

Supplementary Document for “VSD-MOEA: A Dominance-Based Multi-Objective Evolutionary Algorithm with Explicit Variable Space Diversity Management”

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This document contains supplementary material to provide a clearer understanding of the specifics of VSD-MOEA. First, a multimedia material that provides a visualization of the internal behavior of VSD-MOEA in comparison to other state-of-the-art schemes is provided. Additionally, some of the results described in the main document are analyzed in terms of the Modified Inverted Generational Distance (IGD+) [1], with the conclusions being quite similar to those obtained in the main document with the hypervolume.

I. MULTIMEDIA MATERIAL

This section provides a description of the video included as supplementary material¹. The main aim of this video is to show the large differences between the way in which VSD-MOEA and state-of-the-art MOEAs explore the search space. The video shows a single execution of VSD-MOEA and R2-EMOA to solve WFG5. Note that NSGA-II and MOEA/D were also executed and their behaviors were similar to that of R2-EMOA. Thus, in order to avoid saturating the video, they were not included. In order to allow a proper visualization, WFG5 was configured with two decision variables, meaning that one distance parameter and one position parameter are used. The main peculiarity of WFG5 is its deceptiveness [2]. In this configuration, a solution x is part of the Pareto set when $x_2 = 1.4$. However, most of the descent directions point towards two local optimal fronts, which appear when $x_2 = 0$ or when $x_2 = 4$. The stopping criterion was set to 100,000 function evaluations and the remaining parameters were set as in the main document. It is worth noting that VSD-MOEA explicitly promotes decision variable space diversity until the halfway point of the execution.

The video is divided into two sides. The left-side represents the objective space and the right-side represents the decision variable space. In the decision variable space, each local optimal region is highlighted with a horizontal blue line, and

the global optimal region is highlighted with a horizontal red line. The video shows that after just a few function evaluations, R2-EMOA has converged prematurely to the deceptive regions, contrarily to the VSD-MOEA, which is still exploring. At approximately 30% of the total number of function evaluations, VSD-MOEA has located three individuals in the global optimal region, and a few later (40% of function evaluations), the number of solutions in this region has significantly increased. Thereafter, at the 50% of all function evaluations, VSD-MOEA has located most of the individuals in the global optimal region and only some individuals are located in the local optimal regions. Thus, the results obtained by R2-EMOA are clearly outperformed by VSD-MOEA. Note that both schemes place a large number of points in the knee of the Pareto front, at the cost of leaving some holes near the boundaries. This is because both the $R2$ metric and the objective space density estimator used in VSD-MOEA prefer these regions. To underscore the superiority of VSD-MOEA, note that most of the solutions obtained by R2-EMOA are dominated by those located by VSD-MOEA. The main feature of VSD-MOEA, which is to delay convergence, is clearly shown in this video.

II. COMPARISON AGAINST STATE-OF-THE-ART MOEAS IN LONG-TERM EXECUTIONS

This section presents the results obtained by VSD-MOEA and state-of-the-art schemes in terms of IGD+[1]. Specifically, we present the results for the long-term executions, meaning the stopping criterion was set to 2.5×10^7 function evaluations. The structure of the tables is the same as in the main document. Thus, the only modification is that instead of using the hypervolume, IGD+ is adopted in this case.

Table I shows the IGD+ values obtained for the benchmark functions with two objectives. Specifically, the minimum, maximum, mean and standard deviation of the IGD+ values is provided for each method and test problem adopted. The last row shows the results considering all the test problems. For each test problem, the data for the method that yielded the lowest mean is shown in **boldface**. Additionally, all the methods that were not statistically inferior to the method that yielded the lowest mean are shown in **boldface**. From here on, the methods shown in **boldface** for a given problem are referred to as the winning methods. Based on the number of functions where each method is in the group of winning

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¹Alternatively, the video can be accessed at <https://youtu.be/dbk5DaFJ8y0>

TABLE I
SUMMARY OF THE IGD+ RESULTS ATTAINED FOR PROBLEMS WITH TWO OBJECTIVES

	MOEA/D				NSGA-II				R2-EMOA				VSD-MOEA			
	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std
WFG1	0.006	0.015	0.008	0.002	0.006	0.014	0.008	0.002	0.006	0.061	0.013	0.014	0.006	0.019	0.008	0.003
WFG2	0.006	0.055	0.052	0.011	0.003	0.053	0.040	0.022	0.053	0.055	0.054	0.000	0.003	0.003	0.003	0.000
WFG3	0.008	0.008	0.008	0.000	0.011	0.013	0.012	0.000	0.008	0.009	0.008	0.000	0.007	0.007	0.007	0.000
WFG4	0.007	0.007	0.007	0.000	0.007	0.010	0.008	0.001	0.005	0.005	0.005	0.000	0.006	0.006	0.006	0.000
WFG5	0.060	0.069	0.065	0.002	0.060	0.068	0.066	0.002	0.064	0.066	0.065	0.000	0.038	0.057	0.047	0.006
WFG6	0.034	0.073	0.050	0.010	0.034	0.064	0.051	0.007	0.034	0.076	0.053	0.010	0.068	0.088	0.081	0.004
WFG7	0.007	0.007	0.007	0.000	0.008	0.010	0.009	0.000	0.005	0.006	0.005	0.000	0.006	0.006	0.006	0.000
WFG8	0.103	0.120	0.112	0.005	0.116	0.139	0.125	0.005	0.103	0.120	0.110	0.004	0.026	0.099	0.043	0.025
WFG9	0.011	0.125	0.067	0.053	0.014	0.127	0.101	0.046	0.009	0.125	0.067	0.053	0.009	0.014	0.011	0.001
DTLZ1	0.001	0.001	0.001	0.000	0.002	0.002	0.002	0.000	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000
DTLZ2	0.002	0.002	0.002	0.000	0.002	0.003	0.003	0.000	0.002	0.002	0.002	0.000	0.002	0.002	0.002	0.000
DTLZ3	0.002	0.002	0.002	0.000	0.002	0.003	0.002	0.000	0.002	0.002	0.002	0.000	0.002	0.002	0.002	0.000
DTLZ4	0.002	0.363	0.105	0.163	0.002	0.363	0.064	0.136	0.002	0.363	0.167	0.180	0.002	0.002	0.002	0.000
DTLZ5	0.002	0.002	0.002	0.000	0.002	0.003	0.003	0.000	0.002	0.002	0.002	0.000	0.002	0.002	0.002	0.000
DTLZ6	0.022	0.149	0.076	0.027	0.126	0.315	0.205	0.036	0.019	0.128	0.078	0.027	0.002	0.002	0.002	0.000
DTLZ7	0.003	0.003	0.003	0.000	0.002	0.003	0.003	0.000	0.002	0.002	0.002	0.000	0.003	0.003	0.003	0.000
UF1	0.004	0.004	0.004	0.000	0.005	0.006	0.006	0.000	0.003	0.005	0.004	0.001	0.003	0.003	0.003	0.000
UF2	0.003	0.005	0.004	0.000	0.008	0.010	0.010	0.000	0.004	0.006	0.005	0.001	0.004	0.007	0.005	0.001
UF3	0.141	0.237	0.180	0.022	0.052	0.127	0.084	0.020	0.119	0.210	0.183	0.021	0.038	0.095	0.057	0.013
UF4	0.024	0.031	0.026	0.001	0.027	0.039	0.033	0.003	0.019	0.023	0.021	0.001	0.020	0.024	0.022	0.001
UF5	0.079	0.593	0.265	0.120	0.091	0.254	0.142	0.033	0.079	0.521	0.215	0.131	0.088	0.154	0.132	0.014
UF6	0.066	0.529	0.380	0.108	0.037	0.542	0.193	0.114	0.064	0.432	0.266	0.103	0.021	0.065	0.038	0.011
UF7	0.003	0.005	0.004	0.000	0.007	0.008	0.007	0.000	0.003	0.242	0.046	0.082	0.003	0.009	0.004	0.001
Mean	0.026	0.105	0.062	0.023	0.027	0.095	0.051	0.019	0.026	0.107	0.060	0.027	0.016	0.029	0.021	0.003

TABLE II
STATISTICAL TESTS AND DETERIORATION LEVEL OF THE IGD+ FOR PROBLEMS WITH TWO OBJECTIVES

	↑	↓	↔	Deterioration
MOEA/D	23	34	12	0.979
NSGA-II	11	49	9	0.725
R2-EMOA	34	22	13	0.922
VSD-MOEA	51	14	4	0.036

TABLE III
STATISTICAL TESTS AND DETERIORATION LEVEL OF THE IGD+ FOR PROBLEMS WITH THREE OBJECTIVES

	↑	↓	↔	Deterioration
MOEA/D	15	37	5	0.787
NSGA-II	6	46	5	1.214
R2-EMOA	35	16	6	0.669
VSD-MOEA	49	6	2	0.039

methods for the cases with two objectives, the best methods are VSD-MOEA and R2-EMOA with 13 and 8 wins, respectively. Thus, VSD-MOEA is the most competitive method in terms of this metric. More impressive is the fact that the mean IGD+ attained by VSD-MOEA, when all the problems are considered simultaneously, is much lower than that attained by R2-EMOA. In fact, the total means of R2-EMOA (0.060), NSGA-II (0.051) and MOEA/D (0.062) are quite similar. In contrast, VSD-MOEA yielded a much lower value (0.021). When the data is inspected carefully, it is clear that in the cases where VSD-MOEA loses, the difference with respect to the best method is not very large. For instance, the difference between the mean IGD+ attained by VSD-MOEA and by the best method was never larger than 0.05. However, all the other methods exhibited a deterioration greater than 0.05 in several cases. Specifically, it happened in 7, 5 and 8 problems for MOEA/D, NSGA-II and R2-EMOA, respectively. This means that even if VSD-MOEA loses in some cases, its deterioration is always small, exhibiting a much more robust behavior than

any other method. Exactly the same situation appeared when analyzing the data in terms of hypervolume.

In order to better clarify these findings, pair-wise statistical tests were done between each method tested in each test problem. Table II shows the results, with the same meaning as in the main document. The calculated data confirms that although VSD-MOEA loses in some cases, the overall numbers of wins and losses favor VSD-MOEA. More importantly, the total deterioration is considerably lower in the case of VSD-MOEA, confirming that when VSD-MOEA loses, the deterioration is not very high.

Tables III and IV show the same information for the problems with three objectives. In this case, the superiority of VSD-MOEA is even clearer. Taking into account the mean of all the test problems, VSD-MOEA again yielded a much lower mean IGD+ than the other methods. Specifically, VSD-MOEA obtained a value of 0.059, whereas the second-ranked algorithm (R2-EMOA) obtained a value of 0.093. Once again, the difference between the mean IGD+ obtained by VSD-MOEA and by the best method was never greater than 0.05. However, all the other methods exhibited a deterioration greater than 0.05 in several cases. In particular, this happened in 5, 8 and 7 problems for MOEA/D, NSGA-II and R2-EMOA, respectively. Moreover, VSD-MOEA is considerably superior than the other methods not only in terms of total deterioration, but also in terms of total wins and losses. VSD-MOEA was in the group of winning methods for 14 out of 19 test problems, whereas the second best-ranked algorithm (R2-EMOA) was in the group of winning methods for only 5 test problems. These conclusions are again quite similar to those drawn for the hypervolume in the main document.

REFERENCES

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TABLE IV
SUMMARY OF THE IGD+ RESULTS ATTAINED FOR PROBLEMS WITH THREE OBJECTIVES

	MOEA/D				NSGA-II				R2-EMOA				VSD-MOEA			
	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std
WFG1	0.080	0.100	0.090	0.005	0.142	0.179	0.160	0.010	0.058	0.098	0.079	0.010	0.049	0.070	0.058	0.006
WFG2	0.057	0.068	0.063	0.002	0.073	0.133	0.097	0.014	0.102	0.104	0.103	0.000	0.031	0.048	0.037	0.004
WFG3	0.023	0.023	0.023	0.000	0.031	0.061	0.039	0.005	0.022	0.023	0.022	0.000	0.033	0.033	0.033	0.000
WFG4	0.127	0.127	0.127	0.000	0.121	0.144	0.132	0.005	0.095	0.098	0.097	0.001	0.090	0.094	0.093	0.001
WFG5	0.177	0.184	0.181	0.002	0.160	0.186	0.170	0.005	0.147	0.158	0.153	0.003	0.140	0.150	0.146	0.003
WFG6	0.155	0.205	0.175	0.012	0.159	0.196	0.177	0.009	0.122	0.151	0.140	0.007	0.156	0.173	0.166	0.005
WFG7	0.127	0.127	0.127	0.000	0.113	0.138	0.123	0.007	0.094	0.102	0.097	0.001	0.092	0.094	0.094	0.001
WFG8	0.189	0.194	0.192	0.001	0.244	0.274	0.256	0.008	0.161	0.166	0.163	0.001	0.099	0.154	0.109	0.015
WFG9	0.130	0.240	0.154	0.036	0.138	0.246	0.224	0.025	0.099	0.211	0.119	0.037	0.099	0.210	0.118	0.036
DTLZ1	0.014	0.014	0.014	0.000	0.017	0.020	0.018	0.001	0.013	0.014	0.014	0.000	0.014	0.014	0.014	0.000
DTLZ2	0.027	0.027	0.027	0.000	0.030	0.036	0.032	0.001	0.023	0.024	0.023	0.000	0.024	0.025	0.024	0.000
DTLZ3	0.027	0.027	0.027	0.000	0.027	0.032	0.030	0.001	0.023	0.023	0.023	0.000	0.024	0.025	0.024	0.000
DTLZ4	0.027	0.595	0.092	0.181	0.028	0.036	0.032	0.001	0.023	0.595	0.190	0.225	0.024	0.025	0.024	0.000
DTLZ5	0.003	0.003	0.003	0.000	0.003	0.003	0.003	0.000	0.002	0.002	0.002	0.000	0.002	0.002	0.002	0.000
DTLZ6	0.022	0.163	0.087	0.032	0.126	0.224	0.187	0.027	0.003	0.136	0.069	0.033	0.002	0.002	0.002	0.000
DTLZ7	0.045	0.045	0.045	0.000	0.038	0.052	0.044	0.003	0.060	0.087	0.079	0.008	0.027	0.029	0.028	0.000
UF8	0.048	0.365	0.069	0.051	0.093	0.220	0.178	0.031	0.027	0.159	0.033	0.022	0.025	0.034	0.029	0.002
UF9	0.041	0.151	0.086	0.049	0.106	0.314	0.139	0.049	0.025	0.137	0.094	0.053	0.022	0.028	0.024	0.001
UF10	0.163	0.565	0.294	0.125	0.198	0.658	0.261	0.080	0.159	0.553	0.257	0.131	0.070	0.187	0.103	0.026
Mean	0.078	0.170	0.099	0.026	0.097	0.166	0.121	0.015	0.066	0.150	0.093	0.028	0.054	0.074	0.059	0.005

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