An Interactive Framework for Offline Data-Driven Multiobjective Optimization: Supplementary Material

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1 Additional Test Results

Comparing and validating interactive approaches is still a challenge in the field of multiobjective optimization. The main paper showed the results of utilizing the proposed optimization approach to solve the GAA problem using offline data. Additionally, tests were conducted using two different benchmark problems from the distance-based many-objective visualizable test problem (DBMOPP) [1]. The configuration of the two problems are as follows:

Table 1: Configuration of benchmark problems used.

Problem Name	Configuration	Dimension (n)	Objectives (K)
DBMOPP (P1)	number_of_disconnected_set_regions=0, number_of_local_fronts=0, number_of_dominance_resistance_regions=0, number_of_discontinuous_regions=0	10	5
DBMOPP (P2)	number_of_disconnected_set_regions=1, number_of_local_fronts=0, number_of_dominance_resistance_regions=0, number_of_discontinuous_regions=0	10	5

The proposed approach was tested with these two problem configurations with five objectives and ten decision variables. The offline dataset consisted of 109 samples that were acquired by Latin Hypercube Sampling (LHS). The optimization settings considered were kept exactly the same as mentioned in the main paper. The purpose of the tests was to validate that the proposed approach produced solutions with the given preferences of objectives and uncertainties (tolerances). Additionally, we showed how the solutions would look like and the possible final decisions of the DM if (s)he had no way to provide preferences for uncertainty in an offline interactive multiobjective optimization process.

1.1 Test Results

As the tests were conducted on benchmark problems, the preferences for objectives and uncertainties do not represent real-life problems. Figures 1 and 2 shows the test results while solving problems P1 and P2 for one iteration using the proposed approach. The figures also show the solutions that are available to the DM when (s)he does not have any option to provide preferences for uncertainty. The colour represents the normalized average for the uncertainty vector of the solutions.

In sub-figures (a) the solutions present in the archive before any interaction are shown. Sub-figure (b) shows the pre-filtered solutions done in the proposed approach. In sub-figures (c), we can see the solutions the DM can observe when preferences for uncertainty are not provided. The difference between sub-figures (b) and (c) is the diversity in the uncertainties in the solutions. This is primarily because of the non-dominated sorting operation in the pre-filtering stage of the proposed approach. In sub-figures (d), we can observe the solutions visible to the DM in the proposed approach after providing the preferences. The red line represents the preferences for objectives provided by the DM. Here as well, we can see that the DM can choose from a diverse set of solutions with different uncertainties. However, in sub-figures (e), we can see the solutions that the DM observes while solving the problem without any pre-filtering stage. It is quite clear that the DM has quite a few solutions to choose from. Also, it can be noticed that the solutions have good objective values but have quite high uncertainties. In sub-figure (f) the DM proves the preferences for uncertainty (or cuttoff tolerances). The solutions visible to the DM do not have good objective values (compared to sub-figure (c)), but have much lower uncertainties.

The solutions that the DM observes may change the preferences for objectives that (s)he provides. This also applies to the solutions observed after the DM provides the tolerances. The major advantage in using the proposed approach is the flexibility and choices in the solutions that the DM has. Moreover the DM can change the tolerances and view solutions with different uncertainties. While using the proposed approach the DM can select a solution that suits the tolerances specific to the problem. Providing uncertainty information and allowing the DM the provide preferences for uncertainty inherently guides the optimization process in a way that is different from a generic approach.

References

1. Fieldsend, J.E., Chugh, T., Allmendinger, R., Miettinen, K.: A feature rich distance-based many-objective visualisable test problem generator. In: Proceedings of the Genetic and Evolutionary Computation Conference. p. 541–549. GECCO '19, Association for Computing Machinery, New York, NY, USA (2019)

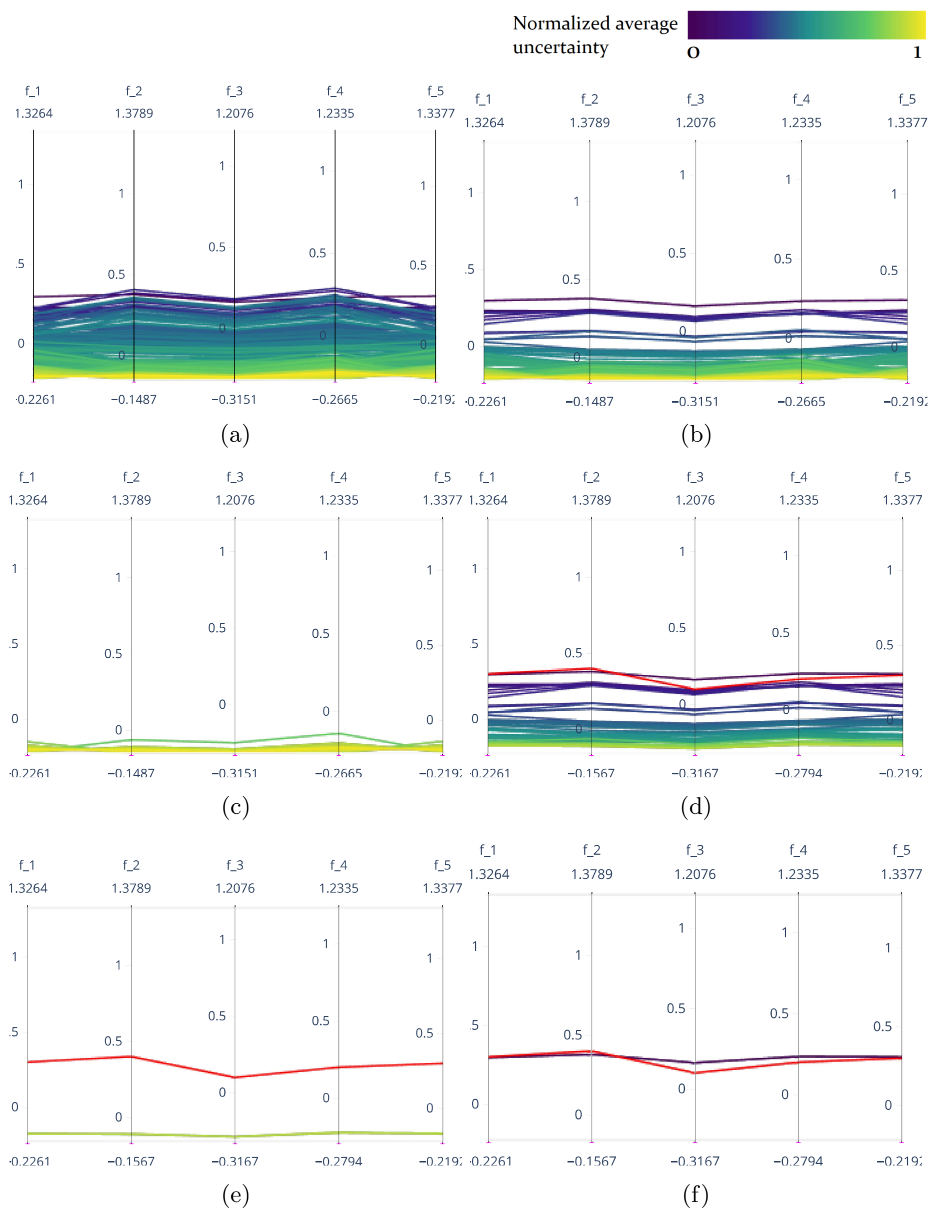

Fig. 1: Solutions at various stages of the optimization while solving problem P1. The red line denotes the preferences for objectives provided by the DM.

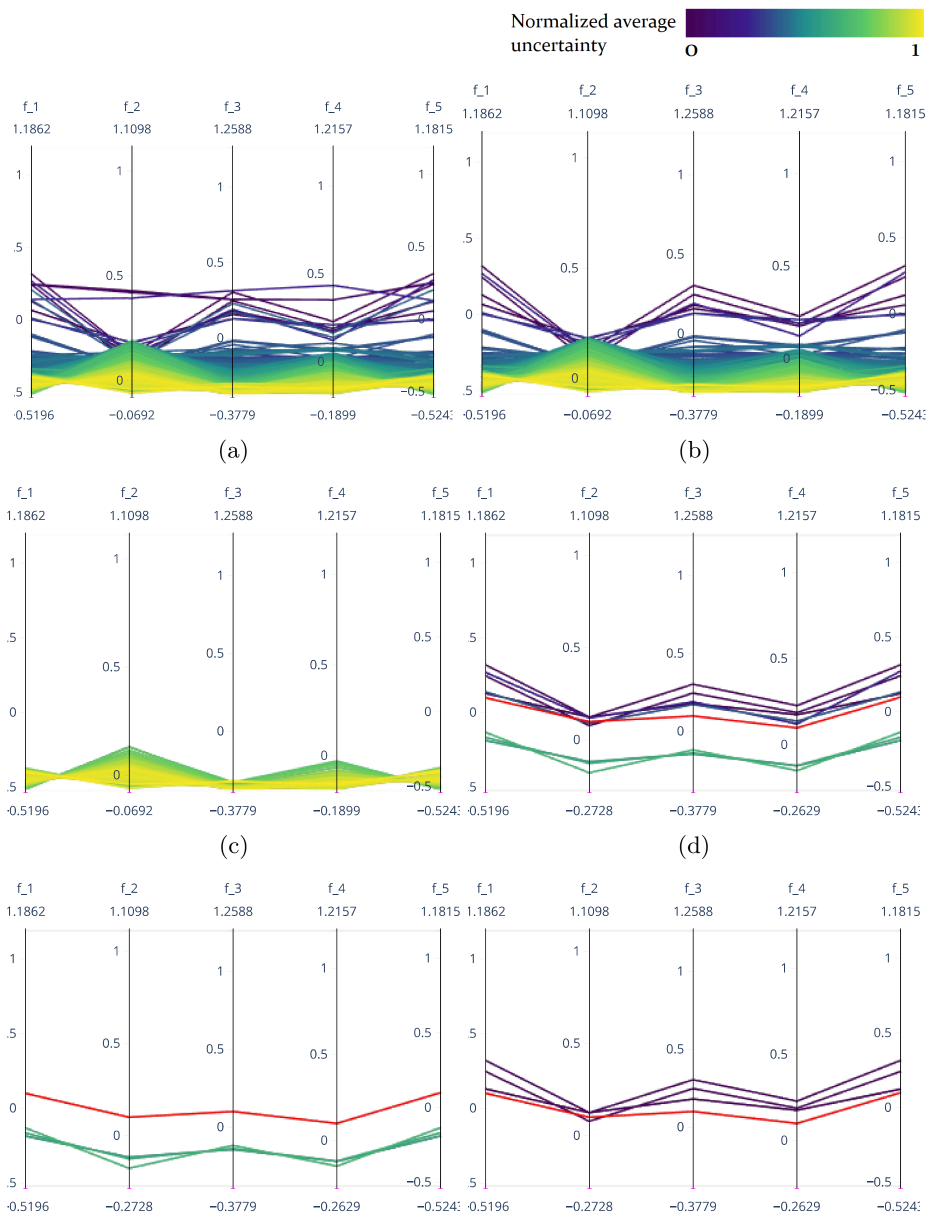

Fig. 2: Solutions at various stages of the optimization while solving problem P2. The red line denotes the preferences for objectives provided by the DM