Supplementary Document for "A Survey of Multiobjective Evolutionary Algorithms based on Decomposition"

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S.I Studies on Modifications in the Reproduction Operators

S.I.A Reproduction Operation based on PSO

Peng and Zhang [S1], Martinez and Coello Coello [S2], and Zhao and Liu [S3] proposed different versions of decomposition-based multi-objective particle swarm optimization (MOPSO) for continuous MOPs. The limitation of these studies is that the proposed algorithms have not been exhaustively compared with other state-of-the-art MOEAs and only selected benchmark functions have been used in the experimental study.

Al Moubayed *et al.* [S4] proposed a MOPSO based on decomposition and dominance, termed D2MOPSO. The characteristic feature of D2MOPSO is that the leader for a particle is selected from the leaders' archive (instead of the particles neighborhood) using aggregation value as the selection criterion. The leaders' archive is constructed using non-dominated particles and is bounded based on crowding distance in both objective and solution spaces. The experimental study demonstrated the effectiveness of D2MOPSO on several standard MOPs with 2-3 objectives.

S.I.B Reproduction Operation based on SA

Li and Landa-Silva [S5] presented an adaptive hybrid EA based on combination of MOEA/D and SA, termed EMOSA. Unlike the original MOEA/D, EMOSA does not incorporate a crossover operator. Instead, corresponding to each subproblem, EMOSA employs a SA based local search to improve the current solution. The improved solution is then used to update the other solutions in the neighborhood. An important feature of EMOSA is that it employs competition between solutions with respect to both scalarizing function and Pareto dominance. An improved solution through SA is compared with the current solution based on scalarizing function while the comparison between improved solution and the neighboring solutions is based on Pareto dominance. This helps in the preservation of diversity when the current population is close to the PF. The experimental study demonstrated that EMOSA outperforms several state-of-the-art algorithms on both constrained MOKP and unconstrained MTSP.

S.I.C Reproduction Operation based on Probability Models

Zhou *et al.* [S6] proposed an algorithm based on combination of MOEA/D and multivariate Gaussian distribution models, known as MOEA/D-MG. In the reproduction step in MOEA/D-MG, Gaussian distribution model is probabilistically built either using the T neighboring solutions or T randomly selected solutions from the whole population. An offspring solution is then sampled from the model built. In [S7], Zhou *et al.* extended MOEA/D-MG [S6] and introduced the idea of subproblem exploitation through probabilistically employing another reproduction operator. In particular, in the resulting algorithm, termed MOEA/D-NS, the new reproduction operator is based on multivariate Gaussian distribution model which utilizes the historical solutions of a subproblem and its neighboring solutions to build the model.

Zangari de Souza *et al.* [S8] investigated using probabilistic graphical models (PGMs) within MOEA/D and proposed a framework, termed MOEA/D-GM, to solve multi-objective deceptive optimization problems. PGMs belong to the class of EDAs which use more expressive probabilistic models and are able to capture the dependencies between decision variables. Among the PGMs that exists in the literature, the authors adopted tree-based models which are capable of capturing pairwise interactions between decision variables and illustrated the efficiency of a MOEA/D-GM variant named MOEA/D-Tree on bi-objective trap problem.

Shim *et al.* [S9] integrated estimation of distribution algorithm (EDA) into the MOEA/D framework for solving the multi-objective multiple traveling salesman problem (MmTSP). The authors adopted a univariate model (UM) [S10] based EDA and proposed three hybrid algorithms namely, UMHC, UMSA, and UMEGS by hybridizing decomposition-based EDA with hill climbing, SA, and evolutionary gradient search (EGS), respectively. The experimental study demonstrated that the proposed hybrid algorithms outperform several state-of-the-art MOEAs on the mTSP with different number of objective functions, salesmen, and problem sizes.

Based on the concept of generalized decomposition and an EDA, known as cross entropy (CE) [S11], Giagkiozis *et al.* [S12] presented an algorithm termed MACE-gD. The primary optimizer in MACE-gD is the CE method for continuous optimization. Unlike other MOEA/D variants which probabilistically build the distribution model using T neighboring solutions or T randomly selected solutions from the whole population (e.g. MOEA/D-MG [S6]), MACE-gD utilizes a percentage of top solutions in the current population with respect to a subproblem to build the model. The experimental study displayed that the CE method can be a strong candidate in comparison to complex probability models as the main optimizer for evolutionary multi-objective optimization.

Martinez *et al.* [S13] integrated CMA-ES (covariance matrix adaptation evolution strategy) into MOEA/D framework and proposed an algorithm, termed MOEA/D-CMA. In MOEA/D-CMA, a single CMA-ES engine is assigned to each subproblem. MOEA/D-CMA utilizes the ability of CMA-ES to handle injection of solutions, thereby incorporating information from neighboring scalarizing subproblems into the search distributions. The experimental study demonstrated that MOEA/D-CMA variant with injection i.e., MOEA/D-CMA+I, outperforms MOEA/D-CMA, MOEA/D [S14], and MOEA/D-DE [S15] on UF1-UF10 [S16] test instances.

The drawback of most the above MOEA/D variants based on probability distribution models is their computational complexity as a distribution model needs to be built at every generation corresponding to each subproblem.

S.I.D Reproduction Operation based on Hyper-heuristics

Hyper-heuristics [S17] is a high level methodology for automatic selection and/or generation of heuristics for solving complex problems.

Goncalves *et al.* [S18] proposed an algorithm termed MOEA/D-HH which integrates hyper-heuristics within the MOEA/D-DRA [S19] framework. In MOEA/D-HH, the pool of low level heuristics consists of five DE strategies, namely DE/rand/1, DE/rand/2, DE/current-to-rand/1, DE/current-to-rand/2, and DE/nonlinear [S20]. To determine the DE mutation strategy (i.e., low level heuristics) to be applied to each individual, a novel adaptive choice function is implemented. The experimental study on UF [S16] test instances demonstrated that MOEA/D-HH performs better that MOEA/D with individual DE strategies.

Goncalves *et al.* [S21] later proposed an adaptive choice function with sliding window to improve the performance of their earlier presented algorithm MOEA/D-HH [S18]. In the resulting algorithm, termed MOEA/D-HH$_{sw}$, the choice function normalizes the rewards provided to the low level heuristics and uses a sliding window to store the recent performance of low level heuristics which can be of relevance in the current stage of the dynamic optimization process. The experimental study on UF [S16] test instances demonstrated that MOEA/D-HH$_{sw}$ outperforms MOEA/D-HH [S18] and several other state-of-the-art MOEAs.

S.I.E Reproduction Operation based on other Strategies

In [S22], Wang *et al.* suggested use of two different reproduction operators, namely DE and neighbor learning (NL) operator, within the MOEA/D framework. The NL operator is a variant of neighborhood competition operator employed in multi-agent genetic algorithm [S23] and generates an offspring solution corresponding to a current solution by learning from a better neighboring solution. The authors first demonstrated that the NL operator is favorable for convergence while the DE operator promotes diversity. In the resulting algorithm, termed MOEA/D-NL&DE, the NL operator is used for generating offspring solution corresponding to a subproblem i if a better solution to the subproblem i exists in the neighborhood, otherwise the DE operator

Table S1: SUMMARY OF STUDIES ON WEIGHT VECTOR GENERATION METHODS

Ref.	Weight vector generation method	Main Idea(s)	Application
[S14]	Simplex-lattice design	Uniform distribution of weight vectors on the simplex lattice	MOKP with 2-4 objectives, ZDT [S25], 3-objective DTLZ1-DTLZ2 [S26]
[S27]	WS-transformation	Uniform distribution of solution mapping vectors resulting from WS transformation of uniformly distributed weight vectors	DTLZ1-DTLZ4 [S26] with 3-objectives
[S28]	Uniform design for experiment with mixtures (UDEM)	Uniform distribution of weight vectors using UDEM	DTLZ1-DTLZ4 [S26] and F1-F2 [S28] with 3-5 objectives, MOKP with 2-4 objectives
[S29]	Uniform decomposition measurements	Combination of simplex lattice design [S14] and UDEM method	DTLZ1-DTLZ4 [S26] and WFG4-WFG9 [S30] with 3-6 objectives
[S31]	Generalized decomposition	Generation of optimal set of weight vectors corresponding to the TCH approach using a reference PF	Test problems having linear PF with 2-11 objectives, DTLZ1-DTLZ2 [S26] with 3-objectives
[S12]	Generalized decomposition	Generation of optimal set of weight vectors corresponding to the TCH approach using a reference PF	Test problems having different PF geometries with 2-11 objectives, WFG2-WFG9 [S30] with 2-11 objectives
[S32]	Two-layer weight vector generation method	Generation of relatively small number of evenly spread weight vectors for MaOPs	DTLZ1-DTLZ4 with {3,5,8,10,15} and WFG1-WFG9 with {3,5,8,10} objectives

is applied. The experimental study on MOP1-MOP5 [S24] and F1-F5 [S15] test problems demonstrated that MOEA/D-NL&DE is highly promising.

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Table S2: SUMMARY OF STUDIES ON DECOMPOSITION METHODS

Ref.	Decomposition Approach / Algorithm	Main Idea(s)	Application
Studies on Improved Decomposition Approaches			
[S33]	Inverted PBI	Evolving solutions from the current nadir point n by maximizing the scalarizing function value	MOKP and WFG4 problem with 2-8 objectives
[S34]	Improved PBI	1) Adaptive penalty scheme (APS) and 2) Subproblem-based penalty scheme (SPS), to set the value of the parameter θ in the PBI approach	F1-F6 [S34]
[S35]	Constrained decomposition approach	To impose constraint on the subproblems and reduce the volume of the improvement region corresponding to subproblems	ZDT problems [S25], F1-F9 [S15], and MOP1-MOP7 [S24]
[S36]	Angle-penalized distance (APD)	Modified PBI approach in which the diversity criterion is measured by the acute angle between the candidate solution and the reference vector	DTLZ1-DTLZ4 and WFG1-WFG9 with {3,5,8,10} objectives
Studies on Combination/Adaptation of Scalarizing Functions			
[S37]	Combination of decomposition methods	A two-phase strategy involving the TCH in first phase and reverse TCH in second phase	F1-F6 [S37], UF4 [S16], mF4 [S37], convex DTLZ2 [S38], POL
[S39]	Combination of decomposition methods	Simultaneous use of the WS and the TCH functions	MOKP with {2,4,6} objectives
[S40]	Adaptation of decomposition methods	Adaptive use of the TCH method and the WS method	Modified MOKPs with {2,4,6}
[S41]	Combination of decomposition methods	Simultaneous use of the ASF with respect to both nadir point and utopian point	ZDT problems [S25], F1-F9 [S15], UF1-UF10 [S16], 3-objective DTLZ1-DTLZ7 [S26], and WFG1-9 [S30] problems with {2,3,5} objectives
[S42, S43]	Adaptation of decomposition methods	Adaptation of p value in L_p weighted approaches based on PF estimation	WFG41, WFG42, and WFG43 with {2,4,7} objectives
Studies on Alternate Ways of Decomposition			
[S24]	MOEA/D-M2M	Decomposition of a MOP into a set of simple multi-objective optimization subproblems	MOP1-MOP7 [S24]
[S32], [S36], [S38]	MOEA/DD, RVEA, NSGA-III	Use of reference vectors to decompose the objective space into multiple subspaces (refer Section IX for details)	MaOPs

Table S3: SUMMARY OF STUDIES ON COMPUTATIONAL RESOURCE ALLOCATION

Ref.	Algorithm	Main Idea(s)	Application
Studies on Efficient Computational Resource Allocation with Fixed Weight Vectors			
[S19]	MOEA/D-DRA	Dynamic allocation of computational resources to different subproblems	UF1-UF10 [S16]
[S44]	MOEA/D-GRA	1) Extension of MOEA/D-DRA, 2) Introduction of generalized resource allocation strategy based on online measurement of subproblem hardness	F1-F9 [S15], UF1-UF10 [S16]
[S45]	EAG-MOEA/D	Use of external archive to dynamically allocate computational resources	MNRP and MTSP
[S46]	MOEA/D-RW	Use of external archive for generation of new solution in random search direction to subproblem which get stuck	ZDT3 [S25], DTLZ5, DTLZ7-DTLZ8 [S26], UF5, UF9 [S16], CPFT1-CPFT4
[S47]	BCE-MOEA/D	A bi-criterion evolution framework based on collaboration of a Pareto criterion population and a non-Pareto criterion population	A set of 42 MOPs from ZDT [S25], DTLZ [S26], UF [S16], DTLZ2 and DTLZ5(I,m) test suites
[S48]	MOEA/D-EGO	Use of Gaussian stochastic process modeling in MOEA/D for solving expensive MOPs	ZDT [S25], F1-F4 [S15], DTLZ2, KNO1, VLMOP2
[S49]	MOEA/D-RBF	Use of cooperative RBF networks in MOEA/D for solving expensive MOPs	ZDT [S25], airfoil design problem
[S50]	MOEA/D-SVM	Use of classification approach based on SVM to dynamically allocate computational resources to mainly the promising solutions	ZDT [S25], DTLZ1-DTLZ2 [S26], UF1-UF10 [S16]
Studies on Efficient Computational Resource Allocation with Weight Vector Adaptation			
[S51]	$pa\lambda$-MOEA/D	Automatic adjustment of weight vectors according to the shape of the PF	ZDT [S25] and DTLZ [S26]
[S27]	MOEA/D-AWA	Adjustment of weight vectors such that some subproblems are removed from the crowded parts of the PF and new subproblems are added into actual sparse regions of the PF	ZDT [S25], DTLZ [S26], and 2 newly constructed test problems with complex PF shapes
[S52]	FV-MOEA/D	Inclusion of a fast hypervolume archive and periodic adaptation of weight vectors based on solutions in the external archive	58 test instances from ZDT [S25], DTLZ [S26], WFG [S30], CEC2009 [S16], and LZ09F [S15] test suites
[S53]	MOEA/D	Investigation into the cost of adaptation in decomposition-based MOEAs on convergence	DTLZ1-DTLZ4 [S26] and WFG4-WFG9 [S30] with {3,5,7,11} objectives

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Table S4: SUMMARY OF STUDIES ON MODIFICATIONS IN THE REPRODUCTION SECTION

Ref.	Algorithm	Main Idea(s)	Application
Studies on Reproduction Operators based on DE			
[S15]	MOEA/D-DE	Replacement of SBX operator with DE operator in the reproduction operation	Nine newly introduced test instances with complicated PS shapes (F1-F9) [S15]
[S54]	MOEA/D-gDE	Introduction of gDE operator in the reproduction operation	MOKP with 2-4 objectives
[S55]	MOEA/D-DE	Investigation on use of different DE mutation schemes in MOEA/D-DE [S15]	F1-F9 [S15]
Studies on Reproduction Operators based on PSO			
[S1]	MOPSO/D	Replacement of SBX operator with traditional PSO operators	F1-F5 [S15]; ZDT test problems
[S2]	dMOPSO	1) Replacement of SBX operator with traditional PSO operators, 2) Memory re-initialization process	ZDT test problems; 3-objective DTLZ2, DTLZ6, and DTLZ7
[S3]	MOPSO-PD	A sub-regional strategy is employed and local best solution of sub-region also participates in the particle update mechanism	ZDT test problems; 3-objective DTLZ1, and DTLZ2
[S4]	D2MOPSO	Construction of the leaders' archive using non-dominated particles and restricting the archive size based on crowding distance in both objective and solution spaces	22 unconstrained and 5 constrained problems with 2 and 3 objectives
Studies on Reproduction Operators based on ACO			
[S56]	MOEA/D-ACO	Incorporation of ACO algortihm in MOEA/D framework	MOKP and MTSP
Studies on Reproduction Operators based on SA			
[S5]	EMOSA	Replacement of crossover operator by SA based local search	MOKP and MTSP
Studies on Reproduction Operators based on Probability Models			
[S6]	MOEA/D-MG	Use of multivariate Gaussian distribution models for offspring creation	F1-F9 [S15]
[S7]	MOEA/D-NS	Probabilistic application of another reproduction operator in [S6] based on multivariate Gaussian distribution model built using historical solutions of subproblems in a neighborhood	F1-F9 [S15]
[S8]	MOEA/D-GM	Introduction of probabilistic graphical models (PGMs) in MOEA/D to solve deceptive optimization problems	Bi-objective trap problem
[S9]	UMHC, UMSA, and UMEGS	1) Integration of EDA into MOEA/D, 2) Hybridization of decomposition based EDA with local search techniques	MmTSP
[S12]	MACE-gD	1) Use of CE as the primary optimizer, 2) Utilization of a percentage of top solutions in the current population with respect to a subproblem to build the model	WFG2-WFG9 [S30] with 2-11 objectives
[S13]	MOEA/D-CMA	Integration of CMA-ES in MOEA/D	UF1-UF10 [S16]
Studies on Reproduction Operators based on Hyper-heuristics			
[S18]	MOEA/D-HH	1) Introduction of hyper-heuristics in MOEA/D-DRA [S19] framework, 2) Incorporation of a novel adaptive choice function to select DE mutation strategy from a pool of 5 DE strategies	UF1-UF10 [S16]
[S21]	MOEA/D-HH$_{sw}$	1) Extension of MOEA/D-HH [S18], 2) Introduction of sliding window strategy to store the recent performances of DE strategies and use them while rewarding strategies	UF1-UF10 [S16]
Studies on Reproduction Operators based on Adaptive Operator Selection			
[S57]	ADEMO/D	1) Integration of DE strategy adaptation mechanism of AdapSS [S58] within MOEA/D, 2) Investigation of different operator selection and credit assignment techniques	UF1-UF10 [S16]
[S59]	MOEA/D-FRRMAB	Introduction of AOS method termed FRRMAB within MOEA/D-DRA	UF1-UF10 [S16]; 5-objective WFG1, WFG8, and WFG9
[S60]	MOEA/D-UCB-tuned, MOEA/D-UCB-V	Integration of operator selection strategies named UCB-tuned and UCB-V in MOEA/D	UF1-UF10 [S16]
[S61]	mMOEA/D	Adaptive synergestic combination of GA, DE, and EDA in MOEA/D framework	ZDT [S25], DTLZ1-DTLZ7 [S26] with 3- and 5- objectives, UF1-UF10 [S16], WFG1-WFG9 [S30]
Studies on Reproduction Operators based on other Strategies			
[S22]	MOEA/D-NL&DE	Selective use of DE and neighbor learning (NL) [S62] operator for reproduction in MOEA/D	MOP1-MOP5 [S24], F1-F5 [S15]
[S63]	MOEA/D-CMA	1) Simultaneous use of both CMA-ES and DE in MOEA/D to deal with bias feature in MOPs, 2) Clustering of subproblems into several groups and use of CMA-ES to evolve only one subproblem from each group at every generation, and use of DE to evolve rest of the subproblems	Nine newly introduced test instances with bias (BT1-BT9) [S63]

Table S5: SUMMARY OF STUDIES ON MATING SELECTION AND REPLACEMENT MECHANISM

Ref.	Algorithm	Main Idea(s)	Application
		Studies on Improved Mating Mechanism	
[S37]	MOEA/D-TPN	A niche-guided scheme for the setting of mating selection range	F1-F6 [S37], UF4 [S16], mF4 [S37], convex DTLZ2 [S38], POL
		Studies on Improved Replacement Mechanism	
[S64]	MOEA/D-GR	Introduction of global replacement scheme in MOEA/D	ZDT, DTLZ1-DTLZ2, MOP1-MOP7 [S24], F1-F9 [S15]
[S65]	MOEA/D-AGR, gMOEA/D-AGR	Introduction of adaptive global replacement scheme in MOEA/D	ZDT, DTLZ1-DTLZ2, MOP1-MOP7 [S24], F1-F9 [S15]
[S66]	MOEA/D-STM	Introduction of a simple and effective stable matching model (STM) to co-ordinate the selection of promising solutions for subproblems	UF1-UF10 [S16]
[S67]	MOEA/D-IR	1) Extension of MOEA/D-STM [S66], 2) Introduction of an interrelationship based selection for matching subproblems with solutions	UF1-UF10 [S16], MOP [S24], and WFG1-WFG9 [S30]
[S68]	MOEA/D (MRDL)	1) Introduction of online diversity metric for MOEAs, 2) Modification of the replacement operation in MOEA/D based on MRDL	UF1-UF10 [S16], WFG1-WFG9 [S30], TYD1-TYD5
		Studies on Improved Mating Selection and Replacement mechanism	
[S15]	MOEA/D-DE	1) Selection of parent solutions for mating with a low probability from the whole population, 2) Upper bound on the maximal number of solutions that can be replaced by an offspring solution	F1-F9 [S15]
[S69]	MOEA/D	Effect of using distinct mating neighborhood size and replacement neighborhood size	MOKP with 2, 4, and 6 objective
[S70]	ENS-MOEA/D	Ensemble of NSs and dynamic adjustment of selection probability of NS	UF1-UF10 [S16]
[S12]	MACE-gD	1) Neighborhood structure for each subproblem is defined dynamically in the objective space, 2) A new solution to subproblem i is only compared with the current solution to subproblem i in replacement step	WFG2-WFG9 [S30] with 2-11 objectives
[S71]	SMOEA/D	1) Application of SOM to determine population structure and accordingly construct mating pool for every solution, 2) Ensemble of NSs and dynamic adjustment of selection probability of NS, 3) Greedy replacement strategy	ZDT [S25], DTLZ, F1-F9 [S15], WFG1-WFG9 [S30]

Table S6: SUMMARY OF STUDIES ON MANY-OBJECTIVE OPTIMIZATION

Ref.	Algorithm	Main Idea(s)	Application
[S38]	NSGA-III	1) Extension of the NSGA-II framework, 2) Use of reference points to implicitly decompose the objective space and a niche preservation operator to maintain diversity of solutions close to every possible reference point	DTLZ1-DTLZ4 and WFG6-WFG7 with {3,5,8,10,15} objectives, vehicle crash-worthiness design, car cab design
[S72]	Adaptive NSGA-III	Use of reference point adaptation approach in NSGA-III [S38]	Inverted DTLZ1 and C2-DTLZ2 {3,5} objectives, vehicle crash-worthiness design, car-side impact problem
[S32]	MOEA/DD	1) Use of reference vectors to decompose the objective space into multiple small subspaces, 2) Steady-state hierarchical update procedure which is dependent on Pareto dominance, local density estimation, and scalarizing functions, sequentially	DTLZ1-DTLZ4 with {3,5,8,10,15} and WFG1-WFG9 with {3,5,8,10} objectives
[S36]	RVEA	1) Use of reference vectors to decompose the objective space into multiple small subspaces, 2) Use of APD scalarizing function	DTLZ1-DTLZ4 and WFG1-WFG9 with {3,5,8,10} objectives
[S73]	I-DBEA	1) The entire population is considered as a neighborhood, 2) A first-encounter replacement strategy is incorporated, 3) In the replacement step, distance d_2 is given precedence over distance d_1	DTLZ1-DTLZ4 with {3,5,8,10,15} objectives, WFG1-WFG9 with {3,5,10,15} objectives, car-side impact, water resource management, aviation aircraft design
[S74]	MOEA/D-DU	In the update procedure, the perpendicular distance from the solution to the weight vector in the objective space i.e., distance d_2 is explicitly exploited	DTLZ1-DTLZ4, DTLZ7 and WFG1-WFG9 with {2,5,8,10,13} objectives
[S74]	EFR-RR	1) Introduction of ranking restriction scheme in EFR [S75] algorithm	DTLZ1-DTLZ4, DTLZ7 and WFG1-WFG9 with {2,5,8,10,13} objectives
[S76]	MOEA/D-SAS	Introduction of decomposition-based sorting and angle-based-selection in MOEA/D	UF1-UF10 [S16], DTLZ1-DTLZ7 with {3,5,8,10} objectives, and DTLZ1-DTLZ7 [S26] with 15 objectives
[S77]	θ-DEA	Introduction of new dominance relation, termed θ-dominance in decomposition-based framework	DTLZ1-DTLZ4, DTLZ7, SDTLZ1, SDTLZ2, and WFG1-WFG9 with {3,5,8,10,15} objectives
[S78]	MOEA/D-AM2M	Extension of MOEA/D-M2M [S24] with inclusion of adaptive region decomposition and adaptive weight vector design in the subregions	Five newly introduced MaOPs (MaOP1-MaOP5) with degenerated PFs
[S79]	Comparison of many-objective optimizers	Exhaustive performance analysis of many-objective algorithms and investigation of their sensitivity to PF shapes	DTLZ1-4, DTLZ1-4^{-1}, WFG4-9, WFG4-9^{-1} with {3,5,8,10} objectives
[S80]	Enhanced MOEA/D	Introduction of supplemental weight vectors and solutions to enhance the solution search	MOKPs with {4,5,6} objectives

Table S7: SUMMARY OF STUDIES ON CONSTRAINED OPTIMIZATION

Ref.	Algorithm	Main Idea(s)	Application
[S72]	Constrained NSGA-III	Extension of NSGA-III [S38] by using constraint binary tournament selection operator and constraint-domination principle of NSGA-II [S81]	C1-DTLZ1, C1-DTLZ3, C2-DTLZ2, convex C2-DTLZ2, C3-DTLZ1, C3-DTLZ4 with {3,5,8,10,15} objectives [S72]
[S72]	C-MOEA/D	Extension of MOEA/D by using superiority of feasible solutions method in replacement step [S81] [S81]	C1-DTLZ1, C1-DTLZ3, C2-DTLZ2, convex C2-DTLZ2, C3-DTLZ1, C3-DTLZ4 with {3,5,8,10,15} objectives [S72]
[S32]	C-MOEA/DD	Extension of MOEA/DD [S32] by using constraint binary tournament selection operator and superiority of feasible solutions method in replacement step [S81]	C1-DTLZ1, C2-DTLZ2, C3-DTLZ1, C3-DTLZ4 with {3,5,8,10,15} objectives
[S36]	C-RVEA	Extension of RVEA [S36] by using superiority of feasible solutions method in elitist selection	C1-DTLZ1, C2-DTLZ2, C3-DTLZ4 with {3,6,8,10} objectives

Table S8: SUMMARY OF STUDIES ON PREFERENCE INCORPORATION

Ref.	Algorithm	Main Idea(s)	Application
[S38]	NSGA-III	Use of few user-supplied reference points in the weight vector initialization step	DTLZ1-DTLZ2 with 3- and 10-objectives
[S36]	RVEA	Generation of uniformly-distributed reference vectors in the user-specified subspace	DTLZ1-DTLZ2 with 3-objectives
[S66]	r-MOEA/D-STM	Weight vector initialization with vectors closest to the provided reference point	ZDT [S25] and 3-objective DTLZ [S26]
[S82]	R-MEAD	1) Integration of reference point approach in MOEA/D, 2) Dynamic adaptation of weight vectors to converge close to the DM's preferred regions	ZDT [S25], 3-objective DTLZ1-DTLZ2
[S83]	R-MEAD-2	1) Extension of R-MEAD [S82], 2) Use of random number generator (RNG) method to generate weight vectors	DTLZ1-DTLZ6 with 4-10 objectives
[S84]	cwMOEA/D	Co-evolution and dynamic adjustment of weights such that algorithm converges towards the region preferred by the DM	ZDT1, 2-objective WFG2, and WFG4
[S85]	WASF-GA	Use of user-supplied reference point as the reference point in the ASF	ZDT [S25], DTLZ1-DTLZ7 [S26] and WFG1-WFG9 [S30] with 2- and 3-objectives
[S86]	iMOEA/D	Periodical interaction with the DM and renewal of preferred weight region towards the neighborhood of the solution which is most preferred by the DM	ZDT1-ZDT2, 3-objective DTLZ1-DTLZ2

Table S9: SUMMARY OF STUDIES ON APPLICATION TO REAL-WORLD OPTIMIZATION PROBLEMS

Ref.	Real-world MOPs	Algorithm	Main Idea(s)
[S87]	Analog sizing problem	Enhanced MOEA/D-DE	1) A new replacement mechanism, 2) Randomized scaling factor in DE mutation
[S88]	Mobile agent routing problem in WSNs	Modified MOEA/D	Incorporation of problem-specific - selection, crossover, and mutation operators in MOEA/D
[S89]	Energy-efficient dense deployment in WSNs	MOEA/D-GSH	Hybridization of MOEA/D with problem-specific Generalized Subproblem-dependent Heuristic (GSH)
[S90]	Capacity arc routing problem	D-MAENS	Combining the features of MOEA/D, NSGA-II, and MAENS [S91]
[S92]	Capacity arc routing problem	ID-MAENS	Modification of the algorithm D-MAENS [S90]
[S93]	Design of Yagi-Uda antennas	Modified MOEA/D	A new update mechanism is integrated within the MOEA/D framework
[S94]	Antenna design problem	Modified MOEA/D	Controlled mating among the solutions in the main population with those that are best along corresponding direction in the external archive
[S95]	Reactive power handling problem	MOTLA/D	Integration of TLBO algorithm [S96] within the MOEA/D framework
[S97]	Traffic grooming in optical networks	MOEA/D-NBI	Application of MOEA/D based on NBI-style Tchebycheff approach [S98]
[S99]	Optimal power flow problem	MOABC/D; MOTLA/D	Integration of ABC algorithm and TLBO algorithm in the decomposition framework
[S100]	Dynamic VAR planning problem	MOEA/D	Application of MOEA/D
[S101]	Economic emission dispatch problem of wind-thermal power system	MOEA/D	Application of MOEA/D
[S102]	Economic emission unit commitment problem	Enh-MOEA/D-DE	1) Integration of a GA-DE based hybrid strategy [S103] within MOEA/D-DE framework, 2) Introduction of ensemble algorithm based on combination of MOEA/D with uniform and non-uniform weight vector distribution strategy
[S104]	Vehicle routing problem with stochastic demands	MOEA/D-MRDL-VRP	Integration of local seach [S105] and multi-mode mutation [S106] heuristics within MOEA/D-MRDL [S68]
[S107]	Community detection in networks	MOEA/D-Net	Use of problem-specific encoding and modified variation operators in MOEA/D
[S108]	Complex network clustering	MODPSO	Development of a discrete MOPSO framework and use of decomposition mechanism
[S109]	Collaborative filtering recommendation	MOEA/D-RS	Development of a recommendation technique based on MOEA/D
[S110]	Sparse feature learning (SFL) problem	Sa-MODE/D	Development of MO-SFL model and use of self-adaptive multi-objective differential evolution based on decomposition (Sa-MODE/D) in the learning procedure
[S111]	Network structural balance	Improved MODPSO	Development of enhanced MODPSO [S108] and problem-specific model selection strategy to choose ultimate solution from the PF
[S112]	Unsupervised band selection	MOBS	Development of a multi-objective band selection (MOBS) model and use of MOEA/D
[S113]	Change detection in synthetic aperture radar (SAR) images	MOFCM	Development of a multi-objective fuzzy clustering method (MOFCM) which employs MOEA/D