and WFG9 3. CEC 09	1. 5 to 40 Objectives 2. 3 to 13 Objectives 3. 2 to 3 Objectives	[94]
45	Virtual Machine Placement	5 Objectives	[95]
46	SIP: Optimal Product Selection from Feature Models- E-shop and WebPortal	8 Objectives	[96]
47	1. Design Of Welded Beam 2. Design Of Compression Spring 3. Car Side Impact Problem 4. Water Resource Management	1 Objective 1 Objective 2 Objective 5 Objective	[97]
48	1. DTLZ1-DTLZ4 2. WFG1-WFG9	1. 2 to 20 Objectives 2. 2 to 10 Objectives	[98]
49	DTLZ, WFG, 0-1 Knapsack problem	--	[99]
50	1. DTLZ1-DTLZ7 2. WFG 3 3. UF 9 -10	1. 5, 10 Objectives 2. 5, 10 Objectives 3. 3 Objectives	[101]
51	CEC'08	--	[102]
52	1. DTLZ1-DTLZ4, DTLZ7 2. WFG1-WFG9	3 - 15 Objectives	[103]
53	1. DTLZ1-DTLZ4, DTLZ7 2. SDTLZ 1, SDTLZ2 3. WFG1-WFG9	3 - 15 Objectives	[104]
54	1. UF1-UF10 2. WFG1-WFG9	2 - 3 Objectives	[105]
55	1. DTLZ1-DTLZ4 2. SDTLZ 1, SDTLZ3 3. WFG1-WFG9	3 - 10 Objectives	[106]
56	1. DTLZ 1-DTLZ4 2. WFG1-WFG9	3 - 15 Objectives	[107]
57	1. DTLZ1-DTLZ7 2. WFG1-WFG6 3. Car Cab Design	5 - 20 Objectives	[108]
58	DTLZ1-DTLZ7	3 - 10 Objectives	[109]
59	1. ZDT 2. DTLZ 3. WFG	--	[110]
60	DTLZ1-DTLZ7	4 -5 Objectives	[111]
61	1. ZDT1-ZDT4, ZDT6 2. DTLZ1-DTLZ4 3. LZ09_F1-F7, F9	1. 2 Objectives 2. 3 Objectives 3. 2 - 3 Objectives	[112]
62	1. DTLZ1 - DTLZ7 2. WFG1- WFG9	4 - 10 Objectives	[113]
63	DTLZ1- DTLZ4	10, 20 Objectives	[114]
64	1. ZDT1-ZDT3 2. DTLZ1, DTLZ2, DTLZ6 3. DTLZ1, DTLZ3	1. -- 2. 3 - 9 Objectives 3. Up to 7 Objectives 4. 2 - 9 Objectives	[116]
65	1. WFG2 - WFG9	2 - 7 Objectives	[117
66	DTLZ1-DTLZ6	2 - 10 Objectives	[118]
67	DTLZ1 - DTLZ7	3 - 8 objectives	[119]
68	1. DTLZ1 - DTLZ7 2. WFG1 - WFG9	5 and 10 Objectives	[120]
69	g01 - g19, g21, g23 - g24	2 - 39 Objectives	[121]
70	DTLZ1-DTLZ7	3 - 10 Objectives	[122]
71	Constrained DTLZ1, 2, 4	--	[123]
72	1. ZDT1, ZDT2 2. DTLZ1, DTLZ2	1. 2 Objective 2. 3 - 15 Objectives	[124]
73	Interplanetary trajectory design problem in the European Space Agency (ESA) Global Trajectory Optimization Problems (GTOP) database: The 'Cassini1' problem	f1 - f4 (4 Objectives)	[125]
74	WFG1-WFG9	10 Objectives	[126]
75	DTLZ1- DTLZ7	5 - 20 Objectives	[127]
76	1. ZDT1 -ZDT3, UF1–UF3 2. ZDT4, ZDT6 3. DTLZ1 4. DTLZ2 - DTLZ4 5. UF8–UF10	1. 2 Objectives 2. 2 Objectives 3. 3 Objectives 4. 3 Objectives 5. 3 Objectives	[128]
77	1. LSMOP1-LSMOP9	1. 2 - 3 Objectives 2. 6 - 10 Objectives	[129]
78	1. UF1- UF10, CF1-CF10 2. LZ09-F1, F3, F4, F7, F9 3. DTLZ1 - DTLZ7	1. 2 - 3 Objectives 2. 2 Objectives 3. 3 - 10 Objectives	[130]
79	DTLZ and WFG	2 - 10 Objectives	[131]
80	Random Test Sets	2 - 10 Objectives	[132]
81	Many-Objective Hybrid Electric Vehicle Controller Design Problem	7 Objectives	[133]
82	1. DTLZ1 to DTLZ4 2. WFG1 to WFG9 3. DTLZ1-1 to DTLZ4-1 4. WFG1-1 to WFG9-1	3 - 15 Objectives	[134]
83	1. mLFR-128 2. SSRM	2, 3, 4 Objectives	[136]
84	1. DTLZ2 2. DTLZ5 3. WFG3 4. POP-DTLZ2 5. SUM-DTLZ2 6. Water Resource problem 7. Car side-impact problem	1. 6 to 20 Objectives 2. 5 Objectives 3. 11 Objectives	[137]
85	1. MaOP1 - MaOP9 2. DTLZ5, WFG3	1. 10 Objectives 2. 5 -15 Objectives	[138]
86	MaF1- MaF15	5, 10, 15 Objectives	[139]
87	DTLZ1 - DTLZ3	3 to 20 Objectives	[140]
88	1. ZDT1-6 2. DTLZ1, 2, 5 3. BNH 4. SRN 5. TNK 6. OSY 7. Welded 8. Car 9. Water	2, 3, 5, 10 Objectives	[141]

89	1. DO2DK Problem 2. DEB2DK 3. DEB3DK 4. Radar Waveform Design 5. General Aviation Aircraft Problem	1. 2 Objective 2. 2 Objective 3. 3 Objective 4. 9 Objective 5. 10 Objective	[142]
90	DTLZ1-DTLZ4	3, 5, 10 Objectives	[143]
91	Many-Objective Blast Furnace Optimization Problem	8 objectives	[144]
92	Benchmark Problems Provided For Many Objective Knapsack Problem In Literature	2, 3, 5 , 10 Objectives	[145]
93	Real Time Many Objective Optimization Problem	--	[147]
94	Multidimensional Multi-Objective 0–1 Knapsack Problem	4 Objectives	[148]
95	DTLZ1- DTLZ4, ZDT	--	[149]
96	1. DTLZ1-DTLZ7 and 2. WFG1-WFG9	4 to 10 Objectives	[150]
97	1. DTLZ1 to DTLZ4 and 2. WFG1 to WFG9	3 to 15 Objectives	[151]
98	Multicast Routing Problem	4–6 QoS Objectives	[152]

From the Table 2, it is observed that, most of the researchers have used DTLZ benchmark test problems to evaluate many-objective evolutionary algorithms.

MANY-OBJECTIVE OPTIMIZATION ALGORITHMS AND PERFORMANCE METRIC

The existing multi-objective optimization evolutionary algorithms have been reported in literature to solve the optimization problems with more than three objectives. The MOEA have several limitations as these algorithms developed to address the problems with two or three objectives. To solve the optimization problems with more than four objectives, researchers have proposed several many-objective evolutionary algorithms to address such problems.

Recently various review papers have been reported in literature, which focuses on use of multi-objective evolutionary algorithms to solve MaOPs and recently developed many-objective evolutionary algorithms to address MaOPs [81], [100], [110], [146]. These reviews have also discussed the challenges while solving MaOPs, performance evaluation schemes adopted, and future research directions. Authors have presented a classification of MOEAs methods for many-objective optimization.

The MOEAs mainly classified in to four major categories, viz., decomposition based, Pareto dominance, Multi-population co-evolution and Indicator based approach. The MaOEAs are classified in to different categories, viz. relaxed dominance based, diversity-based, aggregation-based, indicator-based, reference set based, preference-based, and dimensionality reduction approaches. Also these categories contain different frameworks or techniques used to solve MaOPs. There are basically three decomposition schemes found in literature, the weighted sum (WS), the weighted Tchebycheff (TCH), and the penalty-based boundary intersection (PBI). The preference relation based includes mainly crisp alternatives and fuzzy alternatives. The indicator based approaches makes use of performance or quality indicators to evaluate the fitness function. Hypervolume, IGD indicators are used by researchers to incorporate with MOEAs [5], [81].

The MOEAs used to address many-objective optimization problems are categorized as, preference relation based and methods based on original problem transformation. The preference relation contains crisp and fuzzy approaches. The original problem transformation methods includes scalarization function based, indicator based, dimension reduction, and space partitioning. The scalarization function based approaches are decomposition and objective aggregation [81]. The Pareto, Aggregation, and Indicator-based many-objective optimization algorithms are presented in [3].

Lafeta et al., in [152] listed the many-objective optimization algorithm's categories, viz. Decomposition-based methods, New dominance relations, New diversity management schemes, Indicator-based approaches, and Objective dimension reduction.

Each category of these algorithms has certain limitations though these algorithms are used to solve many-objective optimization problems. The aggregated fitness value of solutions is used in decomposition-based approaches in the selection process. The evolutionary process gets hampered in dominance based approach for large number of objectives. In dominance based approach, when number of objectives gets increased, all the solutions in population become non-dominated with each other, which increase the selection pressure. In the indicator-based framework, some of the indicators like hypervolume (HV) are computational expensive [110].

Some of the widely used multi-objective and many-objective optimization algorithms are MOEA/D, NSGA-II, NSGA-III, and its variations to solve many-objective optimization problems. The NSGA-II is mostly cited algorithm to solve multi-objective optimization problems. The literature reveals that, recently developed different MaOEAs have combined two different categories or hybrid techniques have been proposed. The decision maker's preference is also considered in some approaches. The performance metrics also incorporated to design MaOEAs [5].

The researchers have identified the need to develop algorithms which will address the MaOPs. Several such algorithms found in literature. NSGA-III, modified MOEA/D, RVEA and its variations, SPEA and its variations, MaOPSO and its variations, hybrid approaches, etc. developed by researchers. These algorithms performance is evaluated for benchmark test suits. The real time applications solved includes, Water resource management, car side impact problem, hybrid electric vehicle controller design problem, General aviation aircraft problem, etc. [100].

The algorithms developed specially to address the many-objective optimizations problems are extensions to the existing MOEAs. The basic properties of MOEAs have been utilized. e. g. NSGA-III makes use of non-dominated sorting scheme of NSGA-II, MOPSO uses crowding distance, mutation scheme from other algorithms while keeping basic features of PSO [72].

The many-objective optimization algorithm's performance is evaluated using various metrics.

He and Yen in [149] presented and compared visualization approaches used in many-objective optimization problems. They have categorized these approaches into five different categories. These are Visualization Based on Parallel Coordinate System, Radial Coordinate Visualization, and Visualization Based on Local Information Researvation, Polar Coordinate Visualization, and Visualization Based on Surrogate Models. The purpose of visualization approaches is to visualize population in many-objective optimization problems to evaluate performance of algorithm and for decision making.

There are various quality metric found in literature used for performance evaluation, viz. Hypervolume (HV), Epsilon, Generational distance (GD), and Inverted generational distance (IGD). Each quality metric's different variations proposed [145].

Table 3 presents few evolutionary algorithms used to solve many-objective optimization problems.

Table 3: Many-Objective Evolutionary Algorithms

Sr. No.	Algorithm(s)	Algorithms Category/ Approach	Ref.
1	Multi-objective Evolutionary Algorithm	Parallel	[1]
2	1. NSGA-II, SPEA2, and ε-MOEA 2. MSOPS, RSO 3. IBEA, SMS-EMOA	1. Pareto-based EMOA 2. Aggregation-Based EMOA 3. Indicator-Based EMOA	[3]
3	1. Dynamical multiobjective evolutionary algorithm (DMOEA) 2. MDMOEA	L-Optimality based	[4]
4	User-preference based PSO algorithms	Distance metric based	[8]
5	Local replacement in cellular MOEA/D	Replace-if-better policy	[10]
6	Evolutionary many-objective optimization algorithm	Hypervolume approximation using achievement scalarizing functions	[11]
7	NSGA-II and MOEA/D	Large populations based approach	[12]
8	Clustering based Elitist Genetic Algorithm (CEGA) Multi-Directional Fitness Assignment (MDFA)	Fine-grained ranking procedure	[15]
9	Modified NSGA-II	Objective Space Partitioning based	[16]
10	Many-objective particle swarm optimization algorithm	Reference point based	[18]
11	Grid-based EMOA	Grid based	[19]
12	HypE	Hypervolume-based	[20]
13	Pareto corner search evolutionary algorithm (PCSEA)	Pareto corner search and dimensionality reduction	[21]
14	jMetal: A Java framework	--	[22]
15	Many-objective Algorithm	Bias-aware ensemble Kalman filtering	[23]
16	Many-Objective Optimization Algorithm	Adaptive Objective Space Partitioning	[24]
17	Evolutionary many-objective optimization algorithm	Genetic diversity and effective crossover	[26]
18	EMOA	Pareto-, α-, ε-, and cone ε-dominance.	[27]
19	1. NSGA-II STD 2. NSGA-II OPT 3. NSGA-II/DM1 STD 4. NSGA-II/DM1 OPT 5. NSGA-II/DM2 STD 6. NSGA-II/DM2 OPT 7. NSGA-II/DM STD 8. NSGA-II/DM OPT 9. RS	Pareto dominance	[28]

20	Multiobjective evolutionary algorithms	1. MOEA based on decomposition 2. MOEAs based on preference 3. Indicator-based MOEAs 4. Hybrid MOEAs 5. Memetic MOEAs 6. MOEAs based on 7coevolution	[29]
21	Large Population MOEA	Adaptive ε-Box Dominance and Neighborhood Recombination	[30]
22	MO-NSGA-II	Reference-point based	[32]
23	MICA-NORMOEA	Clustering based approach	[36]
24	1. Borg MOEA 2. ε-NSGA-II 3. MOEA 4. IBEA 5. OMOPSO 6. GDE3 7. MOEA/D 8. SPEA2 and 9. NSGA-II	A methodology for quantifying the reliability, efficiency and controllability of MOEAs.	[37]
25	I-MOPSO	Archiving method	[38]
26	Multi-Objective Particle Swarm Optimization Algorithms	Technique named control of dominance area of solutions (CDAS)	[39]
27	General Cluster-Forming Differential Evolution (GCFDE)	Multi-objective Distinct Candidates Optimization (MODCO)	[40]
28	MOPSO	Archiving method	[41]
29	MOMBI	R2 indicator based	[44]
30	Elitist non-dominated sorting genetic algorithm	Improved adaptive approach	[45]
31	Co-evolutionary algorithm	Preference-inspired approach	[47]
32	PIEMO-VF algorithm	Objective reduction and interactive procedure	[48]
33	Grid based evolutionary algorithm	Grid based Technique	[50]
34	BSTBGA	Hybrid constrained multi-objective approach	[51]
35	1. R2-MOGA 2. R2-MODE	Indicator based approach	[52]
36	Steady state quantum genetic algorithm	Decomposition based Technique	[53]
37	1. NSGA-LR-L, NSGA-SVM-L, NSGA-MLP-L 2. IBEA-LR-L, IBEA-SVM-L, IBEA-MLP-L	Aggregate meta-model based 1. Linear regression 2. Support vector regression 3. Multilayer perceptron	[54]
38	BORG -MOEA	ε-dominance	[55]
39	Preference-inspired co-	Preference-inspired	[56]

	evolutionary algorithm (PICEA-g)		
40	NSGA-Chebyshey	Chebyshev preference relation	[57]
41	MO-CMA-ES	Monte Carlo methods	[58]
42	PI-EMO-VF algorithm	Objective reduction approaches	[59]
43	1. NL-MVU-PCA 2. L-PCA	Objective reduction approach	[60]
44	MOPSO algorithm	Reference point based	[61]
45	SDE based NSGA-II, SPEA2, and PESA-II	Shift-based density estimation	[62]
46	Improved NSGA-III	Reference point based	[64]
47	MOEA/D	Inverted PBI	[65]
48	P-NSGA-II	Preference-based	[67]
49	H-MOPSO	Indicator and Hyper heuristics based	[70]
50	1. NSGA-II 2. SPEA2 3. MSOPS 4. IBEA 5. ε-MOEA 6. SMS-EMOA 7. MOEA/D - TCH 8. AR 9. AR+Grid 10. HypE 11. DMO 12. GrEA 13. FD-NSGA-II 14. SPEA2+SDE 15. MOEA/D – PBI	--	[71]
51	NSGA-III	Reference-Point-Based Non-dominated Sorting Approach	[72]
52	NSGA-III	Reference-Point-Based Non-dominated Sorting Approach	[73]
53	PI-EMO-PC	Preference-based method	[74]
54	Corner sort	Non-dominated sort, Pareto-based	[75]
55	1. NSGA-II 2. AR 3. IBEA 4. DMO 5. TDEA 6. AR+Grid	Proposed Quality metric: diversity comparison indicator	[76]
56	1. NSGA-II 2. FD-NSGA-II 3. SPEA2 4. FD-SPEA2 5. MOEA/D 6. NSGA-II-FO 7. FDD-GA	Fuzzy-Based Pareto Optimality	[77]
57	NSGA-III	Scalable search-based software engineering approach based	[78]

58	R-MEAD2	Decomposition and user preference based methods	[79]
59	Micro-MOPSO-PCA	Performance-based wind engineering (PBWE) framework	[80]
60	Multi-objective evolutionary algorithms	1. Preference relations 2. Transformation of original problem	[81]
61	KnEA	Knee point-driven	[82]
62	Differential evolution	Objective reduction	[83]
63	U-NSGA-III	Unified approach	[85]
64	Many-objective optimization algorithm	R2 indicator based	[87]
65	I-DBEA	Decomposition based Technique	[89]
66	MOEA/DD	Dominance and decomposition-based approach	[90]
67	Bi-Goal Evolution (BiGE)	Meta-objective optimization approach	[91]
68	NSGA/TD	Tomographic scanning based approach	[92]
69	MOABCDE	Hybrid approach	[93]
70	Evolutionary path control strategy (EPCS)	Reference Vector	[94]
71	Memetic Algorithm	Five different Selection strategy	[95]
72	1. NSGA-II 2. IBEA 3. MOEA/D-WS 4. MOEA/D-TCH 5. MOEA/D-PBI 6. SPEA2+SDE	User preferences study of encoding schemes	[96]
73	DBEA-r	Decomposition based Technique and six-sigma quality measure	[97]
74	Two_Archive2 algorithm	Indicator-based and Pareto-based and Hybrid approach	[98]
75	MOEA	Non-dominated Sorting based, Decomposition based, Indicator based, reference point based approach	[99]
76	MaOEA	Relaxed dominance based, diversity-based, aggregation-based, indicator-based, reference set based, preference-based, and dimensionality reduction approaches	[100]
77	Evolutionary algorithm for large-scale many-objective optimization (LMEA)	Decision variable clustering method	[101]
78	Fitness approximation assisted competitive swarm optimizer (FAACSO)	Fitness approximation strategy	[102]
79	HEA-DP	Hybrid approach with Dual Population	[103]
80	θ-DEA	Dominance Relation-Based	[104]
81	MOEA/D-RDG	Random-based dynamic grouping strategy	[105]
82	Reference vector-guided EA (RVEA)	Reference vectors based	[106]
83	1. KnEA 2. KnPSO 3. HypE 4. MOEA/D 5. MOEA/DD 6. NSGA-III 7. dMOPSO 8. SrEA 9. CDAS-SMPSO	Study of scalability of selected algorithms	[107]
84	SetGA	A set-based Pareto dominance relation	[108]
85	K-RVEA	Surrogate-assisted reference vector guided strategy	[109]
86	MOEA	Decomposition based Strategy	[110]
87	TPEA-PBA	Two Phase method with penalty based adjustment for reference line	[11]
88	Strength Pareto Evolutionary Algorithm (SPEA2)	Adaptive selection evolution operators based approach	[112]
89	A-ENS	Approximate non-dominated sorting approach	[113]
90	DEMO	Correlation based objective reduction algorithm	[114]
91	1. AS-MODE 2. MOEA/D-DE 3. DEMO 4. MyO-DEMR 5. α-DEMO	--	[115]
92	1. OMOEA 2. Thermodynamic based dynamical multi-objective evolutionary algorithm 3. NNIA 4. AHM 5. MDMOEA 6. MOEA/D-DU 7. EFR-RR	--	[116]
93	MOEA/D-LWS	Weighted sum method	[117]
94	MaOPSO	Set of reference points based	[118]

95	EDAGEA	E-dominance and adaptive-grid strategies based	[119]
96	MaOEA-R&D	Objective Space Reduction and Diversity Improvement Strategy	[120]
97	MaDC	DE and Reference-point-based non-dominated sorting approach	[121]
98	MaOPSO/2s-pccs	Two-stage strategy and parallel cell coordinate system	[122]
99	1. cK-RVEA1 2. cK-RVEA2 3. cK-RVEA3-I 4. cRVEA	Constraint handling approaches for MaOP	[123]
100	1. MOEA/D-a 2. MOEA/D-b 3. MOEA/D-c	Combination of preference-based strategy with decomposition based algorithms	[124]
101	ACOMOD	An ant colony optimization based decomposition approach with a massive parallelization framework	[125]
102	1. KnPSO 2. KnDE	The knee point driven approaches	[126]
103	1. PAR (ε)-DEMO 2. PAR(nds)-DEMO	Use of preference information	[127]
104	R2-MOPSO	R2 performance measure indicator based	[128]
105	1. IM-MOEA 2. MOEA/D-EA 3. NSGA - II 4. IBEA 5. RVEA 6. NSGA - III	1. Gaussian process-based inverse modeling 2. Decomposition-based approach 3. Non-dominated sorting based 4. Indicator based 5. Reference vector based 6. Non-dominated sorting based	[129]
106	ε-MOABC	Performance indicator based	[130]
107	1. Two_Arch2 2. NSGA - III 3. IBEA (with Iε+) 4. MOEA/D	Proposed Pure Diversity Metric	[131]
108	LONSA	Non dominated sorting based	[132]
109	1. MOEA/D 2. NSGA-III 3. RVEA	1. Decomposition based 2. Non-dominated sorting based 3. Reference vector guided	[133]
110	MOEA/AD	Adversarial decomposition based	[134]
111	MLMaOP (Multi-Layer Many-objective Optimization algorithm)	Locus-based adjacency representation	[136]
112	1. NSGA-II-δ 2. NSGA-II-η 3. NSGA-II-γ	1. Dominance Structure-Based 2. Correlation-Based	[137]
113	MOEA/D-M2M	A new adaptive search effort allocation strategy	[138]
114	NSGA-III	New MaO Test Problems Proposed	[139]
115	FR-NSGA-II	A fast reference point based	[140]
116	1. NSGA-II 2. NSGA -III	Correlation coefficient of exact KKTPM and estimated KKTPM for Optimization Problems	[141]
117	A scheme to identify solutions of interest (SOI) based on recursive use of the expected marginal utility (EMU) measure	--	[142]
118	Weight-based Many-Objective Fish School Search Algorithm	i) Reference points and lines in the objectives space; (ii) Clustering process; and (iii) The decomposition technique Penalty based Boundary Intersection.	[143]
119	RVEA	Data-driven reference vector guided	[144]
120	Evolutionary algorithm for multi/many objective problems	Assessment of IGD performance metric	[145]
121	Multi-stakeholder variant of the MORDM framework	MORDM framework	[147]
122	Modified MOEA/D	Fine Tuning Method	[148]
123	RadViz, Parallel Coordinate System, MDS, and Polar Coordinate System	Comparison of visualization approaches	[149]
124	Ensemble of MaOEAs (EMaOEA) for many-objective problems	Pareto dominance selection, diversity maintenance and elitism strategy	[150]
125	Vector angle based Evolutionary Algorithm (VaEA)	Maximum-vector-angle-first	[151]
126	Many-objective Evolutionary Algorithm based on Non-dominated De-composed Sets (MEANDS)	Non-dominated De-composed Sets	[152]

RESEARCH CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The researchers have studied wide range of multi-objective and many-objective optimization algorithms to solve many-objective optimization problems. After critical study they have listed research challenges while solving such type of problems. This section presents the various challenges from literature and future research direction in the area of many-objective optimization algorithms and problems.

Most of the researchers have modified the existing multi-objective optimization algorithms to solve the optimization problems with more than three or four objectives. These algorithms uses additional properties like problems nature, separability or non-separability property of variables, performance indicators, decomposition of problems or reduction and/or aggregation of objectives, etc.

Li et al. in [43] identified merits, demerits and challenges while designing many-objective optimization algorithms and solving many-objective optimization problems. The comparison of non-dominated solutions becomes challenging when number of objectives get increased. The visualization of solution is also difficult when number of objectives are more than three. The selection pressure towards Pareto front increases in case of Pareto-based approaches, while the aggregation and indicator based approaches does not suffer from this problem. The setting of weight vector is challenging task in case of aggregation based approaches. The indicator based approaches makes use of performance indicator in fitness evaluation. It uses Hypervolume, Generational distance (GD), Inverted Generational distance (IGD). The Hypervolume is compute intensive performance metric. Due to high computational cost, the indicator based approaches are difficult to scale for large number of objectives. The reference set based approaches has challenges like construction of reference set and measuring the quality of population based on reference set. It is also important to balance between convergence and diversity in case of reference set based methods. Selection of preference models and integration of preference information are key issues in preference based algorithms. As the preference based approaches requires frequent interaction with decision maker (DM) to get preference information, so the decision makers may mislead the algorithm if DM is tired. The dimensionality reduction approaches have some merits like, these are not compute intensive, these methods helps to find out redundant or less important objectives. The demerit of these algorithms is that, when dealing with applications without redundant or less important objectives the obtained solution does not cover complete Pareto front.

Lucken et al. in [81] have studied the use of multi-objective optimization algorithms to solve many-objective optimization problems. They have identified several issues while solving many-objective optimization problems. The relationship between all the objectives must be studied to analyze the toughness of selected many-objective optimization problem. Effect of different parameter settings on number of objectives should be studied to determine the difficulty of the problem. Due to lack of natural approach to represent solutions in decision space for many-objective optimization problems, authors suggest development of new performance evaluation metric which will help to provide information about the spread of solutions.

There is need to perform rigorous review of many-objective test problems with different properties like constrained, unconstrained, noisy, problem's decision parameters without any restrictions [2]. The impact of population size and offspring as well as the relationship between Pareto front and Pareto set should be studied to develop new many-optimization algorithm [3] [50]. Weighted objectives scheme can be introduced and rate of convergence to be studied [4]. As Hypervolume calculation requires high computational cost, it is suggested to work on reducing the computational cost. Evolutionary multi-objective and multi-criteria decision making approaches can be combined together [5]. The study of parameter distribution in grid for different dimensions should be carried out for grid-based many-objective evolutionary algorithms [19]. The dominance metric can be included in standard multi-objective evolutionary algorithms and its performance for real time many-objective optimization problems can be investigated. Also the search behavior of dominance based many-objective algorithms needs to study carefully so that it will help to improve performance [27], [104]. The Pareto-dominance based, decomposition based and indicator based approaches can be combined to propose new framework. The many-objective optimization problem's categories needs to study to identify the properties of solvable problems [29]. Different archiving methods can be combined with different evolutionary algorithms and compared its performance for many-objective optimization problems [41]. The sorting methods can be incorporated into MOEAs to solve many-objective optimization problems. The accurate and approximate non-dominated sorting strategies at different search stages can be combined to improve performance of evolutionary many-objective optimization algorithms. [52], [113]. The quantum representation scheme can be used and tested to represent solution of real world many-objective optimization problems [53]. The operator's selection and parameter setting are important issues to be studied to improve the performance of many-objective optimization algorithms [55]. The different preference inspired approaches can be integrated with many-objective evolutionary algorithms and its performance to be investigated [56]. The different machine learning approaches can be used to perform objective reduction. Online objective reduction approach can be employed for real world, high dimensional problems as well as problems with complicated Pareto shape. The non-linear relation between objective pairs could be introduced in objective reduction algorithms and the crowding distance can be modified so that algorithm will maintain diversity in solutions along border as well as along center of Pareto front. The new benchmark functions should be designed which will efficiently evaluate the objective reduction algorithms [59], [60], [114], [137]. Different performance indicators can be combined with hyper-heuristics to guide search process as well as to evaluate the performance [70].

When the real time many-objective optimization problem's shape, scale, orientation, discontinuity, convexity, etc. properties of Pareto front are not known in advance in such cases non-dominated sorting approaches can be applied [72], [73]. A non-dominated corner sort approach can be performed in parallel to reduce the computational time also its performance needs to improve for low dimensional many-objective optimization problems [75]. The diversity comparison indicator can be used to assess the performance of preference based optimization techniques [76]. The fuzzy based many-objective optimization algorithms can be developed as fuzzy based dominated sorting approach improves performance in both convergence and diversity [77]. The researchers have developed and developing numerous algorithms to solve many-objective optimization problems, but there are still number of important many-objective problems exist which needs to address. One can work on limiting the drawback of existing algorithms and improve them. Also the hybrid approach can be proposed by combining two or more approaches. The most of researchers have used DTLZ problems to evaluate the applicability of proposed many-objective optimization algorithms. These algorithms should be applied to solve real time many-objective optimization problems. The new performance metric can be designed by considering the characteristics of many-objective optimization problems [81]. The decision makers interested part can be searched, instead of finding entire Pareto front. Also the existing algorithm's performance can be measured for large scale many-objective optimization problems [90]. By converting many-objective optimization problems into bi-objective optimization problems related with proximity and diversity can be solved. Its performance can be tested for real time applications [91]. For real time many-objective optimizations applications like construction project, when performance metrics are vague, uncertain and imprecise, a model is need to define to address such problems [93]. It is necessary to perform rigorous analysis to determine impact of distance between reference points and Pareto front on algorithm's performance [94]. It is necessary to solve real time applications instead of focusing only on standard benchmark suits [99]. It also interesting to combine two or more performance metrics in indicator based approaches [100]. Decision variable based clustering approaches can be studied to identify the correlation of decision variables with objectives. The dynamic grouping strategies using heuristic information can be implemented to solve many-objective optimization problems [101], [105]. The fitness estimation strategies based algorithms developed to address large scale computationally expensive problems, the similar strategy can also be developed to solve large scale compute intensive many-objective optimization problems [102]. Dual population based hybrid many-objective optimization algorithms will be promising technique to address many-objective optimization problems [103]. Finding the most applicable reference vector's type for many-objective optimization problems is also future work [106] [121]. The scalability analysis of evolutionary algorithms to solve large scale many-objective optimization needs to perform. The large number of function evaluations can be used to spend more time for convergence. The new mating restriction patterns can be employed [107]. Developing innovative evolutionary models to solve Interval many-objective optimization problems is one of the future research direction [108].

Trivedi et al. in [110] presented future research development about decomposition based many-objective optimization algorithms. The scalarizing functions can be adapted in decomposition based approaches. The neighborhood structure for mating and replacement of solutions in the decomposition-based MOEAs can be investigated for MaOPs. The reference vector can be used to decompose the objectives into number of small sub-spaces. The decomposition based approaches can be hybridized with dominance, preference or indicator based approaches. Also the efficient constraint handling techniques for decomposition based approaches can be developed.

Further the decomposition approach can be hybridized with evolutionary multi-criteria decision making approaches. The Pareto and decomposition based methods, if combined together it will help to maintain the uniform solutions. The accurate representation of decision maker's preference information in user preference based decomposition approach needs to address [117] [124]. The massive parallelization based many-objective evolutionary algorithms should be developed [125]. It is necessary to develop a MOEA which will address the large scale MaOPs with complex separability and correlations of the decision variables. The divide and conquer approach can be developed to address the non-separable component of decision vector [129]. The relation between diversity and convergence in many-objective optimization problems needs to be studied deeply [131]. It is recommended to evaluate various data structures used for solution representation and updating solution's array as well as reduce the computational cost required to perform non-dominated sorting [132]. The scalarizing functions is to be determined by developing various adaptive methods for decomposed many-objective optimization problems with respect to its Pareto front's shape [135]. The impact of different parameter settings on performance of algorithm as well as modifying the selection scheme in evolutionary many-objective algorithms for MaOPs with different Pareto front [140].

Searching within interested solutions is important task in optimization of many-objective problems. The gap between decision maker and generated solutions should be minimized. Techniques to minimize this gap can be improved [142]. The performance metric such as IGD and its variation's analysis should be performed for problems with different geometric shapes [145].

The visualization of many-objective optimization problems is critical task. There is need to develop integrated visualization method which will preserve information about global Pareto front as well as local relations between solutions [149]. An EMaOEA developed by combing different MaOEA which executes in parallel. Different reproduction operators can be implemented for each MaOEA and to be tested for performance assessment. An adaptive fitness evaluation allocation scheme for constituent algorithms can be developed [150].

CONCLUSIONS

This paper presents a short review about many-objective optimization problems, many-objective evolutionary algorithms. The research challenges are also listed from the literature. The difficulties associated with many-objective optimization problems are presented. From the literature, it is observed that, researchers have been using standard benchmark suits to evaluate the performance of the many-objective evolutionary algorithms. Very few real-time many-objective optimization problems have been solved. There is need to solve many-objective optimization problems. The various types of algorithm development strategies have been used by researchers. It includes dominance based, decomposition based, preference based, reference based, and indicator based approaches. The hybrid many-objective evolutionary algorithms can be developed. The Pareto front visualization techniques can be developed. The performance metric suitable for many-objective optimization needs to develop and existing metrics needs to carefully study.

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