Supplementary File of ”Knowledge Transfer with Mixture Model in Dynamic Multi-objective Optimization”

I. Compared State-of-the-Arts

To empirically investigate the performance of KTMM, NSGA-II [1] is employed as the SMOEA in all compared response techniques. These techniques are denoted as PPS-NSGA-II [2], AE-NSGA-II [3], IT-NSGA-II [4], KL-NSGA-II [5], KTS-NSGA-II [5], and DIP-NSGA-II [6]. In this section, we will provide a brief introduction to these popular DMOEAs, as well as the typicality for selecting them as compared algorithms.

1) PPS-NSGA-II [2] is a typical population-based prediction strategy, where a widely-used autoregression model is trained based on the previous POS to forecast the new POS. More specifically, it is designed to respond to the new environments based on a center prediction and estimate the manifold of POS that can be integrated into any SMOEA.
2) AE-NSGA-II [3] reacts effectively to the environmental changes by generating two sub-initial populations whenever a change is detected. Specifically, the Autoencoder (AE, a widely-used machine learning model) is firstly adopted to capture the historical search experience for handing DMOPs. Furthermore, a high-quality solution preservation method has been designed to maintain the diversity of the population for further exploration of the uncertain environment.
3) IT-NSGA-II [4] is an individual-based knowledge transfer method where a pre-search procedure eliminates guided solutions with good diversity to avoid the negative transfer. Moreover, the popular transfer learning model, TrAdaboost [7], is trained to form a classifier that can be used to generate an initial population when the environment changes.
4) KL-NSGA-II [8] is a knowledge learning strategy for dynamic multi-objective optimization, responding to changes by learning from the historical search process. It extracts knowledge from previous search experiences to accelerate convergence and introduce diversity for optimizing future environments.
5) KTS-NSGA-II [5] is a knowledge-guided transfer strategy developed recently based on a domain adaptation method (SDA-IS) [9]. Based on the similarity degree of selected knowledge in a knowledge pool, it employs the knowledge reuse or the transfer technique based on SDA-IS to generate an initial population.
6) DIP-NSGA-II [6] is a neural network-based directional improvement method that aims to capture the change patterns (e.g., nonlinear correlations) of the environment. It learns a directional improvement based on the learned change pattern in the decision space, trying to generate a superior initial population with good convergence and diversity for the new environment.

II. Discussions of Experimental Results

In our experimental studies, we validate the effectiveness of the proposed knowledge transfer strategy through a series of experiments. First, the proposed KTMM-NSGA-II is compared with six state-of-the-art methods on DMOPs with irregular changes. Next, we evaluate the initial solution sets generated by each compared algorithm across different environments to further validate the superiority of the proposed knowledge transfer strategy. The proposed KTMM is validated by integrating it with various static algorithms to assess the effectiveness of the framework. Finally, the experimental results regarding the algorithm parameters are presented.

A. Experimental Results on Irregular Changes

This section presents experimental results of all compared algorithms on three benchmark suites (denoted as RFDA, RJY and RDF) with different parameter settings. Tables 1 to 4 present mean and standard deviation values of MIGD, where '$+$', '$-$', and '$\approx$' indicate that each compared algorithm is significantly better than, worse than, and tied with KTMM-NSGA-II, respectively. From TABLE 1 and TABLE 2, KTMM-NSGA-II consistently outperforms the other algorithms across various parameter configurations on the RFDA and RJY. The comparative results demonstrate that KTMM-NSGA-II achieves significantly better results, particularly against IT-NSGA-II and DIP-NSGA-II. This trend is evident in all configurations, highlighting KTMM-NSGA-II as the most effective optimization algorithm for the simpler problems, while the other algorithms generally exhibit inferior performance due to irregular changes.

DF1-DF14 [10] encompass a comprehensive array of properties that adeptly capture a multitude of real-world scenarios, such as time-dependent POF/POS geometries, disconnectivity, and knee points, among others. This test suite is primarily derived from FDA [11] and JY [12] but is enriched with additional features, enhancing its representativeness in the domain of dynamic multi-objective optimization. By building upon the foundational framework of DFs, we have seamlessly integrated our design methodology to develop the RDF. Notably, this change preserves the intrinsic characteristics of the original problems, while achieving irregular changes defined in this paper. Results of mean and standard deviation values of MIGD on RDFs are presented in TABLE 3 and TABLE 4, respectively. It is clear that from these tables that KTMM-NSGA-II consistently outperforms other algorithms across various RDFs, demonstrating superior performance on the more difficult DMOPs with irregular changes. It is worth noting that KTS-NSGA-II also performs well on some test problems, further demonstrating the effectiveness of knowledge transfer from a broader range of historical environments.

TABLE 1

THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS ON RFDAS, WHERE '$+$', '$-$', AND '$\approx$' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	(τ_t, n_t)	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RFDA1	(5,5)	7.1030e-1 (5.79e-2) $-$	5.5140e-1 (3.83e-2) $-$	3.7803e-1 (2.57e-2) $-$	6.6256e-1 (1.20e-1) $-$	1.1977e-1 (2.12e-2) $-$	1.6899e-1 (1.91e-2) $-$	5.9461e-2 (3.33e-3)
	(10,5)	4.3439e-1 (6.63e-2) $-$	4.2849e-1 (3.82e-2) $-$	1.6777e-1 (1.38e-2) $-$	4.0129e-1 (8.52e-2) $-$	4.6043e-2 (1.90e-2) $-$	1.0010e-1 (6.63e-3) $-$	2.4448e-2 (1.85e-3)
	(20,5)	1.6176e-1 (3.82e-2) $-$	1.6179e-1 (2.72e-2) $-$	4.8644e-2 (9.07e-3) $-$	1.2534e-1 (3.83e-2) $-$	1.1506e-2 (1.08e-3) $-$	4.2516e-2 (3.87e-3) $-$	8.7566e-3 (5.32e-4)
	(5,10)	8.9544e-1 (1.46e-1) $-$	4.9278e-1 (9.67e-2) $-$	2.5838e-1 (2.81e-2) $-$	5.5249e-1 (9.53e-2) $-$	1.6798e-1 (7.02e-2) $-$	3.2250e-1 (3.34e-2) $-$	4.0166e-2 (1.47e-3)
	(10,10)	6.7074e-1 (1.39e-1) $-$	4.0241e-1 (2.49e-2) $-$	1.2983e-1 (5.49e-2) $-$	4.1139e-1 (6.69e-2) $-$	5.2842e-2 (2.65e-2) $-$	2.0536e-1 (1.89e-2) $-$	1.7549e-2 (7.71e-4)
	(20,10)	2.6677e-1 (5.86e-2) $-$	1.4412e-1 (1.89e-2) $-$	5.1999e-2 (3.37e-2) $-$	1.9472e-1 (2.77e-2) $-$	1.7564e-2 (8.74e-3) $-$	1.2607e-1 (1.37e-2) $-$	7.5406e-3 (2.52e-4)
RFDA2	(5,5)	3.6388e-2 (4.14e-3) $+$	3.1351e-2 (2.85e-3) $+$	9.3415e-2 (3.05e-2) $-$	1.6357e-1 (1.52e-1) $-$	7.9294e-2 (4.26e-2) $-$	9.2436e-2 (9.60e-3) $-$	3.6853e-2 (1.45e-3)
	(10,5)	2.8163e-2 (1.23e-3) $-$	2.3976e-2 (8.85e-4) $-$	7.3126e-2 (2.74e-2) $-$	7.6473e-2 (4.85e-2) $-$	3.0018e-2 (7.42e-3) $-$	7.8821e-2 (6.31e-2) $-$	2.0735e-2 (8.10e-4)
	(20,5)	1.6911e-2 (1.03e-3) $-$	1.5598e-2 (8.54e-3) $-$	5.6031e-2 (3.95e-2) $-$	6.0263e-2 (4.71e-2) $-$	1.7694e-2 (7.23e-3) $-$	4.6560e-2 (2.69e-3) $-$	1.1828e-2 (9.75e-4)
	(5,10)	9.2605e-2 (1.22e-2) $-$	3.4860e-2 (3.34e-2) $+$	8.5268e-2 (9.72e-3) $-$	2.0350e-1 (1.76e-1) $-$	8.7862e-2 (3.16e-2) $-$	1.1352e-1 (4.62e-2) $-$	3.5109e-2 (3.68e-3)
	(10,10)	4.2077e-2 (2.10e-2) $-$	2.6388e-2 (3.03e-2) $-$	7.7746e-2 (4.10e-2) $-$	6.2388e-2 (2.09e-2) $-$	4.0185e-2 (2.04e-2) $-$	1.0703e-1 (7.39e-2) $-$	2.2898e-2 (7.82e-3)
	(20,10)	1.7605e-2 (7.93e-3) $-$	1.6906e-2 (1.76e-2) $-$	6.3780e-2 (3.11e-2) $-$	4.9186e-2 (2.35e-2) $-$	2.1786e-2 (1.49e-2) $-$	8.9566e-2 (5.18e-2) $-$	1.2778e-2 (4.11e-3)
RFDA3	(5,5)	7.1000e-1 (1.99e-1) $-$	3.7892e-1 (3.19e-2) $-$	3.5432e-1 (8.19e-2) $-$	2.7440e-1 (1.84e-1) $-$	1.3604e-1 (1.59e-1) $-$	1.9260e-1 (1.29e-2) $-$	7.4752e-2 (9.13e-3)
	(10,5)	6.4733e-1 (2.23e-1) $-$	2.9556e-1 (3.70e-2) $-$	1.2154e-1 (2.56e-2) $-$	1.6452e-1 (9.36e-2) $-$	4.6079e-2 (3.44e-2) $-$	1.5482e-1 (4.21e-3) $-$	2.7572e-2 (1.99e-3)
	(20,5)	3.3441e-1 (1.55e-1) $-$	1.5343e-1 (5.39e-2) $-$	4.0267e-2 (2.28e-2) $-$	1.2992e-1 (1.31e-1) $-$	1.8337e-2 (3.25e-2) $-$	1.3994e-1 (3.74e-3) $-$	9.4972e-3 (4.02e-4)
	(5,10)	1.1696e+0 (2.79e-1) $-$	6.8469e-1 (1.60e-1) $-$	4.0816e-1 (1.14e-1) $-$	6.5338e-1 (3.25e-1) $-$	3.6430e-1 (3.47e-1) $-$	3.7092e-1 (1.46e-1) $-$	5.7009e-2 (1.78e-2)
	(10,10)	1.0540e+0 (2.23e-1) $-$	3.8672e-1 (9.76e-2) $-$	1.6129e-1 (5.93e-2) $-$	4.0931e-1 (3.10e-1) $-$	2.6530e-1 (3.08e-1) $-$	4.7955e-1 (3.34e-1) $-$	3.4321e-2 (2.28e-2)
	(20,10)	5.9371e-1 (1.59e-1) $-$	1.5274e-1 (8.97e-2) $-$	6.2767e-2 (3.40e-2) $-$	2.7630e-1 (2.18e-1) $-$	1.4721e-1 (2.35e-1) $-$	4.7380e-1 (3.32e-1) $-$	2.3006e-2 (2.30e-2)
RFDA4	(5,5)	7.6278e-1 (7.72e-2) $-$	8.3406e-1 (1.73e-1) $-$	4.4772e-1 (2.30e-2) $-$	4.2590e-1 (4.61e-2) $-$	2.5662e-1 (2.65e-2) $-$	3.8665e-1 (2.34e-2) $-$	1.9790e-1 (9.74e-3)
	(10,5)	6.5624e-1 (5.54e-2) $-$	8.7725e-1 (1.62e-1) $-$	2.4144e-1 (1.13e-2) $-$	4.1821e-1 (3.06e-2) $-$	1.6755e-1 (1.33e-2) $-$	3.1613e-1 (1.66e-2) $-$	1.2200e-1 (5.28e-3)
	(20,5)	5.0404e-1 (5.26e-2) $-$	6.8300e-1 (7.67e-2) $-$	1.1042e-1 (4.04e-3) $-$	4.0428e-1 (2.80e-2) $-$	1.0674e-1 (7.24e-3) $-$	2.2427e-1 (9.84e-3) $-$	8.2688e-2 (1.68e-3)
	(5,10)	7.8424e-1 (6.94e-2) $-$	1.4679e+0 (2.80e-1) $-$	4.4612e-1 (3.27e-2) $-$	7.8367e-1 (4.81e-2) $-$	2.6103e-1 (3.67e-2) $-$	5.6416e-1 (1.42e-2) $-$	1.5083e-1 (3.92e-3)
	(10,10)	7.4977e-1 (6.31e-2) $-$	1.5167e+0 (9.87e-2) $-$	2.3391e-1 (1.39e-2) $-$	6.9246e-1 (6.21e-2) $-$	1.5092e-1 (1.85e-2) $-$	4.7160e-1 (1.09e-2) $-$	1.0239e-1 (1.74e-3)
	(20,10)	6.0500e-1 (6.09e-2) $-$	9.3656e-1 (3.42e-2) $-$	1.0990e-1 (4.53e-3) $-$	5.4716e-1 (4.28e-2) $-$	9.1684e-2 (7.56e-3) $-$	4.0023e-1 (2.17e-2) $-$	7.8673e-2 (6.72e-4)
RFDA5	(5,5)	1.0786e+0 (1.08e-1) $-$	9.2430e-1 (8.08e-2) $-$	8.3522e-1 (3.91e-2) $-$	5.6676e-1 (3.34e-2) $-$	3.6953e-1 (1.89e-2) $-$	5.8408e-1 (2.91e-2) $-$	3.5099e-1 (1.21e-2)
	(10,5)	1.0144e+0 (2.45e-1) $-$	8.7771e-1 (1.73e-1) $-$	5.0323e-1 (3.89e-2) $-$	5.4829e-1 (2.52e-2) $-$	2.7015e-1 (1.91e-2) $-$	5.5913e-1 (2.81e-2) $-$	2.3264e-1 (6.66e-3)
	(20,5)	8.9978e-1 (1.52e-1) $-$	9.0258e-1 (8.43e-2) $-$	2.9176e-1 (5.71e-2) $-$	5.5286e-1 (2.82e-2) $-$	1.9822e-1 (9.77e-3) $-$	4.8619e-1 (1.95e-2) $-$	1.7678e-1 (1.79e-3)
	(5,10)	1.1200e+0 (8.64e-2) $-$	1.2428e+0 (2.00e-1) $-$	8.1251e-1 (4.93e-2) $-$	8.9580e-1 (8.43e-2) $-$	3.9691e-1 (5.16e-2) $-$	7.4283e-1 (1.61e-2) $-$	2.6242e-1 (7.07e-3)
	(10,10)	1.1343e+0 (2.03e-1) $-$	1.4338e+0 (1.58e-1) $-$	4.9661e-1 (4.87e-2) $-$	8.4795e-1 (1.06e-1) $-$	2.4245e-1 (4.64e-2) $-$	6.3981e-1 (1.63e-2) $-$	1.7625e-1 (3.19e-2)
	(20,10)	1.0098e+0 (1.62e-1) $-$	1.0170e+0 (5.13e-2) $-$	2.6875e-1 (5.55e-2) $-$	6.5031e-1 (6.53e-2) $-$	1.5277e-1 (7.69e-3) $-$	5.3099e-1 (1.25e-2) $-$	1.3224e-1 (1.13e-3)
$+ / - / \approx$		1/29/0	2/28/0	0/30/0	0/30/0	0/30/0	0/30/0	

TABLE 2

THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS ON RJYS, WHERE '+', '−', AND '≈' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	(τ_t, n_t)	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
	(5,5)	8.1707e-1 (1.48e-1) −	1.0888e+0 (1.35e-1) −	4.2569e-1 (2.45e-2) −	8.3095e-1 (9.27e-2) −	2.8635e-1 (4.24e-2) +	1.2608e+0 (2.21e-1) −	3.2810e-1 (2.37e-2)
	(10,5)	5.8912e-1 (9.62e-2) −	9.6066e-1 (9.75e-2) −	3.0016e-1 (2.37e-2) −	6.1309e-1 (5.71e-2) −	2.0823e-1 (2.73e-2) −	9.9288e-1 (1.62e-1) −	1.1661e-1 (1.05e-2)
RJY1	(20,5)	3.6880e-1 (3.73e-2) −	8.0989e-1 (1.09e-1) −	1.9458e-1 (2.13e-2) −	4.3677e-1 (4.75e-2) −	1.3607e-1 (4.34e-2) −	7.8900e-1 (1.51e-1) −	8.6205e-2 (1.05e-2)
	(5,10)	6.6574e-1 (7.13e-2) −	1.2211e+0 (2.29e-1) −	2.7683e-1 (2.25e-2) −	8.4095e-1 (1.04e-1) −	3.2311e-1 (6.20e-2) −	1.0635e+0 (2.54e-1) −	1.6467e-1 (2.09e-2)
	(10,10)	5.2941e-1 (7.07e-2) −	9.7144e-1 (1.88e-1) −	1.9946e-1 (2.03e-2) −	6.8114e-1 (1.11e-1) −	2.2705e-1 (4.74e-2) −	1.0342e+0 (2.31e-1) −	1.4388e-1 (1.83e-2)
	(20,10)	3.6297e-1 (4.57e-2) −	8.0079e-1 (1.50e-1) −	1.3879e-1 (1.38e-2) −	4.8158e-1 (5.86e-2) −	1.3810e-1 (3.70e-2) −	8.5581e-1 (2.49e-1) −	1.0215e-1 (1.51e-2)
	(5,5)	5.1525e-1 (4.33e-2) −	5.2122e-1 (4.14e-2) −	4.5338e-1 (2.17e-2) −	4.3350e-1 (5.29e-2) −	1.7323e-1 (4.77e-2) −	2.2544e-1 (2.72e-2) −	5.7677e-2 (3.01e-3)
	(10,5)	2.9120e-1 (4.45e-2) −	3.4553e-1 (4.28e-2) −	1.8724e-1 (1.36e-2) −	3.0220e-1 (2.49e-2) −	8.5911e-2 (3.19e-2) −	1.3186e-1 (8.87e-3) −	9.0234e-3 (5.77e-4)
RJY2	(20,5)	1.2514e-1 (4.83e-2) −	1.2130e-1 (1.29e-2) −	4.3309e-2 (3.65e-3) −	1.2518e-1 (1.43e-2) −	2.7058e-2 (1.23e-2) −	6.4539e-2 (3.05e-3) −	8.0494e-3 (1.27e-3)
	(5,10)	8.4443e-1 (1.11e-1) −	5.6893e-1 (4.80e-2) −	2.9810e-1 (2.37e-2) −	5.4559e-1 (4.79e-2) −	3.6992e-1 (9.67e-2) −	7.2420e-1 (1.88e-1) −	1.9548e-2 (7.88e-4)
	(10,10)	7.7485e-1 (1.21e-1) −	4.2027e-1 (7.39e-2) −	1.3881e-1 (1.72e-2) −	4.3977e-1 (3.36e-2) −	1.9461e-1 (7.04e-2) −	5.9756e-1 (1.16e-1) −	1.4361e-2 (4.60e-4)
	(20,10)	4.6635e-1 (1.10e-1) −	3.0127e-1 (2.47e-2) −	4.6900e-2 (6.07e-3) −	2.8822e-1 (3.22e-2) −	5.0753e-2 (2.24e-2) −	3.9592e-1 (5.29e-2) −	1.0622e-2 (8.13e-4)
	(5,5)	2.1775e-1 (9.44e-3) −	1.7720e-1 (2.47e-2) +	2.6564e-1 (8.68e-3) −	2.0820e-1 (1.19e-2) −	1.8613e-1 (3.37e-3) +	2.2331e-1 (1.13e-2) −	1.9034e-1 (1.58e-3)
	(10,5)	1.8464e-1 (2.70e-2) −	1.7367e-1 (3.09e-3) −	2.1554e-1 (5.53e-3) −	1.8204e-1 (5.76e-3) −	1.7059e-1 (1.71e-2) −	1.7796e-1 (4.65e-3) −	1.6908e-1 (7.86e-4)
RJY3	(20,5)	1.7322e-1 (2.44e-3) −	1.6072e-1 (1.81e-2) +	1.7412e-1 (1.97e-2) −	1.6387e-1 (2.11e-2) ≈	1.6648e-1 (1.16e-2) ≈	1.6153e-1 (3.84e-3) +	1.6861e-1 (8.80e-4)
	(5,10)	2.3418e-1 (2.82e-2) −	1.9007e-1 (3.84e-2) +	3.0413e-1 (1.15e-2) −	2.0591e-1 (7.70e-3) −	2.0558e-1 (6.75e-3) −	2.7423e-1 (4.45e-2) −	1.9210e-1 (3.03e-3)
	(10,10)	2.0081e-1 (1.03e-2) −	1.7575e-1 (3.25e-2) +	2.4836e-1 (8.70e-3) −	1.8220e-1 (4.86e-3) +	1.8324e-1 (2.08e-2) ≈	2.1978e-1 (5.17e-2) −	1.8746e-1 (2.21e-3)
	(20,10)	1.8441e-1 (4.30e-3) −	1.7672e-1 (1.49e-3) +	2.0119e-1 (1.97e-2) −	1.6651e-1 (2.19e-3) +	1.7237e-1 (2.35e-2) +	1.8673e-1 (1.27e-2) ≈	1.8215e-1 (1.51e-3)
	(5,5)	6.2253e-1 (9.11e-2) −	7.5287e-1 (1.27e-1) −	4.0730e-1 (2.77e-2) −	4.1753e-1 (6.16e-2) −	2.5270e-1 (4.44e-2) +	4.2574e-1 (8.81e-2) −	3.3350e-1 (2.48e-2)
	(10,5)	4.7629e-1 (6.29e-2) −	7.5298e-1 (9.42e-2) −	2.9207e-1 (3.51e-2) −	4.0239e-1 (4.65e-2) −	2.1259e-1 (2.82e-2) −	4.6326e-1 (5.96e-2) −	1.7220e-1 (1.30e-2)
RJY4	(20,5)	3.2519e-1 (4.33e-2) −	5.5135e-1 (6.99e-2) −	2.0209e-1 (2.83e-2) −	3.8007e-1 (3.98e-2) −	1.6466e-1 (2.66e-2) ≈	4.1297e-1 (5.22e-2) −	1.7193e-1 (1.65e-2)
	(5,10)	5.3836e-1 (6.90e-2) −	5.9527e-1 (6.82e-2) −	3.1871e-1 (2.61e-2) −	5.3550e-1 (4.67e-2) −	2.7673e-1 (5.59e-2) −	5.0413e-1 (1.01e-1) −	2.3350e-1 (2.06e-2)
	(10,10)	4.4720e-1 (4.37e-2) −	5.3842e-1 (4.94e-2) −	2.0388e-1 (1.61e-2) +	5.5034e-1 (4.27e-2) −	2.1532e-1 (3.41e-2) ≈	4.8798e-1 (5.79e-2) −	2.1408e-1 (1.56e-2)
	(20,10)	3.2950e-1 (4.79e-2) −	4.4402e-1 (5.08e-2) −	1.2921e-1 (1.15e-2) +	4.9691e-1 (3.11e-2) −	1.6950e-1 (3.61e-2) ≈	3.9128e-1 (5.22e-2) −	1.8087e-1 (1.55e-2)
	(5,5)	2.0340e-1 (4.35e-3) −	1.9727e-1 (1.25e-4) +	2.6336e-1 (2.88e-2) −	1.2793e-1 (3.76e-3) +	2.0724e-1 (1.94e-3) −	1.3258e-1 (1.01e-2) +	1.9865e-1 (6.59e-4)
	(10,5)	2.0335e-1 (6.95e-3) −	1.9903e-1 (8.11e-5) −	2.5724e-1 (1.45e-2) −	1.2168e-1 (2.97e-3) +	2.0409e-1 (1.05e-3) −	9.7816e-2 (8.95e-3) +	1.9879e-1 (2.01e-4)
RJY5	(20,5)	1.9861e-1 (3.32e-4) ≈	1.9908e-1 (1.04e-4) −	2.3807e-1 (1.43e-2) −	1.1713e-1 (1.98e-3) +	2.0118e-1 (7.71e-4) −	8.4208e-2 (5.82e-3) +	1.9877e-1 (2.65e-4)
	(5,10)	9.2305e-2 (5.64e-2) −	5.5945e-3 (1.36e-4) +	1.7478e-1 (4.12e-2) −	1.3483e-1 (8.31e-3) −	3.3518e-2 (3.65e-3) −	1.4029e-1 (1.51e-2) −	1.3670e-2 (4.19e-4)
	(10,10)	6.8332e-2 (4.26e-2) −	5.3679e-3 (1.14e-4) +	1.2729e-1 (2.47e-2) −	1.2248e-1 (2.52e-3) −	1.5874e-2 (1.39e-3) −	1.0943e-1 (6.88e-3) −	1.0843e-2 (4.07e-4)
	(20,10)	2.4673e-2 (1.83e-2) −	5.7670e-3 (1.05e-4) +	8.4533e-2 (2.78e-2) −	1.1604e-1 (2.28e-3) −	9.2420e-3 (4.77e-4) −	9.3492e-2 (5.95e-3) −	8.7943e-3 (2.91e-4)
	(5,5)	3.7667e+0 (2.18e-1) −	3.4415e+0 (1.18e-1) −	2.9614e+0 (1.18e-1) −	3.3592e+0 (1.92e-1) −	1.4541e+0 (1.35e-1) −	2.1856e+0 (1.18e-1) −	1.0286e+0 (5.50e-2)
	(10,5)	2.5081e+0 (2.43e-1) −	2.1289e+0 (1.09e-1) −	1.5383e+0 (7.89e-2) −	2.8629e+0 (1.64e-1) −	7.0832e-1 (9.96e-2) −	1.2955e+0 (1.06e-1) −	7.2905e-2 (5.05e-3)
RJY6	(20,5)	1.3558e+0 (1.59e-1) −	1.0436e+0 (9.07e-2) −	6.1601e-1 (5.15e-2) −	1.7810e+0 (1.32e-1) −	2.7162e-1 (4.73e-2) −	7.2746e-1 (4.70e-2) −	7.3190e-2 (7.81e-3)
	(5,10)	4.4991e+0 (5.27e-1) −	3.0820e+0 (1.24e-1) −	2.6508e+0 (1.55e-1) −	3.5582e+0 (2.14e-1) −	1.7721e+0 (2.70e-1) −	2.5170e+0 (1.42e-1) −	1.9267e-1 (7.66e-3)
	(10,10)	3.5812e+0 (3.46e-1) −	1.8504e+0 (9.48e-2) −	1.4726e+0 (3.41e-1) −	2.7050e+0 (1.46e-1) −	8.4665e-1 (2.17e-1) −	1.5705e+0 (1.26e-1) −	1.1858e-1 (6.30e-3)
	(20,10)	3.1000e-1 (1.76e-1) −	3.0780e-1 (2.30e-2) −	2.2253e-1 (1.47e-2) −	7.7665e-1 (7.81e-2) −	3.4616e-1 (4.38e-2) −	7.1046e-1 (8.71e-2) −	1.5319e-1 (8.06e-3)
	(5,5)	6.0638e+0 (5.46e-1) −	5.1581e+0 (3.77e-1) −	5.7631e+0 (3.23e-1) −	4.3399e+0 (4.11e-1) −	1.9969e+0 (3.07e-1) −	4.9960e+0 (1.07e+0) −	1.6714e+0 (1.44e-1)
	(10,5)	2.6948e+0 (4.14e-1) −	2.1859e+0 (2.30e-1) −	2.3529e+0 (3.14e-1) −	3.2595e+0 (2.84e-1) −	7.6902e-1 (1.80e-1) +	2.8712e+0 (6.77e-1) −	8.7387e-1 (1.35e-1)
RJY7	(20,5)	1.1840e+0 (1.76e-1) −	9.7618e-1 (1.17e-1) −	1.1293e+0 (1.96e-1) −	1.7749e+0 (1.65e-1) −	6.0623e-1 (2.04e-1) +	9.4245e-1 (2.46e-1) ≈	9.0353e-1 (9.49e-2)
	(5,10)	6.2830e+0 (3.92e-1) −	7.9233e+0 (5.25e-1) −	6.7136e+0 (7.66e-1) −	4.3619e+0 (3.52e-1) −	2.7294e+0 (3.89e-1) −	3.8625e+0 (3.05e-1) −	5.8730e-1 (1.23e-1)
	(10,10)	2.7964e+0 (4.58e-1) −	3.9120e+0 (2.96e-1) −	2.5787e+0 (3.97e-1) −	3.4702e+0 (2.47e-1) −	9.5713e-1 (2.04e-1) −	3.2058e+0 (1.54e-1) −	5.5011e-1 (1.37e-1)
	(20,10)	1.1533e+0 (2.64e-1) −	2.1289e+0 (2.62e-1) −	7.7258e-1 (2.97e-1) −	1.6268e+0 (1.60e-1) −	7.2241e-1 (3.90e-1) ≈	2.7823e+0 (1.88e-1) −	5.1106e-1 (1.92e-1)
	(5,5)	3.7805e-2 (1.58e-2) ≈	1.0533e-2 (1.73e-3) +	1.1882e-1 (2.26e-2) −	3.8447e-2 (3.74e-3) −	2.4287e-2 (2.50e-3) +	7.3404e-2 (1.82e-2) −	3.5000e-2 (2.81e-3)
	(10,5)	2.7165e-2 (7.31e-3) −	7.9100e-3 (1.38e-3) +	1.0109e-1 (2.77e-2) −	3.0368e-2 (1.11e-3) −	1.5431e-2 (1.21e-3) −	5.2962e-2 (9.19e-3) −	1.3321e-2 (6.62e-4)
RJY8	(20,5)	1.7272e-2 (5.47e-3) −	8.0470e-3 (1.32e-3) +	5.9776e-2 (1.58e-2) −	2.8258e-2 (8.78e-4) −	1.2696e-2 (1.04e-3) ≈	4.1626e-2 (5.72e-3) −	1.3400e-2 (1.12e-3)
	(5,10)	7.5480e-2 (5.99e-2) −	9.6115e-3 (1.68e-3) +	1.2379e-1 (2.69e-2) −	3.6976e-2 (3.40e-3) −	2.4361e-2 (2.92e-3) −	5.7008e-2 (7.85e-3) −	1.5102e-2 (5.91e-4)
	(10,10)	3.7463e-2 (2.02e-2) −	6.6409e-3 (6.63e-4) +	9.1207e-2 (1.46e-2) −	2.8851e-2 (9.12e-4) −	1.3823e-2 (7.26e-4) −	3.7474e-2 (4.04e-3) −	1.2475e-2 (5.08e-4)
	(20,10)	2.3036e-2 (1.30e-2) −	6.0309e-3 (1.79e-4) +	6.0230e-2 (1.37e-2) −	2.5515e-2 (9.53e-4) −	1.0466e-2 (7.21e-4) ≈	3.0152e-2 (3.04e-3) −	1.0171e-2 (4.66e-4)
+/ − / ≈		0/46/2	13/25/0	2/46/0	5/42/1	7/23/8	4/42/2	

TABLE 3
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS ON BI-OBJECTIVE AND TRI-OBJECTIVE RDFS, WHERE '$+$', '$-$', AND '$\approx$' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	(τ_t, n_t)	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RDF1	(5,5)	6.5994e-1 (9.25e-2) $-$	3.1333e-1 (7.87e-2) $-$	4.1808e-1 (4.14e-2) $-$	3.7572e-1 (7.25e-2) $-$	1.7205e-1 (2.95e-2) $-$	2.7500e-1 (2.03e-2) $-$	5.8626e-2 (3.53e-3)
	(10,5)	5.1347e-1 (5.95e-2) $-$	3.7702e-1 (9.90e-2) $-$	1.8970e-1 (2.50e-2) $-$	4.5074e-1 (9.79e-2) $-$	6.7396e-2 (1.03e-2) $-$	2.1206e-1 (1.49e-2) $-$	2.1964e-2 (1.72e-3)
	(20,5)	2.6914e-1 (3.90e-2) $-$	3.6110e-1 (6.62e-2) $-$	5.2174e-2 (1.24e-2) $-$	2.1902e-1 (5.65e-2) $-$	1.7511e-2 (2.79e-3) $-$	1.2430e-1 (9.12e-3) $-$	8.5057e-3 (4.16e-4)
RDF2	(5,5)	5.5707e-1 (5.74e-2) $-$	4.2652e-1 (5.59e-2) $-$	3.5150e-1 (3.15e-2) $-$	6.5618e-1 (6.72e-2) $-$	2.6836e-1 (5.54e-2) $-$	2.8154e-1 (2.44e-2) $-$	1.0549e-1 (5.96e-3)
	(10,5)	4.7928e-1 (4.10e-2) $-$	4.5101e-1 (5.43e-2) $-$	1.8403e-1 (1.74e-2) $-$	4.2566e-1 (4.70e-2) $-$	1.3186e-1 (2.61e-2) $-$	2.1656e-1 (1.43e-2) $-$	6.4917e-2 (4.63e-3)
	(20,5)	3.0231e-1 (3.31e-2) $-$	4.6318e-1 (4.25e-2) $-$	8.0006e-2 (6.17e-3) $-$	2.8263e-1 (3.19e-2) $-$	7.2055e-2 (1.10e-2) $-$	1.2385e-1 (1.07e-2) $-$	5.0867e-2 (1.52e-3)
RDF3	(5,5)	7.7304e-1 (1.68e-1) $-$	7.3990e-1 (7.79e-2) $-$	5.1342e-1 (2.89e-2) $-$	9.7953e-1 (4.51e-2) $-$	3.8869e-1 (4.22e-2) $-$	6.4423e-1 (7.59e-2) $-$	3.0750e-1 (1.21e-2)
	(10,5)	5.7634e-1 (9.02e-2) $-$	5.0984e-1 (4.64e-2) $-$	3.8566e-1 (1.58e-2) $-$	7.3315e-1 (2.93e-2) $-$	2.9756e-1 (4.23e-2) $-$	4.7350e-1 (8.52e-2) $-$	2.5947e-1 (1.41e-2)
	(20,5)	3.4677e-1 (2.07e-2) $-$	3.4413e-1 (3.18e-2) $-$	3.2537e-1 (1.65e-2) $-$	5.2944e-1 (1.33e-2) $-$	2.4854e-1 (3.09e-2) $-$	3.1788e-1 (4.03e-2) $-$	2.2786e-1 (1.41e-2)
RDF4	(5,5)	5.4714e-1 (1.68e-1) $-$	2.3957e-1 (1.31e-2) $-$	6.2146e-1 (1.50e-1) $-$	3.3742e-1 (3.74e-2) $-$	1.1586e-1 (3.94e-3) $+$	4.2549e-1 (6.02e-2) $-$	1.3455e-1 (5.12e-3)
	(10,5)	2.1452e-1 (6.46e-2) $-$	1.5208e-1 (7.62e-3) $-$	4.0122e-1 (8.19e-2) $-$	2.2349e-1 (1.23e-2) $-$	9.3235e-2 (2.92e-3) $+$	2.3227e-1 (1.68e-2) $-$	1.0057e-1 (2.63e-3)
	(20,5)	9.7417e-2 (3.76e-3) $-$	1.0041e-1 (2.70e-3) $-$	1.6191e-1 (2.14e-2) $-$	1.3557e-1 (6.44e-3) $-$	8.7164e-2 (1.99e-3) $-$	1.6225e-1 (8.83e-3) $-$	8.4021e-2 (2.30e-3)
RDF5	(5,5)	7.2043e-1 (5.55e-2) $-$	6.9605e-1 (5.71e-2) $-$	4.5769e-1 (2.75e-2) $-$	4.3738e-1 (6.01e-2) $-$	1.5529e-1 (1.29e-2) $-$	2.4000e-1 (2.50e-2) $-$	1.1688e-1 (5.52e-3)
	(10,5)	4.7287e-1 (4.59e-2) $-$	5.0838e-1 (4.89e-2) $-$	1.9757e-1 (1.43e-2) $-$	3.7891e-1 (2.75e-2) $-$	6.5421e-2 (8.03e-3) $-$	1.5827e-1 (1.68e-2) $-$	5.4000e-2 (4.39e-3)
	(20,5)	2.5191e-1 (3.50e-2) $-$	2.6219e-1 (2.44e-2) $-$	5.4004e-2 (4.98e-3) $-$	1.8447e-1 (1.29e-2) $-$	1.4687e-2 (1.90e-3) $+$	1.1329e-1 (4.17e-2) $-$	1.8737e-2 (1.34e-3)
RDF6	(5,5)	7.2344e+0 (6.16e-1) $-$	5.6813e+0 (4.47e-1) $-$	6.6892e+0 (4.26e-1) $-$	5.3167e+0 (4.86e-1) $-$	2.2222e+0 (3.21e-1) $\approx$	6.1334e+0 (1.10e+0) $-$	2.0754e+0 (2.55e-1)
	(10,5)	2.7655e+0 (3.30e-1) $-$	2.0312e+0 (2.33e-1) $-$	2.2556e+0 (3.35e-1) $-$	3.9549e+0 (2.65e-1) $-$	8.2784e-1 (1.89e-1) $-$	3.9109e+0 (1.28e+0) $-$	6.4746e-1 (8.02e-2)
	(20,5)	9.6893e-1 (1.63e-1) $-$	5.5854e-1 (7.78e-2) $-$	5.3515e-1 (1.33e-1) $-$	1.9964e+0 (2.25e-1) $-$	3.0261e-1 (5.39e-2) $-$	1.8079e+0 (8.12e-1) $-$	2.4168e-1 (1.73e-2)
RDF7	(5,5)	4.7558e-1 (1.25e-1) $-$	4.3603e-1 (2.54e-2) $-$	1.4400e+0 (5.61e-1) $-$	2.1959e-1 (1.91e-2) $-$	2.7824e-1 (5.47e-2) $-$	3.4263e-1 (1.10e-2) $-$	1.9734e-1 (1.34e-2)
	(10,5)	4.1671e-1 (4.66e-2) $-$	4.0390e-1 (2.48e-2) $-$	9.3135e-1 (7.12e-1) $-$	1.9267e-1 (9.79e-2) $\approx$	2.5386e-1 (4.48e-2) $-$	3.3272e-1 (8.11e-2) $-$	1.6597e-1 (1.52e-2)
	(20,5)	3.6689e-1 (2.06e-2) $-$	4.1393e-1 (2.35e-2) $-$	3.0312e-1 (6.00e-2) $-$	1.6586e-1 (1.02e-1) $+$	2.3281e-1 (6.14e-2) $-$	4.3394e-1 (1.20e-1) $-$	1.6855e-1 (1.56e-2)
RDF8	(5,5)	2.6395e-2 (1.25e-2) $+$	1.6725e-2 (1.85e-3) $+$	3.0160e-1 (5.61e-2) $-$	7.2365e-2 (3.92e-3) $-$	1.6569e-2 (1.11e-3) $+$	7.0255e-2 (5.85e-3) $-$	3.6033e-2 (1.27e-3)
	(10,5)	1.4120e-2 (1.24e-3) $+$	1.3114e-2 (6.23e-4) $+$	2.3948e-1 (3.63e-2) $-$	5.7850e-2 (2.17e-3) $-$	1.3546e-2 (7.47e-4) $+$	5.4670e-2 (2.70e-3) $-$	2.2611e-2 (1.16e-3)
	(20,5)	1.2610e-2 (1.30e-3) $+$	1.2188e-2 (4.47e-4) $+$	1.5176e-1 (1.66e-2) $-$	5.0268e-2 (1.90e-3) $-$	1.1359e-2 (4.79e-4) $+$	4.9772e-2 (2.33e-3) $-$	1.3397e-2 (4.11e-4)
RDF9	(5,5)	1.0028e+0 (9.70e-2) $-$	6.5428e-1 (4.83e-2) $-$	2.1864e+0 (1.38e-1) $-$	1.0362e+0 (4.88e-2) $-$	4.0242e-1 (5.80e-2) $-$	6.8709e-1 (7.86e-2) $-$	2.2638e-1 (1.35e-2)
	(10,5)	7.8963e-1 (7.26e-2) $-$	3.6728e-1 (1.86e-2) $-$	1.4654e+0 (1.16e-1) $-$	8.6274e-1 (6.04e-2) $-$	2.2313e-1 (3.42e-2) $-$	5.3829e-1 (5.75e-2) $-$	1.3292e-1 (7.62e-3)
	(20,5)	4.2766e-1 (7.28e-2) $-$	1.9919e-1 (9.13e-3) $-$	7.2471e-1 (5.82e-2) $-$	5.0410e-1 (2.71e-2) $-$	9.9544e-2 (1.93e-2) $-$	3.9246e-1 (5.71e-2) $-$	7.9051e-2 (3.56e-3)
RDF10	(5,5)	3.0973e-1 (1.32e-2) $-$	2.7741e-1 (3.87e-3) $\approx$	3.1159e-1 (6.01e-2) $-$	2.1092e-1 (1.85e-2) $+$	2.8011e-1 (4.59e-3) $\approx$	2.5320e-1 (2.77e-2) $+$	2.7778e-1 (3.56e-3)
	(10,5)	2.8977e-1 (1.37e-2) $-$	2.7095e-1 (2.92e-3) $+$	3.0140e-1 (8.69e-3) $-$	1.5998e-1 (1.13e-2) $+$	2.7543e-1 (2.67e-3) $\approx$	2.3835e-1 (7.22e-2) $+$	2.7459e-1 (4.53e-3)
	(20,5)	2.7056e-1 (3.92e-3) $\approx$	2.6742e-1 (2.63e-3) $+$	2.8893e-1 (4.77e-3) $-$	1.5135e-1 (1.19e-2) $+$	2.7197e-1 (4.22e-3) $\approx$	2.1451e-1 (5.58e-2) $+$	2.7177e-1 (2.76e-3)
RDF11	(5,5)	6.3175e-1 (2.37e-3) $-$	6.3027e-1 (3.02e-3) $-$	6.9867e-1 (9.13e-3) $-$	4.5064e-1 (3.03e-3) $+$	6.0291e-1 (1.65e-3) $+$	4.8459e-1 (9.09e-3) $+$	6.2691e-1 (1.56e-3)
	(10,5)	6.2189e-1 (1.97e-3) $-$	6.2334e-1 (1.67e-3) $-$	6.4414e-1 (3.99e-3) $-$	4.3990e-1 (2.16e-3) $+$	6.0067e-1 (1.33e-3) $+$	4.1974e-1 (2.36e-3) $+$	6.1305e-1 (1.46e-3)
	(20,5)	6.1175e-1 (1.68e-3) $-$	6.1427e-1 (1.43e-3) $-$	6.1380e-1 (1.44e-3) $-$	4.3738e-1 (2.30e-3) $+$	6.1380e-1 (1.81e-3) $-$	4.3565e-1 (1.70e-3) $+$	6.0441e-1 (1.17e-3)
RDF12	(5,5)	4.9943e-1 (3.84e-2) $-$	5.6461e-1 (9.80e-3) $-$	3.5880e-1 (8.91e-3) $-$	5.1968e-1 (1.93e-2) $-$	3.3347e-1 (3.72e-2) $-$	4.6415e-1 (3.62e-2) $-$	2.9799e-1 (5.28e-3)
	(10,5)	4.7337e-1 (5.10e-2) $-$	5.3677e-1 (1.64e-2) $-$	2.5677e-1 (9.31e-3) $+$	4.6594e-1 (3.64e-2) $-$	2.8645e-1 (3.64e-2) $-$	3.8328e-1 (3.60e-2) $-$	2.6875e-1 (9.16e-3)
	(20,5)	4.2096e-1 (4.08e-2) $-$	4.7685e-1 (1.90e-2) $-$	1.7490e-1 (8.55e-3) $+$	3.7505e-1 (2.44e-2) $-$	2.4675e-1 (1.09e-2) $-$	3.4955e-1 (2.73e-2) $-$	2.2732e-1 (1.16e-2)
RDF13	(5,5)	1.2790e+0 (1.09e-1) $-$	1.3439e+0 (1.61e-1) $-$	6.9759e-1 (4.48e-2) $-$	6.7080e-1 (8.44e-2) $-$	3.4765e-1 (2.34e-2) $-$	4.0987e-1 (2.37e-2) $-$	2.3127e-1 (7.34e-3)
	(10,5)	9.8072e-1 (8.75e-2) $-$	1.0716e+0 (9.15e-2) $-$	3.7270e-1 (2.89e-2) $-$	6.2305e-1 (6.58e-2) $-$	1.8624e-1 (1.41e-2) $-$	2.7067e-1 (1.20e-2) $-$	1.4741e-1 (5.04e-3)
	(20,5)	5.2254e-1 (9.16e-2) $-$	5.4287e-1 (2.86e-2) $-$	1.6396e-1 (1.11e-2) $-$	3.9069e-1 (3.62e-2) $-$	1.2427e-1 (3.55e-3) $-$	1.8707e-1 (5.11e-3) $-$	1.1546e-1 (2.05e-3)
RDF14	(5,5)	5.2254e-1 (9.16e-2) $-$	5.4287e-1 (2.86e-2) $-$	1.6396e-1 (1.11e-2) $-$	6.0365e-1 (7.57e-2) $-$	1.2427e-1 (3.55e-3) $-$	7.8104e-1 (2.39e-1) $-$	1.1546e-1 (2.05e-3)
	(10,5)	4.3145e-1 (9.01e-2) $\approx$	9.2973e-1 (1.24e-1) $-$	1.9320e-1 (1.48e-2) $+$	4.5538e-1 (3.77e-2) $-$	2.4382e-1 (2.31e-2) $+$	8.6367e-1 (2.74e-1) $-$	3.9217e-1 (4.78e-2)
	(20,5)	3.2205e-1 (5.43e-2) $\approx$	6.1042e-1 (9.42e-2) $-$	1.5162e-1 (1.11e-2) $+$	3.6874e-1 (3.04e-2) $\approx$	2.2352e-1 (7.47e-2) $+$	6.3013e-1 (2.21e-1) $-$	3.7317e-1 (1.12e-1)
$+/-/\approx$		3/36/3	5/36/1	4/37/1	7/33/2	10/28/4	6/36/0	

TABLE 4
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS ON BI-OBJECTIVE AND TRI-OBJECTIVE RDFS, WHERE '+', '−', AND '≈' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	(τ_t, n_t)	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RDF1	(5,10)	8.5324e-1 (1.10e-1) −	6.3538e-1 (8.58e-2) −	4.2796e-1 (4.49e-2) −	8.0916e-1 (1.01e-1) −	1.1304e-1 (3.12e-2) −	4.2268e-1 (1.32e-2) −	4.1358e-2 (1.48e-3)
	(10,10)	6.5862e-1 (8.50e-2) −	5.0409e-1 (4.89e-2) −	1.1117e+0 (6.51e-2) −	5.6544e-1 (8.39e-2) −	4.5146e-2 (2.00e-2) −	3.4397e-1 (1.70e-2) −	1.7561e-2 (9.67e-4)
	(20,10)	3.8368e-1 (8.09e-2) −	3.3298e-1 (4.67e-2) −	7.3047e-2 (1.76e-2) −	2.9733e-1 (4.84e-2) −	1.2138e-2 (2.95e-3) −	2.4806e-1 (1.22e-2) −	8.1806e-3 (2.96e-3)
RDF2	(5,10)	5.1163e-1 (7.35e-2) −	2.6731e-1 (1.56e-2) −	2.4231e-1 (3.00e-2) −	7.0280e-1 (6.93e-2) −	1.1609e-1 (2.04e-2) −	3.3013e-1 (2.11e-2) −	4.2168e-2 (3.17e-3)
	(10,10)	4.4123e-1 (5.45e-2) −	4.6219e-1 (4.45e-2) −	6.8889e-1 (7.70e-2) −	5.1592e-1 (5.39e-2) −	6.1423e-2 (1.37e-2) −	3.0395e-1 (1.70e-2) −	2.0593e-2 (1.82e-3)
	(20,10)	2.3050e-1 (4.02e-2) −	3.7633e-1 (4.90e-2) −	5.6649e-2 (2.99e-2) −	3.1810e-1 (4.06e-2) −	2.2751e-2 (4.60e-3) −	2.4085e-1 (1.96e-2) −	1.2306e-2 (7.55e-4)
RDF3	(5,10)	9.9931e-1 (2.25e-1) −	6.3680e-1 (8.89e-2) −	5.0649e-1 (2.86e-2) −	9.7562e-1 (6.46e-2) −	3.1105e-1 (3.98e-2) −	7.5473e-1 (1.32e-1) −	2.7957e-1 (9.33e-3)
	(10,10)	5.9980e-1 (9.85e-2) −	4.8723e-1 (6.83e-2) −	9.4090e-1 (7.48e-2) −	7.7802e-1 (3.90e-2) −	2.8342e-1 (2.92e-2) −	5.0670e-1 (7.79e-2) −	2.5204e-1 (8.07e-3)
	(20,10)	3.6393e-1 (3.16e-2) −	3.3866e-1 (3.37e-2) −	3.1947e-1 (1.40e-2) −	5.7180e-1 (4.89e-2) −	2.3830e-1 (3.29e-2) −	3.7695e-1 (5.43e-2) −	2.2429e-1 (6.97e-3)
RDF4	(5,10)	2.8230e-1 (4.20e-2) −	2.3057e-1 (1.09e-2) −	5.8406e-1 (8.73e-2) −	3.4842e-1 (3.38e-2) −	1.3080e-1 (8.50e-3) ≈	4.8165e-1 (6.38e-2) −	1.3431e-1 (2.87e-3)
	(10,10)	1.7544e-1 (1.16e-2) −	1.5016e-1 (5.21e-3) −	2.1053e+0 (2.81e-1) −	2.0714e-1 (1.59e-2) −	1.0665e-1 (6.22e-3) −	2.3520e-1 (1.89e-2) −	1.0069e-1 (3.06e-3)
	(20,10)	1.0077e-1 (3.23e-3) −	9.9188e-2 (2.26e-3) −	1.5164e-1 (1.51e-2) −	1.2764e-1 (6.10e-3) −	9.1771e-2 (2.11e-3) −	1.5142e-1 (6.09e-3) −	8.5763e-2 (2.82e-3)
RDF5	(5,10)	6.2874e-1 (7.89e-2) −	5.6586e-1 (5.54e-2) −	2.9632e-1 (1.75e-2) −	5.2396e-1 (4.62e-2) −	1.2865e-1 (6.16e-2) ≈	3.5586e-1 (1.47e-2) −	9.3935e-2 (7.05e-3)
	(10,10)	4.0159e-1 (5.56e-2) −	5.5203e-1 (6.76e-2) −	7.2223e-1 (4.53e-2) −	4.0091e-1 (3.06e-2) −	1.0243e-1 (5.27e-2) −	2.5244e-1 (2.98e-2) −	4.4042e-2 (2.78e-3)
	(20,10)	1.9204e-1 (4.56e-2) −	2.8377e-1 (4.05e-2) −	3.6361e-2 (9.35e-3) −	2.4190e-1 (2.90e-2) −	6.3954e-2 (3.84e-2) −	2.2527e-1 (3.29e-2) −	2.0005e-2 (1.88e-3)
RDF6	(5,10)	7.9333e+0 (8.43e-1) −	8.9024e+0 (4.66e-1) −	7.6057e+0 (7.21e-1) −	5.1829e+0 (4.42e-1) −	2.9761e+0 (4.23e-1) −	4.1309e+0 (3.23e-1) −	2.1206e+0 (2.75e-1)
	(10,10)	2.8282e+0 (3.70e-1) −	4.2959e+0 (1.87e-1) −	1.9578e+1 (1.16e+0) −	4.1989e+0 (3.44e-1) −	1.0358e+0 (2.08e-1) −	2.8080e+0 (1.69e-1) −	6.3999e-1 (7.91e-2)
	(20,10)	1.0386e+0 (2.10e-1) −	1.9823e+0 (2.45e-1) −	7.1805e-1 (2.71e-1) −	2.0432e+0 (2.10e-1) −	2.1871e-1 (3.29e-2) −	2.3565e+0 (1.15e-1) −	1.8628e-1 (1.62e-2)
RDF7	(5,10)	6.6189e-1 (2.30e-1) −	3.9634e-1 (2.79e-2) −	1.5028e+0 (6.90e-1) −	3.3195e-1 (1.47e-1) ≈	2.9023e-1 (2.87e-2) −	3.3793e-1 (8.94e-3) −	2.4062e-1 (2.25e-2)
	(10,10)	4.2441e-1 (1.99e-2) −	3.8809e-1 (2.86e-2) −	3.0289e+0 (1.20e+0) −	2.0762e-1 (1.15e-1) ≈	2.4446e-1 (4.76e-2) −	3.2444e-1 (9.65e-3) −	1.7774e-1 (2.06e-2)
	(20,10)	3.5180e-1 (2.18e-2) −	3.6659e-1 (3.03e-2) −	3.4140e-1 (1.22e-1) −	1.6733e-1 (7.25e-2) −	2.3221e-1 (3.31e-2) −	4.0477e-1 (1.36e-1) −	1.5993e-1 (1.09e-2)
RDF8	(5,10)	6.7560e-2 (1.63e-2) +	5.3871e-2 (7.04e-4) +	3.0733e-1 (4.64e-2) −	7.3993e-2 (4.01e-3) −	5.5756e-2 (9.86e-4) +	7.6153e-2 (7.33e-3) −	6.9989e-2 (1.19e-3)
	(10,10)	5.6262e-2 (2.90e-3) +	5.2343e-2 (2.30e-4) +	5.5482e-1 (5.80e-2) −	5.6890e-2 (3.03e-3) +	5.3238e-2 (5.27e-4) +	5.3923e-2 (2.55e-3) +	5.9815e-2 (1.08e-3)
	(20,10)	5.3029e-2 (1.50e-3) +	5.1514e-2 (2.05e-4) +	1.7162e-1 (1.60e-2) −	4.8599e-2 (3.18e-3) +	5.1698e-2 (5.32e-4) +	4.5235e-2 (3.43e-3) +	5.3243e-2 (5.03e-4)
RDF9	(5,10)	9.3498e-1 (7.86e-2) −	8.9899e-1 (4.55e-2) −	2.0531e+0 (1.33e-1) −	8.7880e-1 (4.10e-2) −	3.9597e-1 (3.28e-2) −	9.3132e-1 (4.42e-2) −	2.3616e-1 (1.21e-2)
	(10,10)	8.4425e-1 (8.25e-2) −	5.4127e-1 (3.73e-2) −	3.5776e+0 (1.93e-1) −	7.6739e-1 (4.10e-2) −	2.5993e-1 (1.37e-2) −	6.8102e-1 (4.56e-2) −	1.3959e-1 (7.67e-3)
	(20,10)	4.9503e-1 (4.23e-2) −	2.6413e-1 (1.91e-2) −	4.4792e-1 (5.33e-2) −	4.2897e-1 (3.83e-2) −	1.6546e-1 (2.52e-2) −	3.9649e-1 (3.76e-2) −	8.6649e-2 (4.49e-3)
RDF10	(5,10)	2.0276e-1 (2.69e-2) −	1.0788e-1 (1.30e-2) +	2.2454e-1 (1.32e-2) −	2.1540e-1 (2.37e-2) −	1.1762e-1 (1.77e-2) +	2.5084e-1 (2.27e-2) −	1.3300e-1 (9.30e-3)
	(10,10)	1.4625e-1 (2.72e-2) −	1.0279e-1 (9.59e-3) +	3.3280e-1 (6.50e-2) −	1.7018e-1 (1.85e-2) −	1.0345e-1 (1.02e-2) +	1.9853e-1 (1.94e-2) −	1.1747e-1 (6.09e-3)
	(20,10)	1.0123e-1 (8.69e-3) +	9.2491e-2 (4.23e-3) +	1.3330e-1 (3.10e-2) −	1.7025e-1 (1.76e-2) −	9.5811e-2 (7.03e-3) +	1.8295e-1 (2.55e-2) −	1.0753e-1 (3.90e-3)
RDF11	(5,10)	6.7424e-1 (4.19e-2) −	6.5691e-1 (1.86e-3) −	7.2668e-1 (7.68e-3) −	4.7542e-1 (3.01e-3) +	6.2954e-1 (2.69e-3) +	4.8431e-1 (5.80e-3) +	6.5336e-1 (1.44e-3)
	(10,10)	6.5396e-1 (1.17e-2) −	6.4946e-1 (1.33e-3) −	9.4519e-1 (2.17e-2) −	4.6533e-1 (1.87e-3) +	6.2642e-1 (1.71e-3) +	4.5767e-1 (2.82e-3) +	6.4044e-1 (1.20e-3)
	(20,10)	6.3708e-1 (1.29e-3) −	6.4082e-1 (1.27e-3) −	6.3908e-1 (1.93e-3) −	4.5994e-1 (1.47e-3) +	6.2401e-1 (1.74e-3) +	4.4430e-1 (1.31e-3) +	6.3012e-1 (6.36e-4)
RDF12	(5,10)	4.2393e-1 (2.93e-2) −	5.1670e-1 (1.38e-2) −	3.4693e-1 (9.96e-3) −	5.3236e-1 (2.76e-2) −	2.6111e-1 (2.65e-2) ≈	4.9220e-1 (2.53e-2) −	2.5368e-1 (1.53e-2)
	(10,10)	4.0574e-1 (3.50e-2) −	4.8840e-1 (1.51e-2) −	5.9245e-1 (1.69e-2) −	4.7915e-1 (3.33e-2) −	2.2106e-1 (4.48e-2) ≈	4.1584e-1 (2.06e-2) −	2.0982e-1 (2.25e-2)
	(20,10)	3.8166e-1 (3.03e-2) −	4.2339e-1 (2.78e-2) −	1.6814e-1 (7.11e-3) −	3.8727e-1 (2.92e-2) −	1.6440e-1 (2.83e-2) ≈	3.1873e-1 (3.29e-2) −	1.5901e-1 (1.10e-2)
RDF13	(5,10)	1.6862e+0 (1.90e-1) −	1.6138e+0 (1.30e-1) −	4.4115e-1 (3.13e-2) −	9.0041e-1 (1.14e-1) −	2.3343e-1 (1.12e-2) −	6.9688e-1 (3.76e-2) −	1.7385e-1 (3.60e-3)
	(10,10)	1.2850e+0 (2.11e-1) −	1.1002e+0 (7.76e-2) −	1.1172e+0 (1.05e-1) −	7.5814e-1 (6.06e-2) −	1.7665e-1 (2.28e-2) −	5.0555e-1 (2.28e-2) −	1.3812e-1 (2.41e-3)
	(20,10)	7.5484e-1 (1.69e-1) −	5.5049e-1 (3.92e-2) −	1.3802e-1 (9.13e-3) −	5.5181e-1 (3.96e-2) −	1.4386e-1 (2.46e-2) −	3.4982e-1 (2.11e-2) −	1.2596e-1 (1.43e-3)
RDF14	(5,10)	5.0263e-1 (6.44e-2) −	8.9543e-1 (9.03e-2) −	1.9320e-1 (1.30e-2) +	6.3157e-1 (7.96e-2) −	2.1392e-1 (3.59e-2) +	8.5260e-1 (1.75e-1) −	3.9326e-1 (4.51e-2)
	(10,10)	3.6528e-1 (3.33e-2) ≈	7.8593e-1 (7.54e-2) −	4.2764e-1 (1.95e-2) −	4.8323e-1 (6.29e-2) −	1.9075e-1 (2.26e-2) +	6.4435e-1 (1.30e-1) −	3.6414e-1 (4.66e-2)
	(20,10)	2.4881e-1 (3.27e-2) ≈	5.9703e-1 (1.14e-1) −	1.1709e-1 (9.99e-3) +	3.6773e-1 (4.23e-2) −	2.2287e-1 (8.09e-2) +	5.3606e-1 (1.13e-1) −	2.5575e-1 (3.62e-2)
+/ − / ≈		4/36/2	6/36/0	2/40/0	5/35/2	12/25/5	5/37/0	

B. Initial Effectiveness of Knowledge Transfer

In dynamic multi-objective optimization, the main role of a response strategy is to generate an initial population with better convergence and diversity, primarily through prediction or knowledge transfer, when environmental changes occur. Therefore, the effectiveness of a response strategy can be evaluated by the quality of the initial population it generates in response to environmental changes. In this section, each compared algorithm independently runs 20 times on RDF1 to RDF14 with $n_t = 10$. The MIGD metric is used to evaluate the quality of the initial population obtained in the first generation after changes. Mean and standard deviation values for MIGD in the benchmark with different problem parameter settings are presented in Tables 5, 6 and 7, respectively. It is clear from these tables that KTMM performs the best on most test problems.

TABLE 5
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS IN THE FIRST GENERATION RIGHT AFTER CHANGES ON RDFS WITH $(\tau_t, n_t) = (5, 10)$, WHERE '+', '−', AND '≈' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RDF1	1.2096e+0 (7.17e-2) −	1.0085e+0 (1.06e-1) −	1.0802e+0 (3.44e-2) −	2.0727e+0 (8.77e-2) −	2.9695e-1 (6.65e-2) −	8.8130e-1 (4.03e-2) −	**1.1393e-1 (4.53e-3)**
RDF2	8.1790e-1 (9.64e-2) −	5.7260e-1 (5.94e-2) −	6.5272e-1 (5.55e-2) −	1.7182e+0 (8.02e-2) −	3.0201e-1 (2.83e-2) −	6.2765e-1 (5.13e-2) −	**1.0586e-1 (3.33e-3)**
RDF3	1.8374e+0 (2.99e-1) −	1.2170e+0 (1.82e-1) −	8.9514e-1 (8.06e-2) −	2.0416e+0 (1.06e-1) −	7.0458e-1 (7.69e-2) −	1.3818e+0 (2.15e-1) −	**3.3490e-1 (1.58e-2)**
RDF4	5.2317e-1 (8.53e-2) −	4.1982e-1 (2.03e-2) −	1.6911e+0 (1.14e-1) −	8.5349e-1 (8.56e-2) −	5.8065e-1 (8.91e-2) −	1.3364e+0 (1.19e-1) −	**2.1329e-1 (6.53e-3)**
RDF5	1.3318e+0 (1.48e-1) −	1.0832e+0 (1.19e-1) −	8.0270e-1 (3.67e-2) −	1.3254e+0 (9.49e-2) −	5.6341e-1 (1.39e-1) −	7.7725e-1 (4.56e-2) −	**1.9503e-1 (1.57e-2)**
RDF6	2.0711e+1 (1.68e+0) −	1.7918e+1 (8.69e-1) −	1.9609e+1 (5.63e-1) −	1.9159e+1 (1.26e+0) −	**7.8759e+0 (8.99e-1) +**	2.4671e+1 (8.78e-1) −	8.9969e+0 (6.98e-1)
RDF7	1.3465e+0 (5.25e-1) −	4.0021e-1 (2.41e-2) −	2.8117e+0 (5.64e-1) −	6.8970e-1 (4.92e-1) −	3.2369e-1 (4.49e-2) ≈	7.7914e-1 (1.66e-2) −	**3.2289e-1 (2.17e-2)**
RDF8	9.9625e-2 (5.23e-2) ≈	**5.7241e-2 (4.27e-4) +**	5.4369e-1 (5.28e-2) −	7.1253e-2 (6.09e-3) +	1.0870e-1 (9.70e-3) −	2.0454e-1 (1.43e-2) −	9.7278e-2 (2.02e-3)
RDF9	1.8196e+0 (1.97e-1) −	2.1251e+0 (8.94e-2) −	3.5554e+0 (1.32e-1) −	1.7062e+0 (6.36e-2) −	8.4498e-1 (8.69e-2) −	2.7119e+0 (3.05e-1) −	**4.7886e-1 (1.85e-2)**
RDF10	3.0038e-1 (4.75e-2) −	**1.1269e-1 (1.35e-2) +**	3.2475e-1 (1.03e-1) −	2.3525e-1 (1.20e-2) −	2.1934e-1 (1.34e-2) −	4.4011e-1 (3.52e-2) −	1.6524e-1 (1.70e-2)
RDF11	6.8763e-1 (1.18e-2) −	**6.7876e-1 (2.75e-3) +**	9.4758e-1 (2.01e-2) −	6.9427e-1 (4.16e-3) −	6.8672e-1 (7.59e-3) ≈	7.2403e-1 (7.60e-3) −	6.8724e-1 (1.98e-3)
RDF12	5.6046e-1 (2.82e-2) −	5.5618e-1 (1.59e-2) −	5.9606e-1 (1.99e-2) −	6.5168e-1 (4.08e-2) −	4.5187e-1 (4.18e-2) −	6.5753e-1 (4.36e-2) −	**3.2104e-1 (6.94e-3)**
RDF13	2.8041e+0 (4.26e-1) −	2.4089e+0 (9.16e-2) −	1.1430e+0 (6.04e-2) −	2.3013e+0 (1.04e-1) −	7.3151e-1 (6.73e-2) −	1.5593e+0 (8.42e-2) −	**2.9771e-1 (3.45e-3)**
RDF14	9.5766e-1 (1.31e-1) −	1.1264e+0 (1.21e-1) −	4.2964e-1 (3.49e-2) +	1.2771e+0 (1.22e-1) −	**3.6298e-1 (7.14e-2) +**	1.1301e+0 (2.94e-1) −	5.3063e-1 (5.10e-2)
+/ − / ≈	0/13/1	3/11/0	1/13/0	1/13/0	2/10/2	0/14/0	

TABLE 6
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS IN THE FIRST GENERATION RIGHT AFTER CHANGES ON RDFS WITH $(\tau_t, n_t) = (10, 10)$, WHERE '+', '−', AND '≈' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RDF1	1.3727e+0 (1.28e-1) −	1.1361e+0 (6.35e-2) −	1.1008e+0 (7.89e-2) −	1.8592e+0 (1.07e-1) −	2.2800e-1 (5.68e-2) −	9.7370e-1 (4.09e-2) −	**1.0382e-1 (4.49e-3)**
RDF2	9.6001e-1 (1.31e-1) −	9.4064e-1 (1.12e-1) −	6.8308e-1 (5.73e-2) −	1.5286e+0 (5.18e-2) −	2.2814e-1 (2.50e-2) −	7.4356e-1 (2.81e-2) −	**9.9177e-2 (2.41e-3)**
RDF3	1.5955e+0 (2.90e-1) −	1.3449e+0 (9.59e-2) −	9.8501e-1 (7.59e-2) −	1.9097e+0 (1.68e-1) −	5.4097e-1 (6.67e-2) −	1.4151e+0 (1.81e-1) −	**3.2952e-1 (1.08e-2)**
RDF4	5.0174e-1 (6.77e-2) −	4.0899e-1 (1.04e-2) −	2.0049e+0 (2.87e-1) −	7.2174e-1 (1.02e-1) −	5.0879e-1 (1.32e-1) −	1.2041e+0 (1.67e-1) −	**1.9659e-1 (6.14e-3)**
RDF5	1.4219e+0 (1.29e-1) −	1.2371e+0 (1.06e-1) −	7.0727e-1 (2.74e-2) −	1.3666e+0 (8.91e-2) −	3.7473e-1 (9.30e-2) −	7.4668e-1 (5.54e-2) −	**1.8337e-1 (1.44e-2)**
RDF6	2.0268e+1 (8.56e-1) −	1.8033e+1 (3.93e-1) −	2.1428e+1 (3.57e+0) −	2.1834e+1 (1.01e+0) −	**5.2378e+0 (8.16e-1) +**	2.2201e+1 (9.18e-1) −	6.8967e+0 (8.13e-1)
RDF7	1.5005e+0 (4.96e-1) −	4.1313e-1 (1.24e-2) −	2.2942e+0 (9.96e-1) −	6.1916e-1 (3.50e-1) −	2.9272e-1 (2.78e-2) ≈	7.5922e-1 (2.00e-2) −	**2.7598e-1 (2.74e-2)**
RDF8	7.2165e-2 (4.99e-3) +	**5.6863e-2 (6.48e-4) +**	5.6136e-1 (4.25e-2) −	6.1223e-2 (1.02e-2) +	9.3737e-2 (1.14e-2) ≈	1.9004e-1 (1.35e-2) −	9.6719e-2 (1.79e-3)
RDF9	2.4192e+0 (2.47e-1) −	2.0755e+0 (1.03e-1) −	3.5747e+0 (2.04e-1) −	2.3441e+0 (1.72e-1) −	7.9953e-1 (8.32e-2) −	2.9168e+0 (4.01e-1) −	**4.5223e-1 (1.51e-2)**
RDF10	2.4529e-1 (4.96e-2) −	**1.1852e-1 (1.51e-2) +**	3.7177e-1 (4.53e-2) −	1.9492e-1 (1.66e-2) −	2.0640e-1 (1.60e-2) −	4.0478e-1 (2.38e-2) −	1.5563e-1 (7.80e-3)
RDF11	7.0264e-1 (2.40e-2) −	6.7853e-1 (2.54e-3) +	9.4207e-1 (2.34e-2) −	6.8295e-1 (3.45e-3) ≈	**6.7297e-1 (4.91e-3) +**	7.1128e-1 (6.90e-3) −	6.8488e-1 (2.77e-3)
RDF12	5.3491e-1 (2.23e-2) −	5.5743e-1 (1.99e-2) −	6.0518e-1 (1.64e-2) −	6.4480e-1 (2.19e-2) −	4.2014e-1 (3.09e-2) −	6.1821e-1 (3.62e-2) −	**3.2780e-1 (1.65e-2)**
RDF13	2.7052e+0 (2.87e-1) −	2.1187e+0 (6.95e-2) −	1.1496e+0 (9.67e-2) −	2.3912e+0 (8.86e-2) −	6.5732e-1 (1.94e-1) −	1.4548e+0 (5.13e-2) −	**2.8717e-1 (4.55e-3)**
RDF14	9.2344e-1 (7.22e-2) −	1.0380e+0 (1.75e-1) −	4.4207e-1 (3.14e-2) +	1.2849e+0 (1.46e-1) −	**3.0848e-1 (3.03e-2) +**	1.4461e+0 (3.42e-1) −	5.7275e-1 (5.53e-2)
+/ − / ≈	1/13/0	3/11/0	1/13/0	1/12/1	3/9/2	0/14/0	

C. Analysis of Computational Efficiency

In this section, we investigate the computational efficiency of KTMM-SMOEA from the perspectives of computational complexity. Specifically, we analyze the computational complexity of the proposed change response technique.

As suggested in [1], the computational complexity of environmental selection in NSGA-II is $O(mN^2)$, where m and N are the number of objectives and the population size, respectively. Regarding the proposed KTMM, the environmental selection it adopts for knowledge extraction also has a complexity of $O(mN^2)$. The time complexity for calculating the mean and variance of solutions is $O(nN)$. Assuming there are K models in the knowledge pool, the update process is triggered if $T > K$, and the similarity calculation has a complexity of $O(K)$. Deleting the most redundant model involves finding the minimum similarity ($O(K)$) and then deleting it ($O(1)$). Therefore, the overall time complexity for knowledge update is $O(K)$. For the process of knowledge fusion and transfer, the time complexity for calculating the similarity of models in the knowledge pool with the approximate model is $O(Kn)$. Similarly, the process for learning the mixture model is $O(K)$. Assuming the population

TABLE 7
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SEVEN COMPARED ALGORITHMS IN THE FIRST GENERATION RIGHT AFTER CHANGES ON RDFS WITH $(\tau_t, n_t) = (20, 10)$, WHERE '+', '−', AND '≈' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-NSGA-II, RESPECTIVELY.

Problem	PPS-NSGA-II	AE-NSGA-II	IT-NSGA-II	KL-NSGA-II	KTS-NSGA-II	DIP-NSGA-II	KTMM-NSGA-II
RDF1	1.3704e+0 (9.29e-2) −	1.2919e+0 (7.00e-2) −	1.0689e+0 (8.52e-2) −	1.7641e+0 (7.41e-2) −	1.4096e-1 (2.81e-2) −	1.1800e+0 (2.52e-2) −	1.0210e-1 (3.76e-3)
RDF2	9.6311e-1 (9.54e-2) −	1.3476e+0 (3.94e-2) −	6.9387e-1 (9.19e-2) −	1.4399e+0 (8.36e-2) −	2.1805e-1 (2.68e-2) −	6.9805e-1 (3.40e-2) −	9.6991e-2 (3.11e-3)
RDF3	1.7158e+0 (2.88e-1) −	1.4898e+0 (1.03e-1) −	1.0502e+0 (9.36e-2) −	1.8141e+0 (1.90e-1) −	4.4853e-1 (3.10e-2) −	1.3900e+0 (8.77e-2) −	3.2201e-1 (7.91e-3)
RDF4	5.3691e-1 (6.01e-2) −	4.1078e-1 (5.11e-3) −	1.9395e+0 (2.06e-1) −	6.7037e-1 (7.51e-2) −	4.3014e-1 (8.37e-2) −	1.1734e+0 (1.32e-1) −	1.8931e-1 (3.58e-3)
RDF5	1.3377e+0 (1.13e-1) −	1.3123e+0 (4.58e-2) −	6.3474e-1 (3.74e-2) −	1.3519e+0 (5.80e-2) −	3.4912e-1 (9.58e-2) −	8.5182e-1 (9.44e-2) −	1.7471e-1 (6.80e-3)
RDF6	2.4135e+1 (2.04e+0) −	1.8123e+1 (6.49e-1) −	1.9139e+1 (1.43e+0) −	2.3531e+1 (1.41e+0) −	5.0462e+0 (8.41e-1) ≈	2.0594e+1 (1.17e+0) −	5.2884e+0 (5.20e-1)
RDF7	1.5091e+0 (4.70e-1) −	4.1583e-1 (8.74e-3) −	3.3545e+0 (7.87e-1) −	7.5633e-1 (4.28e-1) −	2.4653e-1 (3.52e-2) ≈	1.1818e+0 (4.00e-1) −	2.6715e-1 (4.59e-2)
RDF8	7.4956e-2 (6.32e-3) +	5.7173e-2 (4.30e-4) +	5.8883e-1 (6.87e-2) −	5.7365e-2 (9.06e-3) +	9.2316e-2 (8.82e-3) ≈	1.7278e-1 (7.74e-3) −	9.3135e-2 (2.13e-3)
RDF9	2.5879e+0 (1.61e-1) −	2.1775e+0 (1.01e-1) −	3.9523e+0 (3.91e-1) −	3.6617e+0 (2.36e-1) −	8.1477e-1 (8.81e-2) −	3.0158e+0 (2.09e-1) −	4.1402e-1 (3.01e-2)
RDF10	1.8280e-1 (4.83e-2) ≈	1.1345e-1 (9.45e-3) +	3.3321e-1 (1.17e-1) −	1.6642e-1 (1.52e-2) ≈	1.8003e-1 (1.15e-2) −	3.9313e-1 (3.74e-2) −	1.5823e-1 (9.93e-3)
RDF11	6.9075e-1 (4.17e-3) −	6.8102e-1 (2.54e-3) ≈	9.5711e-1 (2.40e-2) −	6.7873e-1 (2.78e-3) ≈	6.6247e-1 (6.48e-3) +	7.0735e-1 (1.51e-2) −	6.8160e-1 (2.75e-3)
RDF12	5.4438e-1 (1.06e-2) −	5.2419e-1 (2.93e-2) −	5.8162e-1 (2.27e-2) −	5.8341e-1 (2.03e-2) −	3.8625e-1 (3.94e-2) −	5.6211e-1 (4.02e-2) −	3.1541e-1 (1.08e-2)
RDF13	2.7461e+0 (1.11e-1) −	2.1874e+0 (7.62e-2) −	1.2157e+0 (1.40e-1) −	2.3683e+0 (1.00e-1) −	5.2723e-1 (8.29e-2) −	1.6596e+0 (4.18e-2) −	2.7464e-1 (4.52e-3)
RDF14	9.2181e-1 (7.94e-2) −	1.0014e+0 (1.08e-1) −	4.1330e-1 (2.86e-2) +	1.2525e+0 (8.14e-2) −	3.2475e-1 (4.79e-2) +	1.2371e+0 (2.48e-1) −	5.5360e-1 (5.68e-2)
+/ − / ≈	0/13/1	3/11/0	1/13/0	1/13/0	2/10/2	0/14/0	

size is N, random sampling from a mixture model is generally $O(N)$. Considering that $N \gg K > n$, the proposed KTMM framework has a computational complexity of $O(mN^2)$. This suggests that developing an efficient environmental selection process is critical for improving the computational complexity of the KTMM framework.

D. Incorporating KTMM with Different SMOEAs

In this paper, we propose a framework in which the change response technique and SMOEA are independent of each other. Therefore, the proposed KTMM can be integrated with any SMOEAs to effectively handle irregular changes in DMOPs. As shown in TABLE 8, the performance of algorithms incorporating KTMM is significantly better across all test problems compared to the original SMOEA.

TABLE 8
THE MIGD VALUES (MEAN) ACHIEVED BY DIFFERENT ALGORITHMS ON RDF1-RDF9 WITH $(\tau_t, n_t) = (10, 10)$.

Problem	NSGA-II	KTMM-NSGA-II	MOEA/D	KTMM-MOEA/D	RMMEDA	KTMM-RMMEDA	SPEA/R	KTMM-SPEA/R
RDF1	8.3043e-2	1.7347e-2	2.5260e-1	5.6171e-2	1.8024e-1	2.4834e-2	1.5243e-1	3.4626e-2
RDF2	6.2614e-2	2.1634e-2	1.6997e-1	6.7870e-2	1.3001e-1	3.2501e-2	1.1504e-1	4.0613e-2
RDF3	6.0512e-1	2.4820e-1	4.7116e-1	3.7648e-1	4.7739e-1	1.4330e-1	6.6727e-1	2.4445e-1
RDF4	6.2206e-1	1.0192e-1	3.8269e-1	2.5515e-1	1.0406e+0	1.1782e-1	1.0862e+0	1.1413e-1
RDF5	2.4162e-1	4.4086e-2	1.2642e-1	2.3812e-2	4.9063e-1	5.8115e-2	2.9708e-1	4.3183e-2
RDF6	1.9682e+0	6.3665e-1	9.2421e-1	4.1628e-1	8.7696e+0	4.9649e+0	3.6084e+0	1.2517e+0
RDF7	2.4324e-1	1.7671e-1	4.2405e-1	2.9559e-1	1.3052e-1	4.4198e-2	2.3792e-1	1.5354e-1
RDF8	1.1785e-1	5.9714e-2	2.0077e-1	1.3768e-1	1.1338e-1	5.7156e-2	1.6242e-1	6.6350e-2
RDF9	3.2797e-1	1.4177e-1	2.5975e-1	1.0114e-1	4.4162e-1	1.3048e-1	3.9821e-1	1.6072e-1

E. Different Ways for Coefficient w

In the algorithm design section, we define the transfer coefficient w, which reflects the similarity between historical and current environments and can be calculated using various methods. To justify the selection of Wasserstein distance (WD) for computing w in the proposed KTMM, we have conducted comparative experiments with various methods, which are described below.

1) EM [13]: In this paper, the w can be computed by maximizing the following equation:

$$\log L = \sum_{i=1}^{N} \log \sum_{k=1}^{K} w_k \varphi_k(\mathbf{x}_i), \tag{1}$$

This equation can be solved by the classical EM method, an iterative optimization strategy for maximum likelihood estimation based on incomplete data sets. EM does not require extra parameters, but its iterative process is time-consuming, and KTMM is sensitive to the initialization when using EM for w.

2) Obj [14]: The objective value-based method (denoted as Obj for simplicity) first stores the mean value of each objective dimension of POF in each environment. Then, for a new environment, we calculate the correlation coefficient between each environmental POF's mean objective value and $randP$'s POF as the similarity metric to obtain w.
3) KLD [15]: This method is a type of statistical distance that is commonly used to evaluate the similarity between two distributions. In the following experiments, KLD will replace WD as the similarity metric to calculate w.
4) M1 [16]: The Euclidean distance (M1) is commonly used to calculate the distance between two points. In this paper, it can be used to evaluate the similarity of a model k and $Model_T^{'}$, and its definition is presented as follows.

$$\mathrm{M1}(k,T)=\frac{1}{\sqrt{\|\mu^k-\mu^T\|^2}}, \tag{2}$$

where μ^k and μ^T are the mean vectors of a model k in the knowledge pool and $Model_T^{'}$, respectively.

The results, presented in Table 9, demonstrate that the WD method consistently outperforms alternative approaches in most test problems. Additionally, to further explore the parameter sensitivity issue in the EM algorithm, we set the weights for each environment to equal values while ensuring $\sum w_i = 1$. This approach is embedded into the KTMM framework (referred to as KTMM-EM) for solving RDFs with $(\tau_t, n_t) = (10, 10)$. Meanwhile, we set three different initial values for w through random initialization, denoted as EM-rand1, EM-rand2 and EM-rand3 for convenience. As shown in TABLE 10, the performance of KTMM is sensitive to parameter initialization, where different parameter initialization w lead to different experimental results. Moreover, it can be observed that random initialization of w does not improve the results, and the performance is still inferior to KTMM-WD. Consequently, we adopt WD for the w in our KTMM framework.

TABLE 9
THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY DIFFERENT WAYS FOR COEFFICIENT w ON RDFS WITH $(\tau_t, n_t) = (10, 10)$, WHERE '$+$', '$-$', AND '$\approx$' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-WD, RESPECTIVELY.

Problem	KTMM-EM	KTMM-Obj	KTMM-M1	KTMM-KLD	KTMM-WD
RDF1	2.6067e-2 (1.63e-3) $-$	1.9982e-2 (2.44e-3) $-$	1.8015e-2 (7.56e-4) $\approx$	1.8043e-2 (8.06e-4) $\approx$	1.7539e-2 (6.57e-4)
RDF2	2.5835e-2 (1.57e-3) $-$	2.1905e-2 (2.41e-3) $-$	2.0179e-2 (1.83e-3) $\approx$	2.0397e-2 (1.40e-3) $\approx$	2.0270e-2 (1.35e-3)
RDF3	3.4572e-1 (1.89e-2) $-$	2.5104e-1 (1.08e-2) $\approx$	2.5870e-1 (9.30e-3) $-$	2.4672e-1 (1.15e-2) $\approx$	2.4846e-1 (1.02e-2)
RDF4	1.8146e-1 (8.75e-3) $-$	1.1030e-1 (9.37e-3) $-$	9.9694e-2 (3.13e-3) $\approx$	1.0258e-1 (2.35e-3) $-$	9.9586e-2 (2.78e-3)
RDF5	1.0615e-1 (7.74e-3) $-$	4.4780e-2 (1.69e-2) $+$	5.4377e-2 (5.84e-3) $-$	4.5747e-2 (4.78e-3) $\approx$	4.5568e-2 (4.42e-3)
RDF6	9.6630e-1 (6.70e-2) $-$	7.5547e-1 (1.03e-1) $-$	6.8318e-1 (8.16e-2) $\approx$	7.5115e-1 (1.22e-1) $-$	6.5239e-1 (7.64e-2)
RDF7	9.6630e-1 (6.70e-2) $-$	7.5547e-1 (1.03e-1) $-$	6.8318e-1 (8.16e-2) $\approx$	7.5115e-1 (1.22e-1) $-$	6.5239e-1 (7.64e-2)
RDF8	7.1033e-2 (1.75e-3) $-$	6.0345e-2 (9.60e-4) $-$	6.0257e-2 (1.04e-3) $\approx$	6.0496e-2 (1.13e-3) $-$	5.9729e-2 (1.07e-3)
RDF9	1.6984e-1 (7.22e-3) $-$	1.5836e-1 (1.64e-2) $-$	1.4411e-1 (7.63e-3) $\approx$	1.4886e-1 (8.04e-3) $-$	1.3957e-1 (5.26e-3)
RDF10	1.7340e-1 (7.94e-3) $-$	1.2275e-1 (6.74e-3) $-$	1.1943e-1 (5.20e-3) $-$	1.2482e-1 (9.65e-3) $-$	1.1636e-1 (5.82e-3)
RDF11	6.4801e-1 (1.56e-3) $-$	6.4227e-1 (1.83e-3) $-$	6.4046e-1 (9.32e-4) $\approx$	6.3997e-1 (1.17e-3) $\approx$	6.4051e-1 (1.35e-3)
RDF12	2.3866e-1 (1.33e-2) $-$	2.0117e-1 (1.99e-2) $\approx$	2.2622e-1 (1.82e-2) $-$	1.9977e-1 (1.58e-2) $\approx$	1.9960e-1 (1.22e-2)
RDF13	1.7243e-1 (5.42e-3) $-$	1.3635e-1 (1.40e-3) $+$	1.4005e-1 (1.50e-3) $-$	1.3881e-1 (2.28e-3) $\approx$	1.3831e-1 (1.92e-3)
RDF14	2.9145e-1 (6.52e-2) $+$	3.5830e-1 (4.47e-2) $\approx$	3.1473e-1 (3.43e-2) $+$	3.2308e-1 (5.23e-2) $\approx$	3.4888e-1 (4.53e-2)
$+/-/\approx$	1/13/0	2/9/3	1/5/8	0/5/9	

F. Sensitivity Analysis of K

In KTMM, the parameter K specifies the number of historical models that can be retained in the knowledge pool, directly affecting the performance of the proposed mixture model. This section presents an experimental study to simply examine how varying K influences the performance of KTMM-SMOEA. For parameter K, we have configured six different values in KTMM-NSGA-II (denoted as KTMM-2, KTMM-6, KTMM-10, KTMM-16, KTMM-18, and KTMM-20), which has the value of K as 2, 6, 10, 14, 18 and 20, respectively. The statistical results are presented in the TABLE 11, it can be found that KTMM-20 outperforms other KTMM-NSGA-II with a smaller K. Meanwhile, it can be observed that as the value of K increases, the algorithm's performance improves; however, beyond a certain point, further increases in K do not result in significant changes.

TABLE 10

THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY DIFFERENT INITIALIZATION WAYS FOR COEFFICIENT w ON RDFS WITH $(\tau_t, n_t) = (10, 10)$, WHERE '$+$', '$-$', AND '$\approx$' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-WD, RESPECTIVELY.

Problem	EM-rand1	EM-rand2	EM-rand3	KTMM-EM	KTMM-WD
RDF1	3.5477e-2 (2.54e-3) $-$	2.8970e-2 (1.82e-3) $-$	2.5432e-2 (1.36e-3) $-$	2.6067e-2 (1.63e-3) $-$	1.7539e-2 (6.57e-4)
RDF2	3.2491e-2 (2.12e-3) $-$	2.8937e-2 (1.83e-3) $-$	2.5937e-2 (1.80e-3) $-$	2.5835e-2 (1.57e-3) $-$	2.0270e-2 (1.35e-3)
RDF3	3.5937e-1 (1.48e-2) $-$	3.5982e-1 (1.49e-2) $-$	3.4357e-1 (1.08e-2) $-$	3.4572e-1 (1.89e-2) $-$	2.4846e-1 (1.02e-2)
RDF4	2.2797e-1 (9.52e-3) $-$	1.9999e-1 (8.88e-3) $-$	1.8268e-1 (7.02e-3) $-$	1.8146e-1 (8.75e-3) $-$	9.9586e-2 (2.78e-3)
RDF5	1.4851e-1 (1.63e-2) $-$	1.1573e-1 (1.46e-2) $-$	1.0685e-1 (1.41e-2) $-$	1.0615e-1 (7.74e-3) $-$	4.5568e-2 (4.42e-3)
RDF6	1.0218e+0 (7.93e-2) $-$	1.0735e+0 (7.46e-2) $-$	9.4892e-1 (7.76e-2) $-$	9.6630e-1 (6.70e-2) $-$	6.5239e-1 (7.64e-2)
RDF7	2.0126e-1 (1.22e-2) $-$	1.8998e-1 (9.19e-3) $-$	1.7564e-1 (7.11e-3) $-$	1.7495e-1 (9.30e-3) $-$	1.7047e-1 (1.27e-2)
RDF8	7.3216e-2 (3.09e-3) $-$	7.2261e-2 (1.69e-3) $-$	7.0666e-2 (1.85e-3) $-$	7.1033e-2 (1.75e-3) $-$	5.9729e-2 (1.07e-3)
RDF9	1.9788e-1 (1.16e-2) $-$	1.8795e-1 (8.99e-3) $-$	1.6910e-1 (6.36e-3) $-$	1.6984e-1 (7.22e-3) $-$	1.3957e-1 (5.26e-3)
RDF10	1.7662e-1 (7.58e-3) $-$	1.8098e-1 (8.01e-3) $-$	1.6857e-1 (8.49e-3) $-$	1.7340e-1 (7.94e-3) $-$	1.1636e-1 (5.82e-3)
RDF11	6.5302e-1 (2.33e-3) $-$	6.4954e-1 (2.18e-3) $-$	6.4673e-1 (1.97e-3) $-$	6.4801e-1 (1.56e-3) $-$	6.4051e-1 (1.35e-3)
RDF12	2.6844e-1 (8.63e-3) $-$	2.5793e-1 (1.26e-2) $-$	2.4083e-1 (9.11e-3) $-$	2.3866e-1 (1.33e-2) $-$	1.9960e-1 (1.22e-2)
RDF13	1.9953e-1 (9.46e-3) $-$	1.8152e-1 (6.21e-3) $-$	1.7197e-1 (4.29e-3) $-$	1.7243e-1 (5.42e-3) $-$	1.3831e-1 (1.92e-3)
RDF14	3.1876e-1 (3.38e-2) $+$	3.0131e-1 (5.41e-2) $+$	2.7362e-1 (2.95e-2) $+$	2.9145e-1 (6.52e-2) $+$	3.4888e-1 (4.53e-2)
$+/-/\approx$	1/13/0	1/13/0	1/13/0	1/13/0	

TABLE 11

THE STATISTICS OF MIGD RESULTS (MEAN AND STANDARD DEVIATION) ACHIEVED BY SIX COMPARED ALGORITHMS ON DFS WITH $(\tau_t, n_t) = (10, 10)$, WHERE '$+$', '$-$', AND '$\approx$' INDICATE EACH COMPARED ALGORITHM IS SIGNIFICANTLY BETTER THAN, WORSE THAN, AND TIED BY KTMM-20, RESPECTIVELY.

Problem	KTMM-2	KTMM-6	KTMM-10	KTMM-14	KTMM-18	KTMM-20
RDF1	2.9786e-2 (1.80e-3) $-$	2.0727e-2 (1.08e-3) $-$	1.8547e-2 (7.37e-4) $\approx$	1.8125e-2 (7.83e-4) $\approx$	1.8164e-2 (6.88e-4) $\approx$	1.8366e-2 (6.97e-4)
RDF2	2.7602e-2 (1.52e-3) $-$	2.1681e-2 (1.50e-3) $\approx$	2.0177e-2 (1.37e-3) $\approx$	1.9827e-2 (8.49e-4) $\approx$	1.9972e-2 (1.31e-3) $\approx$	2.0195e-2 (1.35e-3)
RDF3	3.1635e-1 (1.01e-2) $-$	2.7128e-1 (9.33e-3) $-$	2.5413e-1 (8.48e-3) $\approx$	2.5403e-1 (8.64e-3) $\approx$	2.5585e-1 (9.27e-3) $\approx$	2.5070e-1 (7.75e-3)
RDF4	1.0678e-1 (3.94e-3) $-$	1.0263e-1 (2.27e-3) $\approx$	1.0067e-1 (2.54e-3) $\approx$	1.0126e-1 (2.50e-3) $\approx$	1.0110e-1 (2.79e-3) $\approx$	1.0203e-1 (2.47e-3)
RDF5	1.2631e-1 (1.15e-2) $-$	1.0110e-1 (1.27e-2) $-$	6.6253e-2 (7.09e-3) $-$	4.6070e-2 (3.67e-3) $\approx$	3.2287e-2 (1.93e-3) $\approx$	3.3185e-2 (1.67e-3)
RDF6	9.1283e-1 (7.86e-2) $-$	8.1810e-1 (9.41e-2) $\approx$	6.7389e-1 (7.54e-2) $\approx$	6.9305e-1 (9.53e-2) $\approx$	6.7732e-1 (5.64e-2) $\approx$	6.9768e-1 (9.65e-2)
RDF7	2.1655e-1 (1.24e-2) $-$	1.8116e-1 (1.00e-2) $\approx$	1.7088e-1 (1.20e-2) $\approx$	1.6736e-1 (9.04e-3) $\approx$	1.6565e-1 (9.10e-3) $\approx$	1.6908e-1 (1.18e-2)
RDF8	6.1659e-2 (1.43e-3) $-$	6.0852e-2 (1.59e-3) $\approx$	6.0553e-2 (1.18e-3) $\approx$	5.9550e-2 (5.28e-4) $\approx$	6.0045e-2 (6.79e-4) $\approx$	5.9992e-2 (7.28e-4)
RDF9	1.9107e-1 (1.04e-2) $-$	1.6555e-1 (8.30e-3) $-$	1.4596e-1 (6.10e-3) $\approx$	1.4276e-1 (9.25e-3) $\approx$	1.4358e-1 (7.05e-3) $\approx$	1.3869e-1 (5.72e-3)
RDF10	1.2834e-1 (5.96e-3) $-$	1.2035e-1 (5.97e-3) $\approx$	1.1780e-1 (3.85e-3) $\approx$	1.1948e-1 (4.88e-3) $\approx$	1.1979e-1 (5.98e-3) $\approx$	1.1912e-1 (4.56e-3)
RDF11	6.4673e-1 (1.53e-3) $-$	6.4355e-1 (9.35e-4) $-$	6.4109e-1 (1.09e-3) $\approx$	6.4061e-1 (1.41e-3) $\approx$	6.4023e-1 (1.31e-3) $\approx$	6.4005e-1 (1.10e-3)
RDF12	2.5285e-1 (8.97e-3) $-$	2.4114e-1 (1.18e-2) $-$	2.1890e-1 (2.25e-2) $\approx$	2.0606e-1 (1.69e-2) $\approx$	2.0533e-1 (1.40e-2) $\approx$	2.0550e-1 (1.77e-2)
RDF13	1.8828e-1 (7.73e-3) $-$	1.7076e-1 (7.28e-3) $-$	1.4703e-1 (2.77e-3) $-$	1.3965e-1 (1.84e-3) $\approx$	1.3788e-1 (1.84e-3) $\approx$	1.3867e-1 (1.39e-3)
RDF14	2.8244e-1 (4.46e-2) $+$	3.0093e-1 (4.26e-2) $\approx$	3.3052e-1 (3.03e-2) $\approx$	3.1728e-1 (3.40e-2) $\approx$	3.0560e-1 (3.77e-2) $\approx$	3.1727e-1 (4.51e-2)
$+/-/\approx$	1/13/0	0/7/7	0/2/12	0/0/14	0/0/14	

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