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A Distributed Multifactorial Particle Swarm Optimization Approach

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Abstract

Multifactorial Optimization (MFO) and Evolutionary Transfer Optimization (ETO) are new optimization challenging paradigms for which the multi-Objective Particle Swarm Optimization system (MOPSO) may be interesting despite limitations. MOPSO has been widely used in static/dynamic multi-objective optimization problems, while its potentials for multi-task optimization are not completely unveiled. This paper proposes a new Distributed Multifactorial Particle Swarm Optimization algorithm (DMFPSO) for multi-task optimization. This new system has a distributed architecture on a set of sub-swarms that are dynamically constructed based on the number of optimization tasks affected by each particle skill factor. DMFPSO is designed to deal with the issues of handling convergence and diversity concepts separately. DMFPSO uses Beta function to provide two optimized profiles with a dynamic switching behaviour. The first profile, Beta-1, is used for the exploration which aims to explore the search space toward potential solutions, while the second Beta-2 function is used for convergence enhancement. This new system is tested on 36 benchmarks provided by the CEC'2021 Evolutionary Transfer Multi-Objective Optimization Competition. Comparatives with the state-of-the-art methods are done using the Inverted General Distance (IGD) and Mean Inverted General Distance (MIGD) metrics. Based on the MSS metric, this proposal has the best results on most tested problems.

Keywords: Dynamic Multi-Objective Particle Swarm Optimization, Distributed Algorithm, Evolutionary Transfer Optimization, Large Scale Problem, Multitasking Optimization, Many Objective Optimization Problem.

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1. Introduction

Multifactorial optimization (MFO) for multi-task optimization is a new paradigm in the domain of optimization [1], [2]. Since 2016, the field of evolutionary computing has undergone major evolutions of several complex problems, which are characterized by a large number of decision variables (more than 100) with more than three objective functions performed in multiple tasks. Unlike using Swarm Intelligence (SI) methods [3], [4] and Evolutionary Algorithms (EA) [5], [6] to solve a single task from scratch, the main challenge of Multi-Objective Evolutionary Algorithms (MOEAs) is to optimize multiple independent tasks simultaneously where a task may stand for a static single/multi-objective problem (SOP, MOP) or a Many-Objective Optimization Problem (MaOP) or a dynamic multi-objective problem (DMOP) [7]–[11]. In [1], Gupta *et al.* introduced MFO for multi-task optimization, which is also known as Multi-Objective Multitasking Optimization (MTO). A multi-task optimization problem (MTOP) may be expressed as in Equation (1), where each task k is defined as a minimization problem (MOP, DMOP or MaOP).

$$\begin{aligned} \text{Minimize: } & \begin{cases} F_1(x_1) = (f_1^1(x_1), \dots, f_1^{m_1}(x_1)) \\ F_2(x_2) = (f_2^1(x_2), \dots, f_2^{m_2}(x_2)) \\ \dots \dots \\ F_k(x_k) = (f_k^1(x_k), \dots, f_k^{m_k}(x_k)) \end{cases} \\ \text{Subject to: } & x_i \in \prod_{s=1}^{n_i} [a_i^s, b_i^s], i = 1, \dots, k \end{aligned} \quad (1)$$

where F_k stands for the k^{th} multi-objective optimization task, $\prod_{s=1}^{n_k} [a_k^s, b_k^s]$ represents the decision space, n_k is the dimension of the decision space, and $f_k^1(x_k), \dots, f_k^{m_k}(x_k)$, presents the objective space of the k^{th} task.

Multi-Factorial Optimization, MFO, was introduced in bi-level programming [12], where an implicit genetic transfer across multiple tasks was used to reduce time-processing challenges and enhance convergence. It is characterized by multiple concurrent search spaces corresponding to dependent or independent tasks with different objective spaces. Evolutionary multitasking considers the K tasks to optimize as independent. Each task $T_j, \forall j = 1, \dots, K$ is considered independently in its search space X_j . However, the main goal of MFO is not to find the best trade-off between consecutive objective functions f_j , but to optimize multiple tasks at the same time.

Four main challenges rise when using MOEA for MFO [13]: reducing the intensity of negative transfer knowledge, allocating the necessary resources for each problem, establishing acceptable mapping between tasks, and managing the complexity of transferred knowledge when needed. As mentioned above, the most known MFO method was first proposed by Gupta *et al.* [1], denoted by Multifactorial Evolutionary Algorithm, (MFEA). MFEA is a parallel population-based search method which solves a set of MTOPs using a single fitness function. Transferring positive knowledge among tasks is the main important step of evolutionary multitasking optimization. However, many improved MFEA variants have been proposed. In [14], the Generalized Multifactorial Evolutionary Algorithm (G-MFEA) was proposed to optimize multiple tasks with different dimensions and separate objective space.

Evolutionary multitasking based Effective Knowledge Transfer approach (EMT/ET) [13] was integrated with a set of non-dominated solutions as a positive transferred knowledge across tasks. A Multi-Objective-Multifactorial Evolutionary Algorithm (MO-MFEA) [15] and a Permutation-based MFEA [16] are used for MOP and combinatorial optimization problems, respectively. Evolutionary Transfer Optimization (ETO) [17] used evolutionary algorithm (EA), for multi-task optimization and for transferring useful information across tasks as presented in the explicit multi-population evolutionary framework (MPEF) [18]. ETO aims to make a learnable EA to speed up the computation time and automatically solving related tasks using only positive knowledge. ETO can use several transfer learning tools to improve the efficiency of evolutionary algorithms, such as prediction of new solutions, reuse of previous experience, sharing of similar knowledge and consider non-dominant solutions between related tasks.

The main components of ETO system are presented in Figure 1. They appear through the combination of classic EA and knowledge learning process, when all positive solution is preserved and transferred between related tasks in the same problem or domain. For the EA proposed in [13], only non-dominated solutions are considered in the sharing step between target tasks. Since 2010, the term Transfer Learning (TL) or knowledge transfer [19] has been widely used in a variety of Machine Learning (ML) methods for classification, clustering, regression and deep learning training models. This mechanism has considered to improve the performance of the learner by avoiding much expensive data-labelling efforts taking into consideration the difference between feature space representation and the data distribution. Many TL techniques [20] are used to construct and enhance ML models, such a matrix knowledge, tree knowledge and neural knowledge [21] for face recognition, deep learning, speech recognition and natural language processing applications.

Fig. 1. Evolutionary Transfer Optimization Components.

Furthermore, two requirements are needed to build an efficient learnable EA, so it includes data representation and a transfer learning mechanism across multiple tasks. Different transfer learning (TL) tools have been integrated with EA to solve multi-objective optimization problems with multiple related tasks. These mechanisms are detailed in the next section and resumed in Table 1. The main motivation for this study is the importance of the recent field of MTO in terms of the complexity of the problem. To the best of our knowledge, there is no proposed method based on the PSO system to solve the new set of 36 benchmarks provided by CEC’2021 Evolutionary Transfer Multi -Objective Optimization Competition.

This paper proposes a new Distributed Multifactorial Particle Swarm Optimization (DMFPSO) algorithm for multitasking optimization problems. This new system has a distributed architecture on a set of sub-swarms that are dynamically constructed based on the number of optimization tasks affected by each particle skill factor. The novelty of the DMFPSO approach is reflected in the advantages of using a couple of Beta equation provided by Alimi [22]. Changes in the properties of the beta function can lead to different shapes, such as Gaussian, triangular and trapezoidal, which are suitable for single and multi-dimensional search spaces, and are very flexible to solve different type of optimization problems, including the diversification of data distribution.

DMFPSO method presents a dynamic switching behaviour based on two beta distribution profiles denoted by “Beta-1” and “Beta-2”. The “Beta-1” profile is used for exploration to perform a normally distributed population, pushing particles to explore all search spaces in order to get closer to the best solutions over time. The second “Beta-2” profile aims to exponentially decrease the distribution of all the optimal particles in the convergence phase. The dynamic switching behaviour of each particle (from Beta 1 to Beta 2 level and vice versa) is assumed by the comparison procedure between the fitness function value and the average solution value. For each particle p , if the fitness value $Fit(X)$ is greater than the average $mFit(X)$, the “Beta-1” exploration profile is considered as a mechanism to update the position. Otherwise, the “Beta-2” exploitation profile will be used. These two beta profiles are considered to deal with the issue of treating the concept of convergence and diversity separately, aiming to improve the efficiency of optimization in exploration and exploitation without any deterioration in the optimization process.

The rest of this paper is organized as follows. Section 2, outlines evolutionary multitasking and transfer learning-based approaches. Section 3, details the proposed Distributed Multifactorial Particle Swarm Optimization (DMFPSO) system. The experimental setting and discussion of all quantitative results are presented in Section 4. Finally, Section 5 summarizes the paper and suggested some prospects for future work.

2. State of Art of Evolutionary Multitasking and Transfer Learning-Based Approaches

Recently, MFO and ETO have received great attention in the field of optimization. Inspired by the ability of the human brain to manage multiple tasks simultaneously. MTO has been proposed as a new paradigm, attracting the attention of several researchers in the Evolutionary Computation (EC) community. Many contributions for multi-task optimization have been published, including some useful techniques to guarantee positive knowledge transfer across related tasks or problems. Therefore, four categories of optimization problems are considered, including MOP, MaOP, Large-scale Multi-Objective problem, Many-Task Problems and DMOP with multiple related tasks. Based on the types of problems, Tan *et al* [17] classified ETO approaches into five categories:

- ETO for multi-task optimization,
- ETO method for optimization in uncertain environment or DMOP,
- ETO for multi/many-objective optimization,
- ETO for complex optimization,
- ETO for machine learning applications.

The main differences between a multiple tasks' optimization problem, MTO, and multiple optimization problem, MOP, are the type and the dimension of the search space [2]. When a vector of the M objective functions $\{f_1, \dots, f_M\}$ of MOP are executed on a single search space, while an MTO, involves several search spaces, one for each optimization task. Based on the MFEA approach [1], several approaches are proposed to solve a set of MTOPs with a single objective function. In standard MFEA, a single population is used to perform multiple tasks. This mechanism is called implicit parallelism of population-based search. MFEA was proposed to solve k-factorial problem, when the goal is to find the minimum of the fitness function $\{x_1, \dots, x_k\} = \operatorname{argmin}\{f_1, \dots, f_k\}$; x_j is a feasible solution in X_k . All individuals $\{X_1, \dots, X_k\}$ are performed in a unified search space. In addition, the concept of multifactorial optimization is introduced [1] to solve the K-factorial problem. Each individual p_i is decoded according to the task dimension $\{x_1^i, \dots, x_k^i\}$ where; $x_1^i \in X_1$ and $x_k^i \in X_k$, and is characterized by the five properties including factorial cost, factorial rank, scalar fitness, skill factor and multifactorial optimality. The optimal set of non-dominated solutions is determined using a multifactorial optimality mechanism. A member p^* is optimal in the multifactorial sense, if it is the non-dominated solution for all the objective functions $\{f_1^*, \dots, f_k^*\}$ for each task, where $f_j^* \leq f_j(x_j)$ for all $x_j \in X_j$.

As shown in Table 1, several MFEA variants have been adapted to MTO, involving a variety of TL mechanisms to manage the dimensionality of decision variables [14], and positive transferred data [13], [23]. Furthermore, the uncertainty of the optimization domain or DMO can be maintained by the time variation of the decision variables and/or fitness function and the dynamic approximation to the optimal solution. In DMO, global and local solutions may change, or there may be some similarities from one instance to another. The main goal of the ETO method used for DMOP is the hybridization of transfer learning mechanisms to retain useful knowledge during dynamic optimization. Furthermore, Jiang *et al.* [24], developed a dynamic multi-objective evolutionary algorithm based on transfer learning (Tr-DMOEA) to manage the uncertainty in the search space. Tr-DMOEA system is a time-varying prediction model that takes into account related and identical data distributions. Zhou *et al.* [25] developed an evolutionary search paradigm with learning capabilities, which is based on structured knowledge captured from previous optimized solutions to tackle dynamic vehicle routing problem.

Improved Tr-DMOEA system [26] used a linear kernel function to combine the previous solutions and the transferred solutions to build a new population. Furthermore, the imbalanced learning-based knee point mechanism [27], manifold transfer learning [28] and kernel-based methods [26] are used to manage the uncertainty of the problem by predicting the movements of the optimal solutions. Last but not least, the hybridization of EA with ETO tools may be useful in solving multi/many objective optimization problems. Among the well-known tools used for positive knowledge transfer across related problems are: surrogate models [24],

autoencoder [29] and non-dominated solutions [13], [30]. Taken together, several hybrid models have been proposed using EA and TL tools to solve single-objective (SO) [31], multi-objective (MO) [32] multitask benchmarks and large-scale optimization problems [33]. However, PSO based approaches were not investigated to solve the new 36 benchmarks provided by the CEC'2021 Evolutionary Transfer Multi -Objective Optimization, which is the main motivation of this study.

Table 1. Existing Methods for MFO and ETO

Optimization Domain	References	Proposed Approach	Transfer Learning Mechanism	Tested Benchmarks
ETO for Multitasking Optimization	Gupta <i>et al.</i> (2016) [1]	Multifactorial Evolutionary Algorithm (MFEA)	MFEA is inspired from the multifactorial inheritance models including the transmission of biological and cultural building blocks from parents to their offspring	Sphere, Ackley's, Rastrigin's, Single and Multiple Knapsack Problems, Quadratic Assignment Problem and Capacitated Vehicle Routing Problem [1].
	Gupta <i>et al.</i> (2017) [15]	Multi-Objective-Multifactorial Evolutionary Algorithm (MO-MFEA)	implicit transfer of genetic material between candidate solutions belonging to different tasks based on a random mating probability (rmp) and offspring can randomly select a parental skill factor for imitation	Four variants of the ZDT4 benchmark function (ZDT4-R, ZDT4-G, ZDT4-A, ZDT4-RC) and a real-world manufacturing process design problem [15].
	Yuan <i>et al.</i> (2017) [16]	Permutation-based MFEA	permutation-based MFEA for combinatorial optimization problems (PCOPs) based a new unified representation and a new survivor selection procedure	combinatorial optimization problems including the travel salesman problem (TSP), job-shop scheduling problem (JSP), quadratic assignment problem (QAP) and linear ordering problem (LOP) [16]
	Ding <i>et al.</i> (2019) [14]	Generalized Multifactorial Evolutionary Algorithm (G-MFEA)	improved version of MFEA is generalized over two strategies. One for decision variable translation and the other for decision variable shuffling, to facilitate knowledge transfer between optimization problems having different locations of the optimums and different numbers of decision variables.	Eight MFO problems F1-F8 [14]
	Lin <i>et al.</i> (2020) [13]	Evolutionary multitasking based Effective Knowledge Transfer Approach (EMT/ET)	positive knowledge transfer method using the nondominated solutions of the target task. Otherwise only positive neighbour is considered for the transferring step.	Nine problems, CEC 2017 Evolutionary MultiTask Optimization Competition benchmarks
	Zhou <i>et al.</i> (2021) [23]	A new MFEA with adaptive knowledge transfer (MFEA-AKT)	Adapts the crossover for knowledge transfer	nine multitask problems (CIHS, CIMS, CILS, PIHS, PIMS, PILS, NIHS, NIMS, and NILS)
ETO for Dynamic Multi-Objective Optimization	Jiang <i>et al.</i> (2018) [34]	Transfer Learning-Based Dynamic Multi-Objective Evolutionary Algorithm (Tr-DMOEA)	predict the time-varying optimum taking into consideration the non-independent and identically data distribution	Twelve DMOPs [34] (FDA4, FDA5, FDA5iso, FDAdec, DMOP2iso, DMOP2dec, DIMP2, DMOP2, DMOP3, HE2, HE7 and HE9)
	Zhou1 <i>et al.</i> (2017) [25]	evolutionary search paradigm with learning capability for solving the DVRP	learning capability using the structured knowledge captured from the previous optimized solutions and reused during the evolutionary search	Dynamic Vehicle Routing Problem (DVRP)
	Ruan <i>et al.</i> (2019) [26]	Improved Tr-DMOEA	A linear kernel function to combine the previous solutions with the transferred solutions to construct the new population.	The IEEE CEC 2015 Benchmark problems [35].
	Jiang <i>et al.</i> (2021) [27]	knee point-based transfer learning method based evolutionary algorithm for DMOP (KT-DMOEA)	At each iteration, the initial population is constructed using all estimated knee points presenting the imbalance transfer learning method.	DF1-DF14 benchmarks
	Jiang <i>et al.</i> (2020) [28]	memory-driven manifold TL-based evolutionary algorithm for dynamic multi-objective optimization (MMTL-DMOEA)	Construct the initial population based on the predicted optimal solutions and the previous elites of these individuals.	FDA series, dMOP series and DF series
	Yang <i>et al.</i> (2020) [24]	evolutionary algorithm assisted by coarse and	The coarse surrogate (CS) aims to guide the algorithm to quickly find a promising subregion in the search space, whereas the fine one focuses	four DTLZ test suite and four F1-F4 functions.

ETO for Multi/Many-Objective Optimization		fine surrogates' models	on leveraging good solutions according to the knowledge transferred from the CS.	
	Feng <i>et al.</i> (2017) [29]	Autoencoding Evolutionary Search with Learning Across Heterogeneous Problems	A novel autoencoding evolutionary search paradigm with learning capability across heterogeneous problems using the single layer denoising autoencoder (DA)	12 MOP benchmarks: five MOPs in ZDT family and seven MOPs in DTLZ family problems
	Liang <i>et al.</i> (2020) [30]	evolutionary multitasking optimization algorithm (EMT-PD)	Two-stage adaptive knowledge transfer method by considering population distribution for both multi- and many-objective optimization using evolutionary multitasking	nine multitask problems (CIHS, CIMS, CILS, PIHS, PIMS, PILS, NIHS, NIMS, and NILS)

3. The Proposed Distributed Multifactorial Particle Swarm Optimization Approach

The general flowchart of the proposed Distributed Multifactorial Particle Swarm Optimization (DMFPSO) system is shown in Figure 2. Compared to beta PSO [36], the new DMFPSO method aims to solve K multiple tasks simultaneously based on multiple sub-swarms. Where, each task can stand for: a multi/many-objective optimization problem, a large-scale MOP or DMOP. The novelty of the DMFPSO method consists in the use of distributed architecture on a set of sub-swarms that are dynamically constructed based on the number of optimization tasks affected by each particle skill factor. In addition, DMFPSO presents a new dynamic switching behaviour over a couple of beta functions Beta-1 and Beta-2 as new equations to update the position of each particle p_i in the swarm S . The overall process of DMFPSO starts after defining a set of k tasks as input. According to the task T_j assigned to each particle p_i , the population of N particle is subdivided into k sub-swarms. Then, for each task T_j , only one sub-swarm is considered.

Fig. 2. The General Flowchart of the Proposed Distributed Multifactorial Particle Swarm Optimization (DMFPSO) Algorithm.

The overall steps of the DMFPSO method are presented in Figure 3. The detailed description is as follows:

▪ **Step 1: initialize the swarm of N particles**

The DMFPSO algorithm starts with random initialization of the position (X) of the N particles p_i in the swarm S ; $\forall i = 1 \dots N$ in the n -dimensional search space and zero velocities.

▪ **Step 2: assign skill factors**

The term skill factor was first proposed by Gupta *et al.*[1]. The skill factor is to allocate a single task τ_i among the K tasks to each particle p_i in the initialization step.

▪ **Step 3: build multiple sub-swarms**

After the skill factor is assigned, each particle is sorted according to the ID of each task to construct N sub-swarms (sub-swarm_task1..., sub-swarm_taskK).

▪ **Step 4: initialize leaders archives**

For each task K , the global archive $A_j \forall j = 1, \dots, K$ is initialized to store all non-dominated solutions in the optimization process.

▪ **Step 5: execute DMFPSO in parallel for N sub-swarms.**

▪ **Step 6: verify the stop criteria= maximum number of iterations.**

▪ **Step 7: determine the final set of non-dominated solutions of each task.**

After constructing N sub-swarms, DMFPSO is performed in parallel to evaluate the fitness function ($\text{Fit}(X(t))$) of each particle until the maximum number of iterations. At each iteration t , the position (X) of each particle p is updated using Equation (2). The update process of the velocity V_{t+1} is completed using Equation (3).

$$X_{t+1} = X_t + V_{t+1} \quad (2)$$

Fig. 3. The Overall Steps of the Proposal DMFPSO.

In addition, two switched beta distribution profiles were considered to ensure a dynamic balance between exploration and exploitation concepts during the optimization process. The first beta distribution profile Beta-1 is used in the exploration phase.

The second Beta-2 profile is used in the exploitation phase. Both distribution profiles are fixed in Equation (3). For each particle p the optimization stage is fixed as follows: if the fitness value aggregation $Fit(X(t))$ is greater than the average fitness $mFit(X(t))$ of all particles, then optimize the particle in the exploration profile (Beta-1). Otherwise, the second beta distribution profile (Beta-2) will be considered in the exploitation phase.

$$V_{t+1} = \begin{cases} \text{//Exploration Profile (Beta 1)} \\ \text{if } Fit(X_t) \geq meanFit(X_i(t)) \text{ then:} \\ wV_t + c_1\beta_1(x)(P_{best}(t) - X_t) + c_2\beta_1(x)(g_{best}(t) - X_t) \\ \text{else} \\ \text{//Exploitation Profile (Beta 2)} \\ wV_t + c_2\beta_2(x)(g_{best}(t) - X_t) \end{cases} \quad (3)$$

where; w is the inertia weight with a uniform random distribution in the range $[0,1]$, c_1 and c_2 are the acceleration coefficients. The leader g_{best} is the global best solution for all neighbours in swarm S selected from the global archive, which stores all non-dominated solutions for all optimized K tasks. The p_{best} is the best local experience of each particle. Both g_{best} and p_{best} are used to affect the updated position of each particle at each iteration t .

The one-dimensional Beta function $\beta(x)$ was first proposed by Alimi [22] and presented in Equation (4) aiming to highlight the different distribution forms of Beta functions based on time-varying parameters p and q .

$$\beta(x) = \beta(x_0, x_1, p, q)(x) = \begin{cases} \text{if } x \in [x_0, x_1] \text{ then:} \\ \left(\frac{x-x_0}{x_c-x_0} \right)^p \left(\frac{x_1-x}{x_1-x_c} \right)^q \\ 0 \quad \text{otherwise} \end{cases} \quad (4)$$

where; p, q, x_0, x_1 are real numbers and x_c is defined in the following Equation (5).

$$x_c = \frac{px_1 + qx_0}{p+q} \quad (5)$$

The multi-dimensional Beta function is defined in Equation (6), it is the product of m one-dimensional Beta functions expressed by Equation (4).

$$\beta(x) = \prod_{k=1}^m \beta(x_k, p_k, q_k, x_{0,k}, x_{1,k}) \quad (6)$$

Figure 4 shows a couple of beta distribution profiles. The parameters of β_1 are fixed as follows; ($p = 30$ and $q = 0$) and β_2 ($p = 0.1$ and $q = 20$) while x_0 and x_1 are equal to 0 and 1 respectively.

Fig. 4. Switched Beta distributions profiles: β_1 with ($p=30, q=0$), and β_2 with ($p=0.1$ and $q=20$).

The optimization process of DMFPSO is executed until the maximum number of iterations is reached. Finally, all non-dominated solutions for each task are stored in the archive A_j .

The new DMFPSO has an advantage over the use of few parameters' configurations, when the main update rules for positions and velocities are done using a flexible beta function. In addition, this new system optimizes n sub-swarms in parallel, which are equal to the number of optimization tasks. For each sub-swarm, DMFPSO is executed until the maximum number of iterations, the computational complexity is equal to $O(n \log(n))$. Therefore, due to the increase in the number of optimization tasks, the complexity of the new proposal has become more complicated.

Algorithm: The Pseudo code of DMFPSO Algorithm

1. Input: a problem set with K tasks
2. Initialize the global swarm of N particles with random positions and zero velocities
3. For each particle $P_i \forall (i = 1: N)$:
 - 3.1. Assign a random skill factor τ_i for each particle
4. End for
5. For task $T_j \forall (j = 1: K)$:
 6. Construct N sub-swarms according to the skills factor τ_i .
 7. Initialize the leaders archive Arch_ T_j for each task.
 8. Select the leader gbest_ T_j
 9. End For
 10. While iteration < Max-iterations do:
 11. For each task T_j :
 12. For each particle in the sub-swarm_ T_j :
 13. Select gbest_ T_j
 14. Evaluate the fitness function $Fit(X_i)$
 15. Determine the average of fitness function regarding all best particles ($mFit(X)$).
 16. If $Fit(X_i) \geq mFit(X)$:
 17. Update the velocity using Beta-1 function
 18. Update the particle position (X)
 19. Else:
 20. Update the velocity using Beta-2 function
 21. Update the particle position (X)
 22. End If
 23. Update pbest
 24. End for
 25. Update the leader's archive Arch_ T_j
 26. End for
 27. End While
 28. Return leader archives Arch_ T_j : the non-dominated solutions of each task T_j

Fig. 5. The pseudo code of DMFPSO Algorithm.

4. Experimental Study

This experimental study is conducted using a new set of 36 benchmarks provided by the CEC'2021 Evolutionary Transfer Multi-Objective Optimization Competition², which are classified as follows:

- **C1:** Eight Evolutionary Transfer Multi-Objective Optimization Problems: ETMOF1 to ETMOF8.
- **C2:** Eight Evolutionary Transfer Many-objective Optimization Problems: ETMOF9 to ETMOF16.
- **C3:** Eight Evolutionary Transfer Large-scale Multi- Objective Optimization Problems: ETMOF17 to ETMOF24.
- **C4:** Four Evolutionary Transfer Many-task Optimization Problems: ETMOF25 to ETMOF28.
- **C5:** Eight Evolutionary Transfer Dynamic Multi-Objective Optimization Problems: ETMOF33 to ETMOF40.

² <https://www.scholix.com/vpost.html?pid=160180>

The characteristics of each problem are detailed in Table 3, namely the number of tasks T , the number of decision variables ($n = K + L$), the Pareto Optimal Front (POF) type and the mathematical formula type.

In this case, there is no comparative study using these 36 new problems. This experimental study was conducted through a personal comparison test of the proposed DMFPSO and MO-MFEA [15] designed for SO and MO multitask benchmarks. his test was done using a personal computer equipped with 8 Go memory and i7 intel processor. The Java implementation of the proposed method is done on the jMetal framework [37].

1. Parameters Settings

All parameter settings are fixed in Table 2. For each single task in C1, C2, C3 and C5 (with 2 or 3 related tasks), the population size is fixed at 100. However, for the 4 many-task optimization problems in C4 (with 5 to 20 related tasks), the population size is fixed at 10. For a single task of static MOPs, the maximum number of iterations is set to 500 function evaluations, which is the case for the benchmarks in C1, C2, C3 and C4. In addition, the maximum number of iterations of 8 DMOPs (ETMOF33 to ETMOF 40) in C5 is fixed according to the $(30 \times \tau_t)$ function evaluations of a single task T_j , where τ_t is the frequency of change fixed to 20 and 30 is the number of changes. Both comparison methods were performed during 21 independent runs.

Table 2. Parameters Settings

Parameters	DMFPSO and MO-MFEA	
Population size	100: for a single task in C1, C2, C3 and C5	10: for a single task in C4
Archive size= 100		
Max-Iterations	500 for ETMOF1 to ETMOF28	$(30 \times \tau_t)$ for ETMOF33 to ETMOF 40
Mutation Probability= 1/Number of variables		Perturbation Index=1.0

2. Performance Metrics

The Inverted General Distance (IGD) and the Mean Inverted General Distance (MIGD) are used to measure the diversity and convergence performances of each task T_j . The Mean Standard Score (MSS) is calculated to rank comparison algorithms.

- The IGD metric [38] is presented in Equation (7) and used to measure the minimum distance d based on the generated POF and the true POF^* .

$$IGD(POF, POF^*) = \frac{1}{|POF^*|} \sum_{x \in POF^*} \min_{y \in POF} d(x, y) \quad (7)$$

- The MIGD metric [39] is presented in Equation (8), aims to compute the average value of the IGD metric.

$$MIGD = \frac{1}{T} \sum_{t=1}^T IGD(POF(t), POF^*(t)) \quad (8)$$

where; T is equal to 30 presenting the number of changes in each run.

- The MSS is the overall performance metric [32] presented in Equation (9) to determine the best method taking into consideration the K tasks in one test problem.

$$MSS = \frac{1}{K} \sum_{j=1}^K \frac{I_j - \mu_j}{\sigma_j} \quad (9)$$

where, I_j is the IGD/MIGD value obtained by an algorithm G in a run for one task T_j . , μ_j and σ_j are the mean and the standard deviation values obtained by an algorithm for each task $T_j, \forall j = 1, \dots, K$.

Table 3. Characteristics of the Tested Benchmarks

Problems	Number Tasks (T)	Number of objectives (M)	Number of Variables (n=L+K)		Pareto Optimal Front (POF) Types	Mathematical Formula Types
			L	K		
ETMOF1	2	2 for each task	49	1	T1: convex, and T2: concave	T1: multiplication, and T2: addition
ETMOF2	2	2 for each task	49	1	T1 and T2: convex	T1 and T2: addition
ETMOF3	2	T1: 2 T2: 3	T1: 49 T2: 49	T1: 1 T2: 2	T1: convex T2: sphere	T1 and T2: addition
ETMOF4	2	3 for each task	49	2	T1 and T1: linear	T1 and T2: multiplication
ETMOF5	2	3 for each task	49	2	T1: inverted linear, and T2: inverted sphere	T1 and T2: multiplication
ETMOF6	2	2 for each task	49	1	T1: circle, T2: convex	T1 and T2: multiplication
ETMOF7	3	2 for each task	49	1	T1: convex, T2: concave T3: linear	T1 and T3: multiplication T2: addition
ETMOF8	3	3 for each task	43	7	T1, T2 and T3: inverted linear PF	T1, T2 and T3: addition
ETMOF9	2	5 for each task	T1: 21 T2: 49	T1: 4 T2: 4	T1: inverted linear T2: inverted sphere	T1 and T2: multiplication
ETMOF10	2	8 for each task	49	7	T1 and T2: irregular concave	T1: multiplication, and T2: addition
ETMOF11	2	10 for each task	41	9	T1 and T2: convex	T1: multiplication, and T2: addition
ETMOF12	3	T1: 5 T2: 8 T3: 10	49	T1: 4 T2: 7 T3: 9	T1: linear T2: sphere T3: convex	T1, T2 and T3: multiplication
ETMOF13	3	T1: 5 T2: 8 T3: 10	49	T1: 4 T2: 7 T3: 9	T1: degenerated T2: sphere T3: irregular	T1: multiplication T2 and T3: addition
ETMOF14	3	T1: 5 T2: 8 T3: 10	49	T1: 4 T2: 7 T3: 9	disconnected	T1 and T2: addition T3: multiplication
ETMOF15	2	10 for each task	71	28	sphere	T1: multiplication, and T2: addition
ETMOF16	2	5 for each task	67	13	linear	T1: multiplication, and T2: addition
ETMOF17	2	3 for each task	245	11	T1: linear, and T2: inverted	T1 and T2: multiplication
ETMOF18	2	2 for each task	506	6	T1: circle, T2: convex	addition
ETMOF19	2	2 for each task	1018	6	circle	multiplication
ETMOF20	3	2 for each task	T1: 250 T2: 56 T3: 1018	6	T1: convex T2: linear T3: circle	multiplication
ETMOF21	3	3 for each task	501	11	sphere	T1, T2 and T3: addition
ETMOF22	3	3 for each task	T1: 245 T2: 501 T3: 1013	11	inverted linear	T1 and T3: multiplication T2: addition
ETMOF23	2	2 for each task	2042	6	linear	multiplication
ETMOF24	2	2 for each task	4090	6	circle	multiplication
ETMOF25	5	2 for each task	49	1	convex	addition
ETMOF26	10	2 for each task	49	1	convex, concave and linear	multiplication and addition
ETMOF27	10	3 for each task	43	7	linear	multiplication and addition
ETMOF28	20	3 for each task	49	2	linear, sphere and convex	multiplication and addition
ETMOF33	2	2 for each task	256	2	T1: continuous, convex, T2: continuous, dynamic curvature	multiplication
ETMOF34	2	2 for each task	49	1	convex	multiplication
ETMOF35	2	2 for each task	511	1	dynamic POF-convex to concave	multiplication
ETMOF36	2	2 for each task	1023	1	dynamic POF-convex to concave	multiplication
ETMOF37	2	3 for each task	48	2	T1: dynamic POF-convex to concave T2: time-varying concave POF	multiplication and addition
ETMOF38	2	3 for each task	48	2	concave	multiplication and addition
ETMOF39	3	2 for each task	49	1	dynamic POF-convex to concave	multiplication
ETMOF40	3	2 for each task	49	1	dynamic POF-convex to concave	multiplication

3. Results and Discussion

For the needs of discussions, a one-way analysis of variance (ANOVA) test [40] and a mean standard score (MSS) are used to compare the IGD/MIGD values obtained from 36 benchmarks. The smaller value of the MSS metric indicates that the overall performance of the comparison method is better on all tasks of the test problem. The proposed method is compared with the main state of art method for the used test beds, the MO-MFEA. All quantitative results are shown in the appendix (Table 6-Table 10) presenting the best, worst, mean, median, and the standard deviation of the IGD/MIGD values for each task of all ETMO problems.

All best values are highlighted in bold. Table 6 shows the IGD and MIGD values obtained by the new DMFPSO and MO-MFEA methods for 8 ETMO functions in the first category C1 (ETMOF1- ETMOF8) with 2 or 3 tasks, each task is one Multi-Objective Optimization Problem have 2 or 3 objective functions. Based on the results of the one-way ANOVA test in the IGD metric in Figure 6, we can conclude that the DMFPSO system is the winner in solving the ETMOF problems in C1 with a p-values less than 0.05. It can be seen from Table 4 that DMFPSO is the best among the 8 functions (ETMOF1- ETMOF8) using IGD, and it only fails to solve ETMOF4 on MIGD, as shown in Table 5. Table 7 presents the IGD and MIGD quantitative results of the 8 test problems (ETMOF9- ETMOF16) in C2. It presents a set of Many-objective Optimization Problems with 2 or 3 tasks. When each task has 5, 8 or 10 objective functions.

Table 4. Mean Standard Score (MSS) Obtained by DMFPSO and MO-MFEA based on **IGD** Metric.

Prob.	MO-MFEA	DMFPSO	Best Method
ETMOF1	196.69	114.66	DMFPSO
ETMOF2	265.45	28.13	DMFPSO
ETMOF3	206.37	66.66	DMFPSO
ETMOF4	72.65	45.62	DMFPSO
ETMOF5	66.85	54.19	DMFPSO
ETMOF6	64.93	71.07	DMFPSO
ETMOF7	222.66	95.29	DMFPSO
ETMOF8	74.53	49.14	DMFPSO
ETMOF9	46.17	17.134	DMFPSO
ETMOF10	181.99	229.59	MO-MFEA
ETMOF11	116.37	63.39	DMFPSO
ETMOF12	80.44	79.63	DMFPSO
ETMOF13	218.98	113.91	DMFPSO
ETMOF14	277.86	184.92	DMFPSO
ETMOF15	205.03	80.16	DMFPSO
ETMOF16	46.788	34.64	DMFPSO
ETMOF17	368.87	18.08	DMFPSO
ETMOF18	1205.66	265.29	DMFPSO
ETMOF19	355.60	12.13	DMFPSO
ETMOF20	723.99	244.68	DMFPSO
ETMOF21	55.91	18.39	DMFPSO
ETMOF22	194.41	21.35	DMFPSO
ETMOF23	478.02	17.97	DMFPSO
ETMOF24	405.66	19.77	DMFPSO
ETMOF25	227.69	28.22	DMFPSO
ETMOF26	178.99	94.82	DMFPSO
ETMOF27	310.38	177.27	DMFPSO
ETMOF28	341.44	67.09	DMFPSO
ETMOF33	795.36	578.14	DMFPSO
ETMOF34	186.64	190.85	MO-MFEA
ETMOF35	484.68	313.19	DMFPSO
ETMOF36	499.91	79.53	DMFPSO
ETMOF37	168.81	127.99	DMFPSO
ETMOF38	299.48	161.94	DMFPSO
ETMOF39	234.09	493.34	MO-MFEA
ETMOF40	77.02	222.36	MO-MFEA

The MSS values in Table 4 and Table 5 show the merits of DMFPSO compared with MO-MFEA in solving different functions using IGD and MIGD indicators. Compared with MO-MFEA, DMFPSO has almost similar MSS value in the IGD for ETMOF10. It is characterized by 2 tasks; each task is a MaOP with 8 objective functions and irregular concave POF. The results of the one-

way ANOVA test in Figure 7 suggest the relevance of the proposed system for solving almost all the problems in C2. Table 8 and Table 9 details the obtained results of the ETMO problems in C3 and C4 respectively. In C3, comparison methods were used to test eight Large-scale Multi- Objective Optimization Problems (ETMOF17- ETMOF24). These problems are characterized by a large number of decision variables (245, 506, 1018, 2042 or 4090) with 2 or 3 objective functions. In C4, four Many-task Optimization Problems (ETMOF25 to ETMOF28) are considered with 5, 10 or 20 tasks, and each task is a MOP with 2 or 3 fitness functions.

Table 5. Mean Standard Score (MSS) Obtained by DMFPSO and MO-MFEA based on **MIGD** Metric.

Prob.	MO-MFEA	DMFPSO	Best Method
ETMOF1	199.46	102.07	DMFPSO
ETMOF2	208.07	41.94	DMFPSO
ETMOF3	232.15	82.09	DMFPSO
ETMOF4	65.44	89.61	MO-MFEA
ETMOF5	82.12	39.27	DMFPSO
ETMOF6	63.75	43.35	DMFPSO
ETMOF7	186.44	63.73	DMFPSO
ETMOF8	76.389	51.07	DMFPSO
ETMOF9	44.964	14.49	DMFPSO
ETMOF10	226.79	156.31	DMFPSO
ETMOF11	145.59	73.25	DMFPSO
ETMOF12	106.55	69.06	DMFPSO
ETMOF13	234.29	85.24	DMFPSO
ETMOF14	254.44	97.54	DMFPSO
ETMOF15	238.56	82.71	DMFPSO
ETMOF16	59.87	36.59	DMFPSO
ETMOF17	301.39	12.05	DMFPSO
ETMOF18	728.81	188.65	DMFPSO
ETMOF19	315.25	9.13	DMFPSO
ETMOF20	629.24	106.05	DMFPSO
ETMOF21	69.23	14.74	DMFPSO
ETMOF22	191.83	9.38	DMFPSO
ETMOF23	409.30	22.32	DMFPSO
ETMOF24	438.16	27.86	DMFPSO
ETMOF25	227.82	75.23	DMFPSO
ETMOF26	207.71	29.98	DMFPSO
ETMOF27	361.65	30.84	DMFPSO
ETMOF28	254.95	33.29	DMFPSO
ETMOF33	865.08	135.89	DMFPSO
ETMOF34	214.21	105.24	DMFPSO
ETMOF35	456.34	116.19	DMFPSO
ETMOF36	648.79	71.27	DMFPSO
ETMOF37	207.59	98.42	DMFPSO
ETMOF38	254.26	82.24	DMFPSO
ETMOF39	203.39	108.86	DMFPSO
ETMOF40	126.69	105.92	DMFPSO

Fig. 6. One-way ANOVA Results in a Boxplot of DMFPSO and MO-MFEA over IGD of (a) ETMOF1, (b) ETMOF2, (c) ETMOF3, (d) ETMOF4, (e) ETMOF5, (f) ETMOF6, (g) ETMOF7, (h) ETMOF8.

(a)

(c)

(b)

(d)

(e)

(g)

(f)

(h)

Fig. 7. One-way ANOVA Results in a Boxplot of DMFPSO and MO-MFEA over IGD of (a) ETMOF9, (b) ETMOF10, (c) ETMOF11, (d) ETMOF12, (e) ETMOF13, (f) ETMOF14, (g) ETMOF15, (h) ETMOF16.

(a)

(b)

(c)

(d)

(e)

(g)

(f)

(h)

Fig. 8. One-way ANOVA Results in a Boxplot of DMFPSO and MO-MFEA over IGD of (a) ETMOF17, (b) ETMOF18, (c) ETMOF19, (d) ETMOF20, (e) ETMOF21, (f) ETMOF22, (g) ETMOF23, (h) ETMOF24.

Fig. 9. One-way ANOVA Results in a Boxplot of DMFPSO and MO-MFEA over IGD of (a) ETMOF33, (b) ETMOF34, (c) ETMOF35, (d) ETMOF36, (e) ETMOF37, (f) ETMOF38, (g) ETMOF39, (h) ETMOF40.

Figure 8 demonstrates that DMFPSO is the best method to solve of majority of problems ETMOF17- ETMOF24, based on the average IGD value which is not statistically significant when the p-values less than 0.05. In addition, Table 4 and Table 5 detail the MSS over IGD and MIGD respectively. Compared with MO-MFEA, DMFPSO got the smallest MSS value when solving 8 problems in C3 and 4 functions in C4. Furthermore, category C5 has 8 Dynamic Multi-Objective Optimization Problems with 2 or 3 tasks, and each task has 2 or 3 DMOPs executed simultaneously. Based on Figure 9, we can conclude that DMFPSO is a competitive system to the MO-MFEA system using IGD metric. Table 10 reports the IGD and MIGD values obtained through the

comparison approaches. Also, Table 4 presents the MSS values on the IGD, and we can prove the effectiveness of the new proposal in solving ETMOF33, ETMOF35, ETMOF36, ETMOF37, ETMOF38. For three test beds only, which are: ETMOF34, ETMOF39 and ETMOF40, DMFPSO returned similar results to MO-MFEA.

As mentioned in [15], the MO-MFEA is a variant of the baseline Non-dominated Sorting Genetic Algorithm (NSGA- II) proposed by Deb et al.[41] in 2000. The main differences are investigated in the use of implicit parallelism, to attempt multitask as well as the use of an implicit genetic transfer mechanics like the binary crossover (SBX) operator. Compared with the MO-MFEA system, the proposed method was the best due to the simplicity to manage multiple tasks using a distributed architecture of multiple sub-swarms. Each particle in the sub-swarm aims to optimize a specific task. In contrast, the multitasking management in MO-MFEA is more complicated due to the negative exchange of genetic material to create the skill factor of offspring close to the parents.

5. Conclusion

This paper proposed a new Distributed Multifactorial Particle Swarm Optimization algorithm (DMFPSO) for multi-task optimization. This new system starts with a global swarm of N particles. Then, one random skill factor is affected to each particle. DMFPSO was equipped with a set of sub-swarms constructed according to the number of the assigned skill factors. Therefore, each particle has one skill factor referred to optimized task. In more details, each sub-swarm was designed for a specific task. In addition, each particle could be assigned with two optimization profiles. DMFPSO method showed the advantages of using a couple of beta functions (Beta-1 and Beta-2) to update the velocity and position at each iteration. The first Beta-1 function was used to explore the search space and push particles closer to the optimal solution set. The second Beta-2 function was used for convergence enhancement. The proposed DMFPSO was tested on 36 benchmarks provided by CEC 2021 using IGD, MIGD, and MSS quality indicators. Compared with MO-MFEA, DMFPSO has proven to be the best method to solve a set of multi-task optimization problems. Each task can be expressed as; Multi-Objective Optimization Problem, Many-objective Optimization Problem, Large-scale Multi- Objective Optimization Problem, Many-task Optimization Problem and Dynamic Multi-Objective Optimization Problem. In this case study, both IGD and MIGD metrics are used to obtain the best, worst, mean, median, and the standard deviation values. However, MSS metric is used as a comprehensive criterion, and a smaller MSS value indicates that the overall performance of the DMFPSO algorithm on the test problem is better. In conclusion, there is no PSO based method designed for ETMO problems in the literature, and this is the main motivated of this study. For future works, it is recommended to investigate the impact of the beta profiles on the performances of DMFPOS of solving a set of multi-task optimization problems (ETMO) based on its specific characteristics. Future investigations will focus on extending the proposal with a focus on the test beds where the proposed method returned moderate results. Such with dynamic multi-objective optimization problems (ETMO34, 39, and 40) characterised by a time-varying Pareto Optimal Set (POS) from concave to convex shape. So, the main goal will be an additional dynamic processing strategy for solving DMOP through multi-task optimization. Also, a new investigation will be considered to assume a positive transfer knowledge between related tasks.

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Appendices

Table 6. IGD and MIGD Results for Eight Multi-Objective Optimization Problems from ETMOF1 to ETMOF8.

Problems	QI	Task No.	MO-MFEA					DMFPSO				
			Best	Worst	Mean	Median	Std.	Best	Worst	Mean	Median	Std
ETMOF1	IGD	T1	6,9E-1	4,6E-1	5,82E-1	5,47E-1	6,2E-2	5,2E-2	2,38E-2	3,8E-2	4,71E-2	6,95E-3
		T2	1,75E0	1,29E0	1,57E0	1,62E0	1,52E-1	1,28E-1	5,39E-2	9,44E-2	9,78E-2	1,57E-2
	MIGD	T1	1,41E-2	7,63E-3	1,18E-2	1,27E-2	1,55E-3	4,92E-4	2,39E-4	3,7E-4	3,08E-4	6,83E-5
		T2	3,62E-2	2,68E-2	3,19E-2	3,02E-2	2,6E-3	1,24E-3	5,43E-4	9,51E-4	1,13E-3	1,99E-4
ETMOF2	IGD	T1	1,75E0	1,3E0	1,55E0	1,48E0	1,1E-1	6,43E0	8,19E-2	3,75E0	1,73E-1	2,56E0
		T2	7E0	4,75E0	6,08E0	6,08E0	4,87E-1	2,64E1	2,15E-1	1,45E1	2,12E1	1,08E1
	MIGD	T1	3,75E-2	2,63E-2	3,09E-2	3,36E-2	3E-3	6,97E-2	6,33E-4	4,73E-2	1,05E-3	2,24E-2
		T2	1,4E-1	9,94E-2	1,21E-1	9,94E-2	1,15E-2	2,85E-1	3,26E-3	1,79E-1	2,59E-1	8,58E-2
ETMOF3	IGD	T1	1,96E0	1,28E0	1,62E0	1,28E0	1,87E-1	6,41E0	3,91E-2	3,58E-1	4,47E-2	1,35E0
		T2	7,74E-1	5,5E-1	6,49E-1	5,86E-1	5,42E-2	3,22E-2	1,87E-2	2,48E-2	2,03E-2	3,87E-3
	MIGD	T1	3,56E-2	2,45E-2	3,09E-2	3,17E-2	2,92E-3	8,58E-4	3,62E-4	6,2E-4	6,25E-4	1,5E-4
		T2	1,54E-2	1,15E-2	1,29E-2	1,34E-2	1,02E-3	4,74E-4	2E-4	3,01E-4	2,36E-4	7,37E-5
ETMOF4	IGD	T1	3,15E8	1,47E8	2,18E8	2,34E8	4,4E7	4,45E8	1,33E8	2,62E8	3,15E8	7,76E7
		T2	7E7	1,44E7	3,86E7	5,94E7	1,67E7	1,98E8	1,19E7	5,11E7	3,3E7	4,32E7
	MIGD	T1	5,27E6	1,71E6	3,78E6	5,27E6	9,45E5	3,55E6	2,07E6	2,82E6	3,51E6	3,96E5
		T2	1,45E6	3,2E5	7,65E5	6,49E5	3,01E5	1,04E6	1,17E5	4,47E5	4,8E5	2,43E5
ETMOF5	IGD	T1	1,53E4	3,03E2	1,86E3	8,24E2	3,16E3	4,06E7	9,99E4	1,16E7	2,47E6	1,27E7
		T2	7,4E2	3,94E2	5,77E2	5,41E2	9,47E1	3,17E2	1,32E2	2,34E2	1,79E2	5,19E1
	MIGD	T1	6,88E1	4,78E0	2,24E1	1,59E1	1,58E1	9,1E5	4,44E1	1,99E5	4,44E1	2,21E5
		T2	1,56E1	8,6E0	1,15E1	1,25E1	1,7E0	4,59E0	1,01E0	2,47E0	1,72E0	8,16E-1
ETMOF6	IGD	T1	4,95E15	1,14E15	2,73E15	2,92E15	1,1E15	3,87E13	6,66E12	2,11E13	1,47E13	9,24E12
		T2	2,01E4	7,01E3	1,46E4	1,79E4	3,65E3	3,13E4	1,17E4	2,35E4	2,56E4	4,87E3
	MIGD	T1	1,28E14	2,18E13	5,59E13	5,16E13	2,89E13	1,02E12	8,02E10	3,09E11	5,82E11	2,3E11
		T2	4,26E2	1,47E2	2,9E2	2,59E2	6,53E1	3,35E2	7,53E1	2,13E2	1,93E2	7,1E1
ETMOF7	IGD	T1	1,87E1	1,27E1	1,56E1	1,55E1	1,52E0	8,01E0	3,76E0	5,71E0	5,71E0	1,26E0
		T2	1,92E2	1,51E2	1,66E2	1,63E2	1,22E1	8,86E1	3,7E1	6,08E1	7,51E1	1,26E1
		T3	9,36E1	6,35E1	7,83E1	6,93E1	8,19E0	3,97E1	1,69E1	2,86E1	2,32E1	5,81E0
	MIGD	T1	5,57E-1	3,49E-1	4,53E-1	4,42E-1	5,28E-2	1,12E-1	2,89E-2	5,15E-2	4,86E-2	1,76E-2
		T2	5,82E0	3,82E0	5,19E0	5,21E0	4,33E-1	9,78E-1	3,46E-1	6,02E-1	9,06E-1	1,49E-1
		T3	2,76E0	1,66E0	2,37E0	2,76E0	3,2E-1	5,44E-1	1,22E-1	2,74E-1	2,52E-1	1,05E-1
ETMOF8	IGD	T1	3,33E3	6,27E2	1,89E3	1,46E3	7,49E2	5,75E2	3,66E1	2,17E2	9,23E1	1,5E2
		T2	7,63E-1	3,25E-1	5,44E-1	4,15E-1	1,14E-1	3,43E-1	1,1E-1	1,92E-1	1,82E-1	6,05E-2
		T3	8,25E-1	2,35E-1	5,04E-1	4,47E-1	1,3E-1	2,65E-1	6,71E-2	1,65E-1	8,09E-2	5,98E-2
	MIGD	T1	8,92E1	1,96E1	5,29E1	5,69E1	1,85E1	7,36E0	5,33E-1	2,94E0	2,23E0	1,79E0
		T2	2,16E-2	8,1E-3	1,46E-2	9,94E-3	3,55E-3	3,33E-3	9,62E-4	1,88E-3	2,01E-3	6,13E-4
		T3	1,92E-2	6,79E-3	1,45E-2	1,71E-2	3,23E-3	2,96E-3	7,15E-4	1,53E-3	7,7E-4	5,17E-4

Table 7. IGD and MIGD Results for Eight Many-Objective Optimization Problems from ETMOF9 to ETMOF16.

Problems	QI	Task No.	MO-MFEA					DMFPSO				
			Best	Worst	Mean	Median	Std.	Best	Worst	Mean	Median	Std
ETMOF9	IGD	T1	1,29E6	1,68E5	5,09E5	3,53E5	2,73E5	9,85E4	2,84E2	1,48E4	1,58E4	2,32E4
		T2	1,4E15	14E14	6,75E14	5,87E14	2,45E14	2,99E14	9,41E12	9E13	2,23E13	8,38E13
	MIGD	T1	1,83E4	1,42E3	6,88E3	1,54E4	4,5E3	1,79E3	2,22E0	1,56E2	1,64E2	3,76E2
		T2	2,92E13	9,8E12	1,7E13	1,99E13	5,73E12	3,94E12	1,7E11	9,9E11	4,99E11	9,57E11
ETMOF10	IGD	T1	1,47E0	8,25E-1	1,19E0	9,51E-1	1,78E-1	3,5E-1	1,52E-1	2,36E-1	2,57E-1	4,88E-2
		T2	1,65E1	1,24E1	1,41E1	1,24E1	1,22E0	3,7E0	3,07E0	3,45E0	3,51E0	1,9E-1
	MIGD	T1	2,78E-2	1,62E-2	2,4E-2	2,73E-2	3E-3	3,48E-3	1,62E-3	2,28E-3	1,65E-3	5,43E-4
		T2	3,26E-1	2,44E-1	2,88E-1	2,86E-1	1,97E-2	4,1E-2	2,94E-2	3,52E-2	3,88E-2	3,08E-3
ETMOF11	IGD	T1	2,1E-1	5,25E-2	1,48E-1	2,1E-1	4,07E-2	2,73E-2	6,42E-3	1,59E-2	1,66E-2	5,54E-3
		T2	1,21E0	7,32E-1	1,05E0	1,06E0	1,31E-1	3,07E-1	1,07E-1	1,77E-1	1,74E-1	5,09E-2
	MIGD	T1	5,14E-3	8,83E-4	3,34E-3	4E-3	1,01E-3	2,13E-4	7,97E-5	1,41E-4	1,83E-4	4,43E-5
		T2	2,28E-2	1,67E-2	1,98E-2	2,06E-2	1,76E-3	2,63E-3	8,95E-4	1,75E-3	1,99E-3	4,24E-4
ETMOF12	IGD	T1	3,41E-1	1,62E-1	2,72E-1	2,3E-1	4,19E-2	8,53E-2	3,47E-2	5,48E-2	4,68E-2	1,21E-2
		T2	3,75E-1	4,4E-2	2,03E-1	2,42E-1	7,61E-2	8,87E-2	3,29E-2	6,67E-2	6,61E-2	1,56E-2
		T3	6,23E-2	1,2E-2	3,74E-2	3,28E-2	1,29E-2	2,1E-2	6,55E-3	1,07E-2	1,17E-2	3,45E-3
	MIGD	T1	9,86E-3	5,97E-3	8,49E-3	9,86E-3	9,74E-4	1,06E-3	3,77E-4	6,6E-4	6,54E-4	1,83E-4
		T2	9,97E-3	2,29E-3	6,71E-3	9,54E-3	1,94E-3	1,11E-3	3,82E-4	6,48E-4	7,1E-4	1,55E-4
		T3	1,5E-3	5,47E-4	9,78E-4	1,37E-3	2,57E-4	2,55E-4	4,74E-5	1,06E-4	1,09E-4	4,15E-5
ETMOF13	IGD	T1	2,25E1	1,67E1	1,92E1	1,73E1	1,58E0	1,31E1	8,08E0	1,01E1	8,7E0	1,42E0
		T2	1,53E0	9,76E-1	1,25E0	1,25E0	1,23E-1	3,22E-1	1,53E-1	2,28E-1	1,98E-1	4,48E-2
		T3	1,28E1	8,03E0	1,09E1	1,28E1	1,04E0	2,89E0	1,49E0	2,15E0	2,81E0	4,38E-1
	MIGD	T1	6,68E-1	5,24E-1	5,94E-1	5,64E-1	4,43E-2	1,92E-1	6,3E-2	9,51E-2	9,17E-2	2,43E-2
		T2	4,55E-2	3,23E-2	3,9E-2	3,97E-2	3,5E-3	3,45E-3	1,4E-3	2,18E-3	1,99E-3	5,11E-4
		T3	4,02E-1	2,87E-1	3,44E-1	3,45E-1	3,25E-2	3,16E-2	1,36E-2	1,99E-2	2,46E-2	4,32E-3
ETMOF14	IGD	T1	1,33E0	7,32E-1	1,04E0	9,81E-1	1,55E-1	3,87E-1	1,98E-1	2,91E-1	3,31E-1	5,5E-2
		T2	1,48E-1	1,2E-1	1,36E-1	1,38E-1	7,81E-3	1,33E-1	6,67E-2	1,02E-1	1E-1	1,59E-2
		T3	4E-2	3,15E-2	3,53E-2	3,4E-2	2,01E-3	1,88E-2	1,43E-2	1,72E-2	1,74E-2	1,07E-3
	MIGD	T1	4,32E-2	2,35E-2	3,34E-2	3,19E-2	6,4E-3	4,52E-3	1,65E-3	2,91E-3	3,74E-3	7,63E-4
		T2	4,41E-3	3,41E-3	3,93E-3	3,86E-3	2,25E-4	1,48E-3	6,07E-4	1E-3	8,95E-4	1,84E-4
		T3	1,18E-3	9,13E-4	1,04E-3	1,04E-3	6,74E-5	2,64E-4	1,19E-4	1,83E-4	1,42E-4	3,4E-5
ETMOF15	IGD	T1	1,14E0	6,39E-1	9,23E-1	8,14E-1	1,49E-1	5,15E-2	1,15E-2	2,41E-2	1,51E-2	1,04E-2
		T2	7,52E-1	5,84E-1	6,84E-1	6,74E-1	4,79E-2	2E-1	1,08E-1	1,4E-1	1,27E-1	2,46E-2
	MIGD	T1	2,26E-2	1,25E-2	1,85E-2	2,06E-2	3,17E-3	4,65E-4	1,25E-4	2,12E-4	4,65E-4	9,61E-5
		T2	1,54E-2	1,2E-2	1,38E-2	1,35E-2	7,65E-4	1,94E-3	9,75E-4	1,41E-3	1,25E-3	2,32E-4
ETMOF16	IGD	T1	5,77E1	2,6E0	2,23E1	1,71E1	1,37E1	1,48E0	7,1E-2	5,36E-1	7,1E-2	2,7E-1
		T2	4,73E2	1,07E2	3,22E2	2,43E2	1,06E2	9,91E0	1,25E0	2,78E0	1,25E0	1,88E0
	MIGD	T1	1,09E0	1,5E-1	3,92E-1	2,16E-1	2,29E-1	2,16E-2	1,71E-3	7,24E-3	3,44E-3	5,31E-3
		T2	9,55E0	3,94E0	6,19E0	6,74E0	1,45E0	5E-2	1,36E-2	2,73E-2	2,35E-2	1,19E-2

Table 8. IGD and MIGD Results for Eight Large-Scale Multi-Objective Optimization Problems from ETMOF17 to ETMOF24.

Problems	QI	Task No.	MO-MFEA					DMFPSO				
			Best	Worst	Mean	Median	Std.	Best	Worst	Mean	Median	Std
ETMOF17	IGD	T1	2,07E1	1,47E1	1,8E1	1,7E1	1,41E0	8,66E0	7,91E-1	1,96E0	1,22E0	1,76E0
		T2	1,69E1	1,45E1	1,57E1	1,53E1	6,49E-1	1,08E1	5,6E-1	1,51E0	6,16E-1	2,17E0
	MIGD	T1	4,29E-1	3,29E-1	3,73E-1	3,76E-1	2,93E-2	1,7E-1	8,36E-3	2,27E-2	1,32E-2	3,36E-2
		T2	3,48E-1	2,84E-1	3,2E-1	3,33E-1	1,83E-2	1,53E-1	4,85E-3	1,63E-2	7,6E-3	3,08E-2
ETMOF18	IGD	T1	7,36E1	6,68E1	6,98E1	7,06E1	1,65E0	4,76E0	3,11E0	4,1E0	3,62E0	3,99E-1
		T2	2,8E0	2,66E0	2,72E0	2,7E0	3,48E-2	6,85E-1	5,23E-1	6,16E-1	5,62E-1	3,79E-2
	MIGD	T1	1,48E0	1,28E0	1,41E0	1,28E0	4,43E-2	6,25E-2	3,13E-2	4,16E-2	3,64E-2	7,83E-3
		T2	5,68E-2	5,17E-2	5,42E-2	5,26E-2	1,33E-3	7,36E-3	5,53E-3	6,33E-3	5,79E-3	4,67E-4
ETMOF19	IGD	T1	1,29E4	1,84E2	2,82E3	5,85E3	2,83E3	5,99E3	4,53E0	3,75E2	2,61E1	1,27E3
		T2	5,97E1	5,38E1	5,68E1	5,58E1	1,64E0	4,38E1	2,64E0	1,03E1	1,71E1	1,12E1
	MIGD	T1	7,11E2	4,02E0	7,91E1	1,78E1	1,46E2	6,62E3	4,14E-2	3,16E2	5,19E-1	1,41E3
		T2	1,21E0	1,07E0	1,13E0	1,15E0	3,66E-2	6,45E-1	2,89E-2	1,11E-1	3,74E-2	1,61E-1
ETMOF20	IGD	T1	6,28E1	5,25E1	5,9E1	5,93E1	2,66E0	1,66E2	1,22E2	1,43E2	1,42E2	1,19E1
		T2	2,97E0	2,72E0	2,87E0	2,88E0	5,71E-2	5,4E0	4,06E0	4,68E0	4,36E0	3,44E-1
		T3	8,25E1	7,21E1	7,84E1	7,75E1	2,17E0	2,11E2	1,42E2	1,82E2	1,84E2	1,64E1
	MIGD	T1	1,91E0	1,63E0	1,78E0	1,73E0	8,63E-2	2E0	1,13E0	1,46E0	1,62E0	2,37E-1
		T2	8,91E-2	8,17E-2	8,63E-2	8,77E-2	1,84E-3	7,39E-2	3,35E-2	5,02E-2	4,44E-2	9,85E-3
		T3	2,52E0	2,2E0	2,33E0	2,26E0	8,65E-2	2,74E0	1,32E0	1,82E0	2,07E0	3,9E-1
ETMOF21	IGD	T1	4,26E3	7,6E1	1,35E3	4,26E3	1,25E3	2,16E5	6,99E0	3,49E4	6,99E0	5,12E4
		T2	2,34E3	2,75E1	7,64E2	2,82E2	7,21E2	1,92E5	1,62E1	2,99E4	2,92E1	4,39E4
		T3	1,44E1	8,49E0	1,18E1	1,27E1	1,88E0	1,68E1	9,38E-1	6,5E0	1,23E0	4,66E0
	MIGD	T1	1,14E2	8,13E-1	2,92E1	3,69E1	2,85E1	2,86E3	9,09E-2	4,88E2	2,54E0	8,33E2
		T2	1,55E2	6,57E-1	3,67E1	3,29E0	3,61E1	4,09E3	2,66E-2	4,5E2	2,54E-1	9,07E2
		T3	4,1E-1	2,51E-1	3,58E-1	3,8E-1	4,29E-2	2,04E-1	6,03E-3	6,19E-2	1,1E-2	5,49E-2
ETMOF22	IGD	T1	8,5E4	3,39E4	5,75E4	6,34E4	1,1E4	3,05E3	1,42E2	6,86E2	4,78E2	6,29E2
		T2	3,41E5	2,47E5	2,92E5	2,98E5	2,37E4	7,09E3	5,51E2	2,15E3	1,94E3	1,69E3
		T3	4,77E5	3,48E5	4,18E5	4,54E5	3,6E4	2,47E4	1,3E3	4,07E3	2,52E3	4,86E3
	MIGD	T1	2,14E3	1,26E3	1,69E3	1,63E3	2,63E2	9,18E2	2,01E0	8,05E1	3,29E0	2,11E2
		T2	1,04E4	7,48E3	8,88E3	8,61E3	6,5E2	9,61E2	7,61E0	1,01E2	1,64E1	2,12E2
ETMOF23	IGD	T1	1,37E4	9,28E3	1,18E4	1,35E4	1,35E3	9,18E2	9,82E0	1,2E2	1,61E1	2,19E2
		T2	7,52E1	6,69E1	7,06E1	7,03E1	1,67E0	3,42E1	4,75E0	7,96E0	6,52E0	6,17E0
	MIGD	T1	1,05E6	4,99E5	7,45E5	7,12E5	1,34E5	1,93E5	5,17E3	2,02E4	9,41E3	3,99E4
		T2	1,51E0	1,35E0	1,42E0	1,38E0	4,04E-2	2,47E-1	4,21E-2	1,02E-1	2,02E-1	5,72E-2
ETMOF24	IGD	T1	2,13E4	1,26E4	1,6E4	1,32E4	2,73E3	3,58E3	6,18E1	3,48E2	1,31E3	7,67E2
		T2	1,1E2	9,95E1	1,05E2	1,03E2	2,64E0	9,74E1	2,12E1	3,25E1	2,38E1	2,06E1
	MIGD	T1	1,04E4	3,54E2	2,01E3	1,78E3	2,04E3	1,47E6	2,53E1	1,38E5	2,53E1	3,49E5
		T2	2,19E0	2,01E0	2,08E0	2,05E0	4,83E-2	7,14E-1	2,03E-1	2,9E-1	2,73E-1	1,17E-1
		T2	1,86E2	3,75E0	4,68E1	5,63E0	5,58E1	4,39E3	2,96E0	3,01E2	6,04E0	9,73E2

Table 9. IGD and MIGD Results for Eight Many-Task Optimization Problems from ETMOF25 to ETMOF28.

Problems	QI	Task No.	MO-MFEA					DMFPSO				
			Best	Worst	Mean	Median	Std.	Best	Worst	Mean	Median	Std
ETMOF25	IGD	T1	1,99E0	1,38E0	1,72E0	1,9E0	1,6E-1	4,96E0	2,72E-1	2,19E0	2,58E0	1,64E0
		T2	5,07E-1	3,56E-1	4,31E-1	4,06E-1	4,27E-2	1,27E0	5,14E-2	5,27E-1	1,12E0	4,21E-1
		T3	9,55E-2	7,51E-2	8,44E-2	8,32E-2	5,99E-3	2,38E-1	2,68E-2	1,18E-1	2,04E-1	7,61E-2
		T4	5,17E-1	3,62E-1	4,35E-1	4,11E-1	3,8E-2	1,3E0	1,26E-1	6,76E-1	1,17E0	4,67E-1
		T5	2,02E0	1,42E0	1,7E0	1,95E0	1,61E-1	4,84E0	3,28E-1	2,23E0	4,84E0	1,52E0
	MIGD	T1	9,67E-2	6,59E-2	8,38E-2	8,14E-2	8,24E-3	5,75E-3	2,29E-3	3,57E-3	4,8E-3	1,02E-3
		T2	2,51E-2	1,76E-2	2,14E-2	1,83E-2	2,04E-3	1,27E-3	3,56E-4	7,72E-4	6,53E-4	2,18E-4
		T3	4,71E-3	3,62E-3	4,2E-3	4,13E-3	3,38E-4	5E-4	2,05E-4	3,57E-4	2,75E-4	7,84E-5
		T4	2,46E-2	1,84E-2	2,11E-2	2,29E-2	1,63E-3	1,35E-3	4,14E-4	7,25E-4	4,8E-4	2,53E-4
		T5	1,01E-1	6,23E-2	8,36E-2	8,82E-2	7,66E-3	5,52E-3	2,36E-3	3,56E-3	3,68E-3	8,22E-4
ETMOF26	IGD	T1	2,29E0	1,49E0	1,89E0	1,91E0	1,98E-1	1,64E0	7,6E-1	1,03E0	1,02E0	1,77E-1
		T2	3,11E-1	2,07E-1	2,71E-1	2,89E-1	3,11E-2	2,51E-1	1,13E-1	1,63E-1	1,91E-1	3,07E-2
		T3	1,11E-1	7,59E-2	9,26E-2	1,11E-1	9,74E-3	1,38E-1	5,53E-2	9,18E-2	1,04E-1	2,34E-2
		T4	2,32E-1	1,46E-1	1,94E-1	1,81E-1	2,41E-2	1,32E-1	6,6E-2	9,71E-2	1,05E-1	1,7E-2
		T5	2,19E0	1,53E0	1,89E0	2,16E0	1,58E-1	1,64E0	5,11E-1	1,01E0	1,1E0	2,59E-1
		T6	1,25E0	6,06E-1	9,25E-1	1,04E0	1,36E-1	6,81E-1	3,3E-1	4,82E-1	5,63E-1	9,3E-2
		T7	5,58E-1	3,68E-1	4,76E-1	5,25E-1	4,38E-2	3,28E-1	1,77E-1	2,45E-1	2,22E-1	4,32E-2
		T8	8,84E-2	5,06E-2	6,53E-2	7,38E-2	8,8E-3	1,04E-1	3,68E-2	6,44E-2	9,19E-2	1,82E-2
		T9	5,9E-1	3,64E-1	4,85E-1	5E-1	4,9E-2	3,21E-1	1,48E-1	2,15E-1	2,09E-1	4,79E-2
		T10	9,61E-1	5,04E-1	7,24E-1	8,49E-1	1,07E-1	5,39E-1	2,37E-1	3,59E-1	4,71E-1	8,67E-2
	MIGD	T1	2,23E-1	1,48E-1	1,86E-1	1,98E-1	1,85E-2	4,85E-2	6,71E-3	2,15E-2	1,84E-2	9,27E-3
		T2	3,29E-2	2,05E-2	2,66E-2	2,05E-2	3,32E-3	2,58E-2	1,39E-3	4,78E-3	2,08E-3	5,24E-3
		T3	1,06E-2	7,33E-3	9,22E-3	8,75E-3	7,06E-4	1,2E-2	7,46E-4	3,47E-3	4,51E-3	2,72E-3
		T4	2,42E-2	1,43E-2	1,87E-2	1,87E-2	2,4E-3	1,65E-2	8,47E-4	2,73E-3	2,58E-3	3,27E-3
		T5	2,19E-1	1,53E-1	1,9E-1	2,06E-1	1,86E-2	4,5E-2	8,21E-3	2,15E-2	1,74E-2	8,57E-3
		T6	1,11E-1	7,16E-2	9,21E-2	9,86E-2	1,02E-2	5,68E-2	3,74E-3	1,29E-2	9,66E-3	1,11E-2
		T7	5,62E-2	4,26E-2	4,82E-2	4,53E-2	4,39E-3	1,44E-2	2E-3	5,49E-3	5,67E-3	3,13E-3
		T8	7,1E-3	5,31E-3	6,28E-3	6,67E-3	5,39E-4	3,28E-3	4,51E-4	1,4E-3	2,7E-3	6,71E-4
		T9	5,72E-2	4,1E-2	4,82E-2	5,3E-2	3,48E-3	2,75E-2	1,93E-3	6,41E-3	2,95E-3	6,12E-3
		T10	9,5E-2	6,04E-2	7,86E-2	7,89E-2	8,58E-3	5,27E-2	4E-3	1,26E-2	9,77E-3	1,12E-2
ETMOF27	IGD	T1	1,06E5	2,43E4	5,71E4	6,42E4	1,49E4	4,7E4	8,12E3	2,23E4	1,76E4	9,72E3
		T2	2,75E-1	2,26E-1	2,5E-1	2,59E-1	1,27E-2	3,62E-1	2,22E-1	2,94E-1	2,69E-1	3,46E-2
		T3	1,72E-1	1,36E-1	1,48E-1	1,42E-1	8,23E-3	2,32E-1	1,68E-1	2,02E-1	2,01E-1	1,57E-2
		T4	2,16E-2	1,56E-2	1,84E-2	1,79E-2	1,64E-3	3,63E-2	1,81E-2	2,73E-2	2,5E-2	4,94E-3
		T5	8,1E0	4,98E0	6,65E0	7,75E0	8,88E-1	8,14E0	2,5E0	4,91E0	5,56E0	1,43E0
		T6	1,03E5	3,38E4	6,31E4	9,71E4	1,69E4	2,64E5	5,16E3	4,66E4	2,77E4	6,09E4
		T7	6,54E-1	5,77E-1	6,17E-1	6,37E-1	2,02E-2	6,13E-1	4,58E-1	5,33E-1	5,47E-1	4,78E-2
		T8	4,1E-1	3,39E-1	3,72E-1	3,69E-1	1,77E-2	4,84E-1	3,79E-1	4,19E-1	4,06E-1	2,75E-2
		T9	4,37E-2	3,75E-2	4,1E-2	4,21E-2	1,55E-3	4,59E-2	3,88E-2	4,26E-2	4,26E-2	1,71E-3
		T10	1,71E1	1,26E1	1,49E1	1,26E1	1,12E0	1,17E1	4,56E0	8,11E0	8,77E0	1,57E0
		T1	1,05E4	2,85E3	5,83E3	6,94E3	1,85E3	1,68E4	1,11E3	7,15E3	9,83E3	5,34E3
		T2	2,66E-2	2,28E-2	2,49E-2	2,59E-2	9,95E-4	4,41E-2	7,08E-3	2,8E-2	3,33E-2	1,06E-2
		T3	1,62E-2	1,3E-2	1,46E-2	1,52E-2	8E-4	3,07E-2	6,43E-3	1,84E-2	1,81E-2	6,91E-3

MIGD	T4	2,27E-3	1,5E-3	1,8E-3	1,78E-3	1,89E-4	4,03E-3	9,08E-4	2,42E-3	1,72E-3	1,02E-3
	T5	8,61E-1	4,68E-1	6,48E-1	6,61E-1	1,06E-1	1,53E0	2,05E-1	6,5E-1	5,16E-1	3,87E-1
	T6	8,24E3	2,49E3	5,93E3	6,87E3	1,56E3	2,61E4	9,28E1	7,37E3	2,75E3	7,01E3
	T7	6,61E-2	5,9E-2	6,31E-2	6,2E-2	1,75E-3	6,87E-2	2,65E-2	5,42E-2	6,18E-2	1,33E-2
	T8	4,02E-2	3,49E-2	3,77E-2	3,8E-2	1,39E-3	4,94E-2	9,74E-3	2,88E-2	2,71E-2	1,4E-2
	T9	4,41E-3	3,98E-3	4,2E-3	3,98E-3	1,01E-4	5,18E-3	2,13E-3	4,08E-3	4,42E-3	1,16E-3
	T10	1,77E0	1,28E0	1,52E0	1,41E0	1,51E-1	1,62E0	2,07E-1	8,63E-1	1,01E0	4,21E-1
	T1	1,52E3	7,79E2	1,08E3	1,14E3	1,55E2	1,26E3	5,77E2	9,68E2	1,02E3	1,97E2
	T2	1,27E5	4,28E4	8,56E4	9,4E4	2,1E4	3,6E4	2,07E4	2,95E4	2,6E4	5,6E3
	T3	3,37E-1	3,19E-1	3,26E-1	3,27E-1	4,7E-3	3,36E-1	2,99E-1	3,2E-1	3,36E-1	1,11E-2
IGD	T4	8,27E-2	5,43E-2	6,96E-2	6,26E-2	7,2E-3	9,51E-2	4,33E-2	5,53E-2	7,74E-2	1,42E-2
	T5	3,58E2	2,39E2	3,06E2	3,08E2	2,44E1	3,88E2	2,21E2	2,96E2	3,13E2	5,25E1
	T6	3,17E2	9,77E1	2,07E2	1,42E2	6,82E1	3,43E2	5,21E1	1,79E2	1,98E2	9,54E1
	T7	2,77E5	1,64E5	2,3E5	2,72E5	3,34E4	3,14E5	1,24E5	2,09E5	1,33E5	6,32E4
	T8	1,97E-1	1,83E-1	1,93E-1	1,92E-1	3,02E-3	1,95E-1	1,79E-1	1,86E-1	1,9E-1	4,4E-3
	T9	6,8E-2	5,42E-2	6,07E-2	6,52E-2	3,43E-3	7,53E-2	5,01E-2	6,2E-2	7,53E-2	1,05E-2
	T10	4,01E2	2,46E2	3,3E2	4,36E1	4,36E1	3,57E2	1,98E2	2,59E2	2,51E2	5,13E1
	T11	5,51E2	3,71E2	4,45E2	4,45E2	5,03E1	4,75E2	3,17E2	3,97E2	3,17E2	5,38E1
	T12	9,66E4	1,97E4	6,15E4	1,97E4	2,19E4	5,54E4	1,52E4	3,55E4	3,24E4	1,18E4
	T13	7,43E-1	7,03E-1	7,3E-1	7,39E-1	1,11E-2	7,57E-1	6,09E-1	7E-1	6,09E-1	4,24E-2
ETMOF28	T14	4,96E-2	3,66E-2	4,23E-2	4,82E-2	3,16E-3	4,1E-2	2,52E-2	3,3E-2	3,44E-2	4,32E-3
	T15	3,92E2	2,83E2	3,38E2	2,57E1	2,57E1	3,47E2	1,92E2	2,68E2	2,71E2	4,58E1
	T16	6,94E2	3,5E2	5,26E2	5,48E2	8,72E1	4,55E2	2,43E2	3,61E2	2,88E2	5,98E1
	T17	1,6E5	7,2E4	1,09E5	1,47E5	1,74E4	1,17E5	5,43E4	7,71E4	7,78E4	1,87E4
	T18	1,78E-1	5,84E-2	9,65E-2	7,15E-2	3,25E-2	1,87E-1	4,82E-2	9,77E-2	5,58E-2	4,49E-2
	T19	1,54E-1	1,21E-1	1,38E-1	1,51E-1	8,7E-3	1,53E-1	1,04E-1	1,25E-1	1,17E-1	1,68E-2
	T20	2,47E2	1,59E2	1,99E2	2,01E2	2,45E1	2,03E2	1,05E2	1,61E2	1,42E2	3,12E1
	T1	2,58E2	1,5E2	2,1E2	1,9E2	2,39E1	6,57E1	1,95E1	4,66E1	5,05E1	1,24E1
	T2	8,62E3	1,6E4	1,13E4	4,34E3	4,34E3	5,57E3	1,23E3	3,48E3	4,84E3	1,33E3
	T3	6,73E-2	6,36E-2	6,51E-2	6,52E-2	9,2E-4	1,66E-2	7,91E-3	1,43E-2	1,66E-2	3,2E-3
MIGD	T4	2,07E-2	1,08E-2	1,41E-2	1,38E-2	2,07E-3	4,17E-3	9,78E-4	2,67E-3	2,39E-3	1,07E-3
	T5	7,18E1	5,04E1	6,03E1	5,04E1	6,34E0	2,08E1	7,87E0	1,21E1	7,87E0	3,81E0
	T6	6,1E1	1,88E1	3,69E1	5,15E1	1,14E1	1,37E1	1,72E0	6,9E0	1,72E0	3,29E0
	T7	6,78E4	2,91E4	4,76E4	3,9E4	9,73E3	1,49E4	1,82E3	8,15E3	1,24E4	4,73E3
	T8	3,96E-2	3,26E-2	3,84E-2	3,79E-2	1,38E-3	9,64E-3	8,78E-3	9,35E-3	9,59E-3	2,8E-4
	T9	1,37E-2	1,04E-2	1,23E-2	1,19E-2	7,95E-4	3E-3	1,13E-3	2,36E-3	1,67E-3	6,35E-4
	T10	9,41E1	4,97E1	7,09E1	6,16E1	1,16E1	1,61E1	2,8E0	1,01E1	1,52E1	4,33E0
	T11	1,14E2	8,12E1	9,66E1	9,13E1	8,37E0	2,96E1	8,92E0	1,91E1	2,39E1	6,58E0
	T12	1,77E4	5,79E3	1,19E4	1,08E4	3,66E3	3,84E3	1,18E3	2,37E3	1,95E3	1,13E3
	T13	1,5E-1	1,24E-1	1,46E-1	1,46E-1	5,26E-3	3,76E-2	1,77E-2	3,43E-2	3,68E-2	5,9E-3
	T14	9,12E-3	7,17E-3	8,08E-3	7,85E-3	5,03E-4	2,12E-3	4,48E-4	1,44E-3	1,57E-3	4,57E-4
	T15	8,62E1	5,05E1	6,22E1	5,81E1	7,62E0	1,93E1	4,53E0	1,12E1	1,62E1	4,26E0
	T16	1,31E2	6,53E1	1,09E2	1,22E2	1,6E1	2,81E1	1,21E1	2,05E1	1,84E1	5,17E0
	T17	3,54E4	9,34E3	2,01E4	1,58E4	5,71E3	7,66E3	1,32E3	4,3E3	4,49E3	1,85E3
	T18	3,87E-2	1,17E-2	2,08E-2	2,52E-2	7,25E-3	8,72E-3	1,44E-3	4,84E-3	1,8E-3	2,48E-3
	T19	3,16E-2	1,93E-2	2,71E-2	2,64E-2	2,63E-3	7,35E-3	5,66E-3	6,5E-3	6,41E-3	6,72E-4
	T20	4,96E1	3,1E1	4,03E1	3,52E1	4,58E0	8,48E0	1,98E0	4,74E0	2,55E0	2,54E0

Table 10. IGD AND MIGD Results for Eight Dynamic Multi-Objective Optimization Problems from ETMOF33 to ETMOF40.

Problems	QI	Task No.	IGD					MIGD				
			Best	Worst	Mean	Median	Std.	Best	Worst	Mean	Median	Std
ETMOF33	IGD	T1	2,48E0	2,21E0	2,38E0	2,38E0	5,92E-2	8,32E0	7,81E0	8,04E0	7,99E0	1,49E-1
		T2	5,88E0	5,34E0	5,57E0	5,56E0	1,42E-1	8,76E0	2,06E0	6,36E0	7,56E0	1,72E0
	MIGD	T1	4,93E-2	4,5E-2	4,75E-2	4,78E-2	1,23E-3	9,86E-2	6,69E-2	8,23E-2	7,39E-2	7,73E-3
		T2	1,14E-1	1,07E-1	1,1E-1	1,11E-1	2,3E-3	9,83E-2	2,27E-2	6,14E-2	8,48E-2	2,08E-2
ETMOF34	IGD	T1	1,4E-1	4,57E-2	9,24E-2	8,26E-2	2,14E-2	4,09E-1	3,18E-1	3,59E-1	3,84E-1	2,23E-2
		T2	1,28E1	9,23E0	1,12E1	1,01E1	7,82E-1	2,17E1	6,73E0	1,64E1	2,04E1	5,48E0
	MIGD	T1	2,31E-3	1,4E-3	1,77E-3	2,15E-3	2,41E-4	4,77E-3	2,69E-3	3,63E-3	3,32E-3	4,63E-4
		T2	2,44E-1	1,78E-1	2,23E-1	2,36E-1	1,58E-2	2,54E-1	6,08E-2	1,62E-1	6,26E-2	6,03E-2
ETMOF35	IGD	T1	3,71E0	3,47E0	3,59E0	3,67E0	7,87E-2	1,28E1	1,09E1	1,14E1	1,14E1	4,06E-1
		T2	4,84E1	1,69E1	2,46E1	1,85E1	8,63E0	1,91E1	5,51E0	9,18E0	7,40E0	2,84E0
	MIGD	T1	7,45E-2	6,79E-2	7,14E-2	7,32E-2	1,62E-3	1,55E-1	8,66E-2	1,13E-1	1,24E-1	1,45E-2
		T2	1,8E0	3,32E-1	5,83E-1	4,71E-1	3,5E-1	1,38E-1	5,63E-2	9,11E-2	9,55E-2	2,39E-2
ETMOF36	IGD	T1	3,88E0	3,56E0	3,69E0	3,88E0	7,81E-2	7,25E-1	2,09E-1	3,92E-1	3,95E-1	1,33E-1
		T2	1,17E2	3,38E1	5,36E1	3,39E1	1,95E1	2,67E1	1,26E1	1,85E1	1,92E1	3,70E0
	MIGD	T1	7,54E-2	7,13E-2	7,32E-2	7,18E-2	1,17E-3	7,67E-3	1,92E-3	3,78E-3	5,73E-3	1,37E-3
		T2	2,21E0	6,41E-1	1,08E0	1,46E0	4,55E-1	3,14E-1	1,27E-1	1,82E-1	1,91E-1	4,17E-2
ETMOF37	IGD	T1	3,4E-1	2,01E-1	2,87E-1	2,67E-1	3,24E-2	1,09E-1	3,33E-2	6,25E-2	9,64E-2	2,29E-2
		T2	1,51E-1	8,82E-2	1,08E-1	1,07E-1	1,35E-2	5,88E-2	4,22E-2	4,94E-2	4,65E-2	4,89E-3
	MIGD	T1	6,81E-3	4,58E-3	5,6E-3	6,29E-3	5,73E-4	1,76E-3	3,06E-4	9,97E-4	1,39E-3	3,57E-4
		T2	2,71E-3	1,85E-3	2,16E-3	2,01E-3	1,97E-4	6,02E-4	3,46E-4	4,69E-4	4,06E-4	6,65E-5
ETMOF38	IGD	T1	2,62E-1	1,85E-1	2,26E-1	2,27E-1	1,85E-2	4,32E-1	5,86E-2	1,78E-1	1,50E-1	8,96E-2
		T2	1,21E-1	9,75E-2	1,08E-1	1,04E-1	6,09E-3	5,34E-2	4,13E-2	4,76E-2	4,66E-2	3,35E-3
	MIGD	T1	5,13E-3	3,83E-3	4,62E-3	4,31E-3	3,56E-4	7,13E-3	8,5E-4	1,98E-3	1,45E-3	1,33E-3
		T2	2,52E-3	1,8E-3	2,19E-3	2,04E-3	1,76E-4	7,3E-4	3,9E-4	5,04E-4	5,05E-4	7,48E-5
ETMOF39	IGD	T1	3,23E-1	2,36E-1	2,81E-1	2,91E-1	2,62E-2	1,23E0	1,04E0	1,12E0	1,11E0	4,25E-2
		T2	5,07E1	2,97E1	4,02E1	4,04E1	6,12E0	5,36E2	3,97E2	4,68E2	4,93E2	3,63E1
		T3	1,04E-2	8,24E-3	9,46E-3	9,58E-3	5,31E-4	2,14E-2	1,95E-2	2,01E-2	1,98E-2	5,77E-4
	MIGD	T1	1,08E-2	7,41E-3	8,99E-3	9,35E-3	7,96E-4	1,47E-2	8,21E-3	1,11E-2	1,05E-2	1,74E-3
		T2	1,43E0	9,66E-1	1,2E0	1,3E0	1,43E-1	7,54E0	3,35E0	5E0	5,43E0	1,05E0
		T3	3,64E-4	2,56E-4	2,92E-4	3,23E-4	2,7E-5	2,79E-4	1,38E-4	1,96E-4	1,93E-4	3,77E-5
ETMOF40	IGD	T1	7,12E1	4,27E1	6,22E1	6,39E1	7,22E0	8,2E1	5,94E1	7,13E1	6,46E1	5,06E0
		T2	5,75E-2	6,63E-3	1,74E-2	1,28E-2	1,08E-2	9,27E-3	5,54E-3	6,34E-3	6,21E-3	8,11E-4
		T3	1,2E1	1,48E0	3,41E0	3,1E0	2,58E0	1,12E0	8,2E-1	9,17E-1	8,21E-1	7,99E-2
	MIGD	T1	2,25E0	1,66E0	1,96E0	1,84E0	1,39E-1	1E0	5,06E-1	7,02E-1	6,41E-1	1,29E-1
		T2	9,97E-4	2,13E-4	4,58E-4	4,57E-4	1,68E-4	1,02E-4	4,66E-5	6,57E-5	8,16E-5	1,47E-5
		T3	1,93E-1	4,62E-2	9,57E-2	1,6E-1	4,34E-2	1,26E-2	6,87E-3	9,02E-3	7,85E-3	1,51E-3

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