Efficient constraint multi-objective optimization with applications in ship design

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Chapter 7

Conclusions and Future Work

In this thesis, research is presented on how constraint multi-objective problems can be optimized with as few function evaluations as possible. This final chapter provides a summary of all previous chapters, followed by an overall conclusion and answer to the main research question. The thesis is finalized by proposing directions for future work.

7.1 Summary

Chapter 1: In the introduction an overview and motivation for the study are provided. The main research question that is answered in this work is:

How to identify the Pareto frontier of constraint multi-objective optimization problems with only a few function evaluations?

The main question is divided into sub-questions that are addressed in the subsequent chapters. The secondary objective is to apply the newly developed algorithms to ship design optimization problems and show their applicability.

Chapter 2: The preliminary chapter presents the formal problem notations, the basic theory of expensive black-box optimization, the benchmark functions used in this work, performance metrics for validation, and visualization techniques for multi-objective optimization. This chapter forms the foundational knowledge and notations that are further developed in the remaining chapters.

Chapter 3: An investigation of ship design optimization problem characteristics is presented in the third chapter. The subquestion *What are typical ship design optimization problem characteristics?* is addressed, providing details about both empirical and simulated design methods. The empirical design method utilizes data from similar vessels for conceptualizing new designs, while the simulated design method is typically employed to create and optimize more detailed versions of ship designs. Alongside these design methods, important ship design software is described, and guidelines for parameterization and optimization problem setup are summarized. Finally, the holistic *accelerated concept design methodology* is introduced that can be used to evaluate ships for multiple key performance indicators at different levels of accuracy.

Chapter 4: The empirical design methodology is elaborated upon in the fourth chapter. A newly proposed empirical design methodology is the *reference finder*, which utilizes machine learning, optimization algorithms, and a dataset with static ship data to identify promising solutions. The reference finder is trained by fitting a random forest regressor to predict key performance indicators and an isolation forest to detect outliers. Finally, the NSGA-II algorithm is coupled with the random forest regressor and isolation forest to discover promising Pareto optimal ship design solutions that do not exist yet but are predicted to be feasible and favorable by the machine learning algorithms. These new preliminary designs can be further developed with the simulation-based design approach as shown in Chapter 6.

Chapter 5: The most significant scientific contribution and the key points of this work are detailed in Chapter 5. In this chapter, the *IOC-SAMO-COBRA* algorithm is introduced, providing the answer to the main research question. The IOC-SAMO-COBRA algorithm adeptly handles constraint multi-objective problems that could have both computationally expensive and inexpensive evaluation functions. It achieves this by fitting surrogates for the computationally expensive functions and directly utilizing the inexpensive functions during the search for promising feasible Pareto optimal solutions. The identification of Pareto optimal solutions is facilitated through the optimization of a multi-point acquisition function capable of proposing one or more feasible solutions per iteration. By proposing multiple solutions per iteration, the computationally expensive evaluations can be run in parallel. With each iteration, the algorithm learns from evaluated solutions by updating surrogates and subsequently continues the search for solutions that maximize the joint hypervolume.

Chapter 6: In the last content-focused chapter of this work, the algorithms introduced in Chapter 5 are used and validated in practice. Five different simulation-based ship design optimization problems are optimized using the accelerated concept design methodology in combination with optimization algorithms. In the first optimization study, the most promising solution from a trailing suction hopper dredger study demonstrated a 19% reduction in resistance and a 14% decrease in steel weight compared to the original design. In the second optimization study, the design of a wind feeder is optimized, revealing a very complete Pareto frontier with improvements in all three objectives: operability, resistance, and lightship weight. The third optimization case focused on optimizing cargo volume and damage stability criteria for a single-hold cargo ship. Here, the power of the multi-point infill criteria (and therefore the possibility of parallel evaluations) and the exploitation of inexpensive functions directly in the algorithm demonstrated significant time savings with the IOC-SAMO-COBRA algorithm compared to traditional approaches. In the final two cases, resistance optimization was conducted for two real-world commercial ship design projects. In the first commercial project, a 26% reduction in resistance was achieved by optimizing the complete hull below the waterline. In the second commercial project, a 4.8% required power reduction was realized by exclusively refitting the bulb of a containership with a capacity of approximately 10,000 containers.

7.2 Conclusions

This study aimed to address the overarching research question: *How to identify the Pareto frontier of constraint multi-objective optimization problems with only a few function evaluations?* The development of innovative algorithms, particularly the *IOC-SAMO-COBRA* algorithm, is a significant scientific contribution that helps in answering this research question. This algorithm demonstrates its effectiveness in handling constraint multi-objective problems, considering both computationally expensive and inexpensive evaluation functions. It does so by iteratively learning and updating surrogates for computationally expensive functions and directly using inexpensive functions when searching for solutions that jointly contribute the most hypervolume.

The practical application of the developed algorithms in real-world ship design optimization problems showcased their impact and flexibility. From reducing the resistance of trailing suction hopper dredgers, ferries, and container ships, to optimizing cargo volume and damage stability in cargo ships, the algorithms consistently demonstrated improvements. Notably, the *IOC-SAMO-COBRA* algorithm's ability to handle parallel simulations and exploit inexpensive functions showcased its efficiency in achieving significant time savings.

In conclusion, this work provided a constraint multi-objective optimization algorithm and the accelerated concept design methodology for ship design that offered valuable insights and practical solutions. The investigation into the research questions, the development of algorithms, and their practical applications have collectively made a substantial contribution to the naval and global multi-objective optimization research fields.

7.3 Future Work

There are many research directions possible to enhance the constraint multi-objective optimization algorithms for computationally demanding problems that are proposed in this thesis. One significant contribution would be to extend the algorithms with functionality that could also deal with discrete, integer, and categorical parameters. This way, computationally expensive mixed-inter constraint multi-objective problems could be solved. Other contributions would be to investigate and extend the limits of the SAMO-COBRA algorithm. For example, what is the limit on the number of objectives, constraints, and parameters that the SAMO-COBRA algorithm can deal with, and does increasing any of these significantly influence the performance? Other directions that require less effort but might improve the performance of the SAMO-COBRA algorithm and its extensions would be an advanced hyperparameter optimization study and validation of the algorithm on different benchmark problems.

From a ship design perspective, setting up the parameters (and their upper and lower limit), constraint functions, and objectives functions correctly before the first run remains challenging. This is problematic, especially when the evaluation functions are computationally demanding. Another open issue is that the parameterization defines the decision freedom and the outcome. Typically, only a small part of the vessel is parameterized and a lot is kept constant which drastically reduces the potential of the optimization process. Therefore, ship design could benefit from more research into generative models to generate feasible optimal solutions and domain-specific optimization algorithms that apply transfer learning to have a warm start in the optimization process.

A final interesting future research direction would be to investigate the applicability of the proposed algorithms in different application domains like aviation, automotive, or civil engineering disciplines.

Appendix A

Appendix

A.1 Empirical Attainment Difference Functions

To visually compare the IOC-SAMO-COBRA and the IC-SA-NSGA-II algorithms, Empirical Attainment Difference Function (EAF) plots are made. The EAF plots of the two-dimensional problems can be found in the 18 Figures. In the EAF difference plots the dark areas mark where the two algorithms obtained different results. The more frequently a certain area is dominated the darker the gray scale is. As can be seen in the majority of the figures (except for BICOP2, MW2 and WB), the IOC-SAMO-COBRA algorithm manages to find solutions that dominate the solutions of the IC-SA-NSGA-II algorithm.

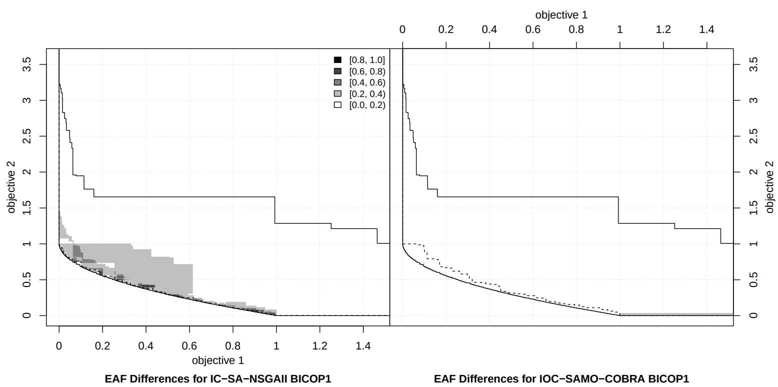

Figure A.1: EAF difference plot BIOCP1

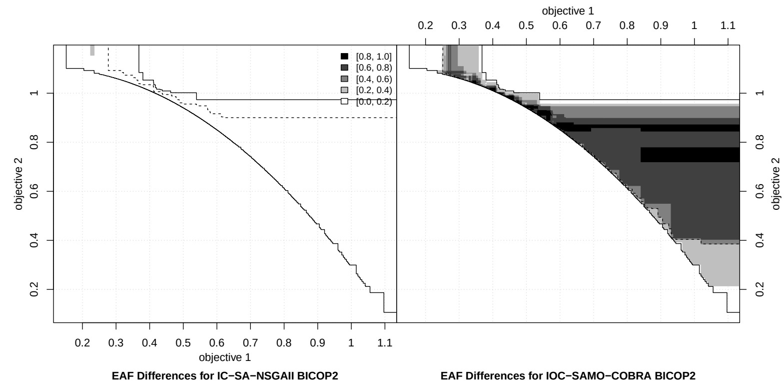

Figure A.2: EAF difference plot BIOCP2

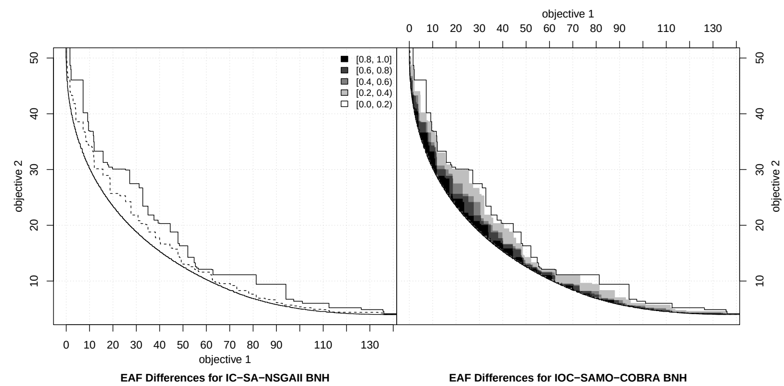

Figure A.3: EAF difference plot BNH

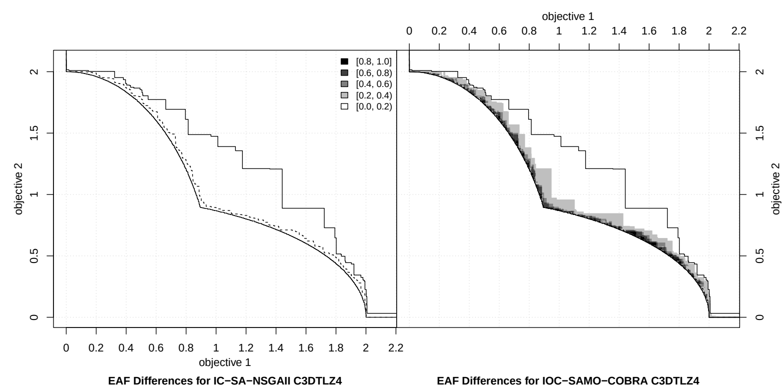

Figure A.4: EAF difference plot C3DTLZ4

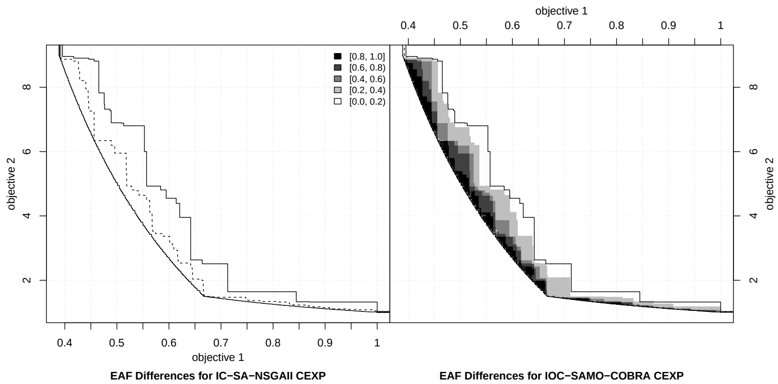

Figure A.5: EAF difference plot CEXP

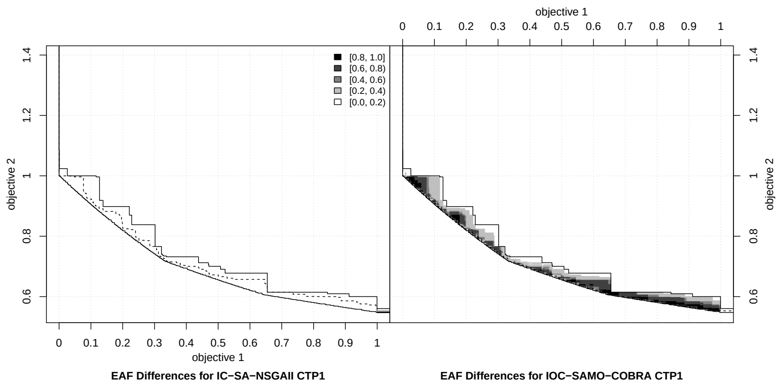

Figure A.6: EAF difference plot CTP1

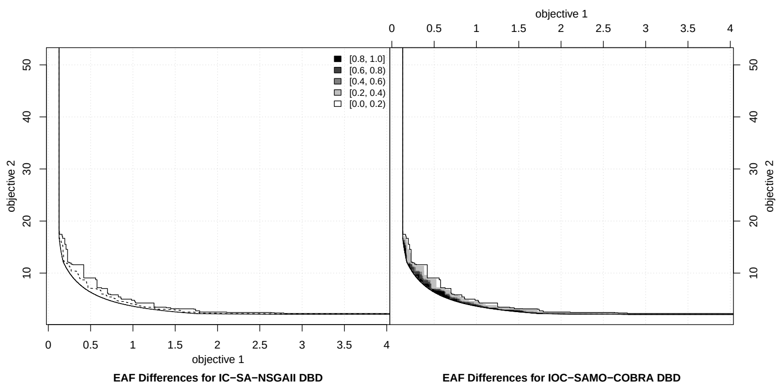

Figure A.7: EAF difference plot DBD

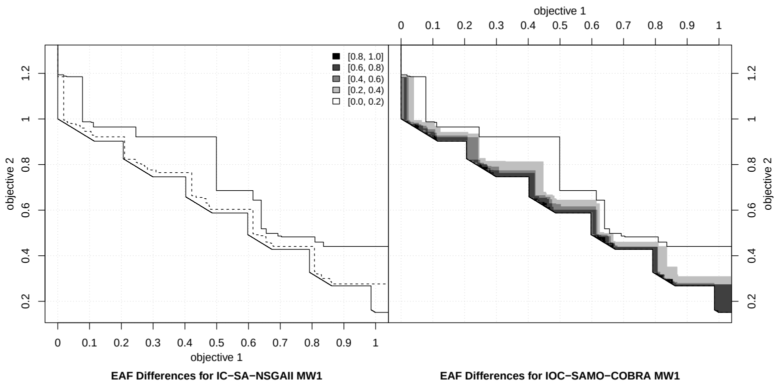

Figure A.8: EAF difference plot MW1

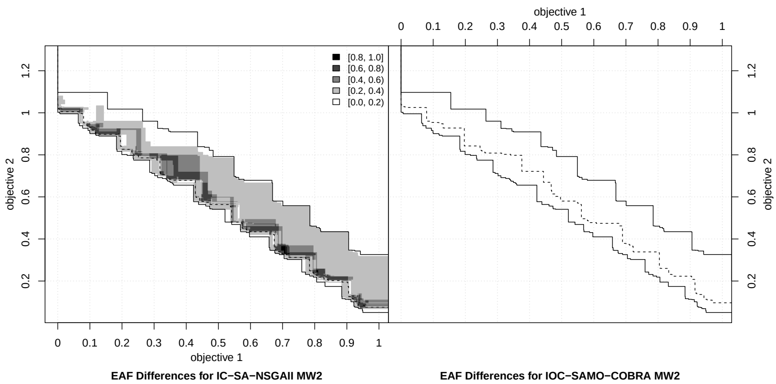

Figure A.9: EAF difference plot MW2

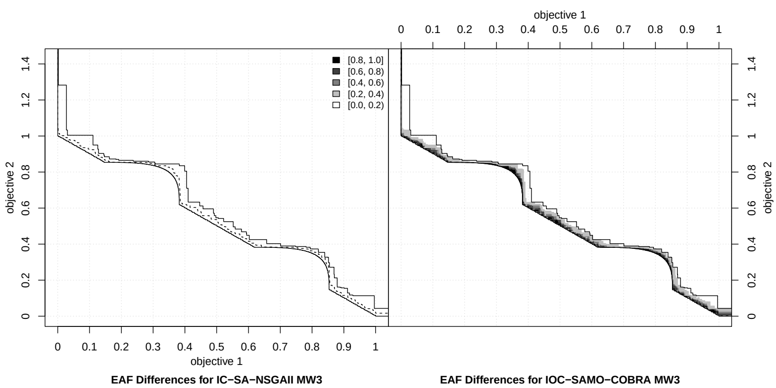

Figure A.10: EAF difference plot MW3

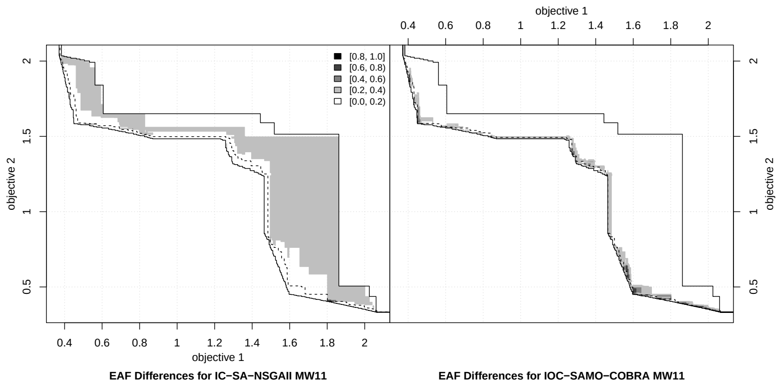

Figure A.11: EAF difference plot MW11

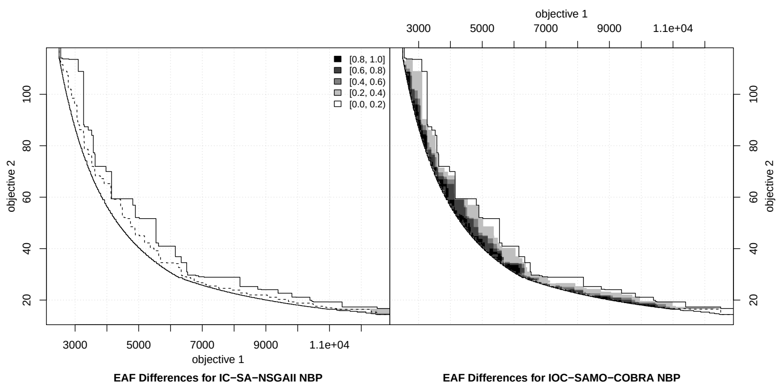

Figure A.12: EAF difference plot NBP

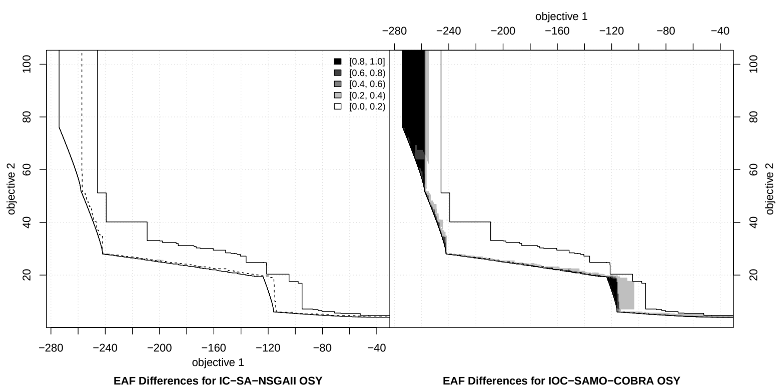

Figure A.13: EAF difference plot OSY

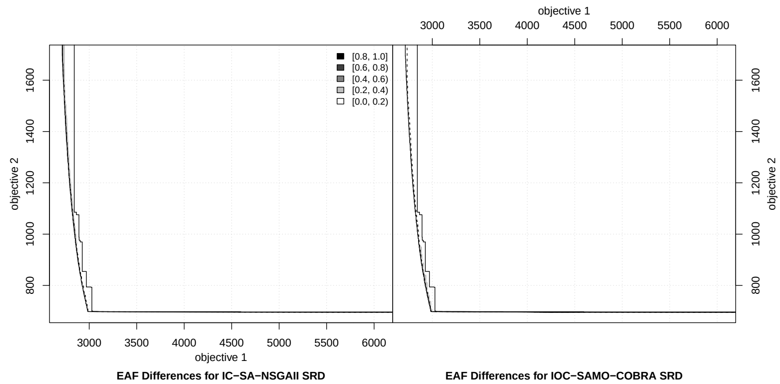

Figure A.14: EAF difference plot SRD

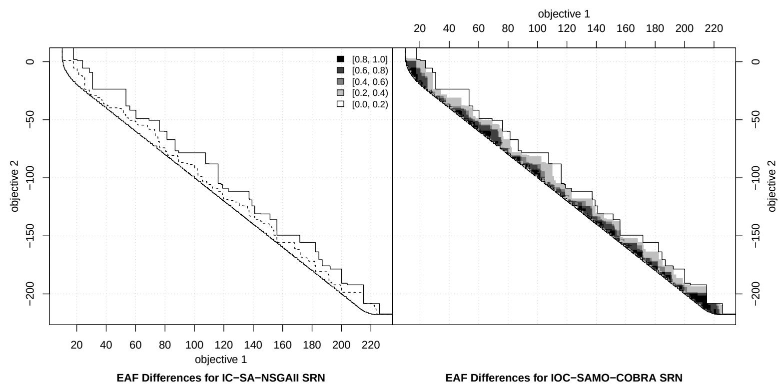

Figure A.15: EAF difference plot SRN

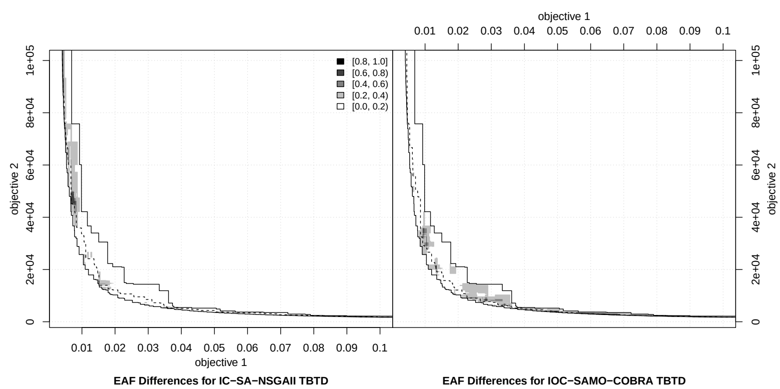

Figure A.16: EAF difference plot TBTD

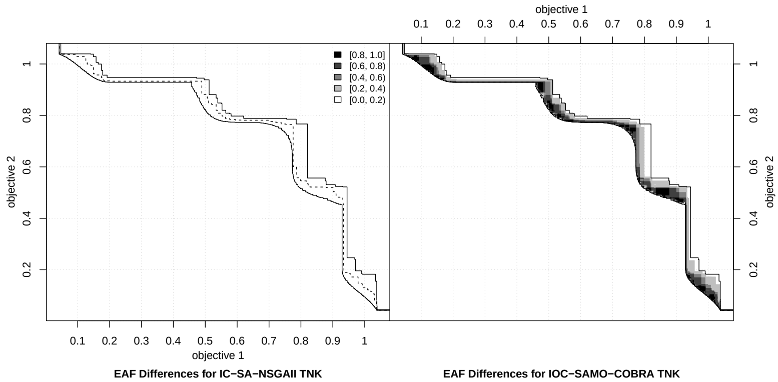

Figure A.17: EAF difference plot TNK

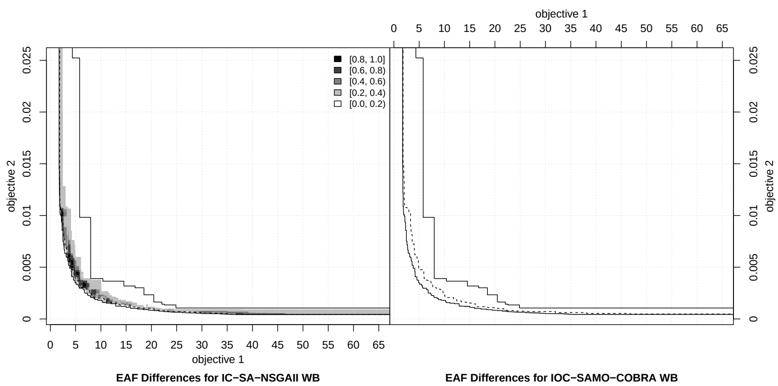

Figure A.18: EAF difference plot WB