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Many-objective optimization approaches for the multi-physics electric motor design problem

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Abstract. Designing electric traction motors involves simultaneously optimizing multiple objectives across electromagnetic, thermal, and mechanical domains. As the number of objectives grows, Pareto-based methods become less effective due to the increase in non-dominated solutions. This work investigates how the number and distribution of non-dominated points vary with the number of objectives, using a dataset of 16000 motor configurations. Results show that many-objective settings (more than four) pose challenges for Pareto ranking. Building on these insights, many-objective optimization techniques such as NSGA-III and game-theory-based aggregation will be investigated and compared, using surrogate models trained on this dataset to reduce the computational effort.

Keywords: electric motor design, many-objective optimization, multi-physics simulation, Pareto dominance, surrogate models.

INTRODUCTION

Multi-objective optimization has become a central paradigm in engineering design, where trade-offs between conflicting objectives must be explored and understood. However, as the number of objectives increases (moving toward many-objective problems, with more than four), standard Pareto-based methods suffer from the so-called "curse of dimensionality": a large fraction of the population becomes non-dominated, making selection and ranking ambiguous [1]. This issue is particularly relevant in electric motor design, where performance indicators span multiple physical domains. In such contexts, scalable optimization techniques and meaningful selection criteria become crucial.

MANY-OBJECTIVE ANALYSIS

An open dataset [2] comprising 16,000 motor configurations was used, each evaluated through FEM simulations for electromagnetic, thermal, and structural metrics, plus material masses. Seven performance metrics were considered: torque, torque ripple, temperature, mechanical stress, power factor, copper mass, and magnet mass.

To assess the scalability of Pareto-based selection, we analyzed all combinations of 2 to 7 objectives. Figure 1 summarizes how the count of non-dominated points increases dramatically with dimensionality. Figure 2 shows how solutions are distributed across Pareto ranks for different numbers of objectives. When few objectives are considered, the distribution spans many ranks, allowing finer discrimination among solutions. In contrast, for 6 or more objectives, the majority of solutions concentrate in the first ranks, reducing the effectiveness of rank-based selection and making it harder for algorithms to guide the search toward well-compromised and diverse solutions.

These insights motivate the adoption of alternative optimization techniques tailored for many-objective scenarios. NSGA-III [3] addresses the issue of diversity loss through reference directions, while game-theory-based scalarization [4] provides a principled way to derive balanced solutions by interpreting objectives as cooperative players. Building on the present analysis, these approaches will be applied to the actual optimization of motor configurations, leveraging surrogate models trained on the dataset to avoid the computational burden of repeated FEM evaluations.

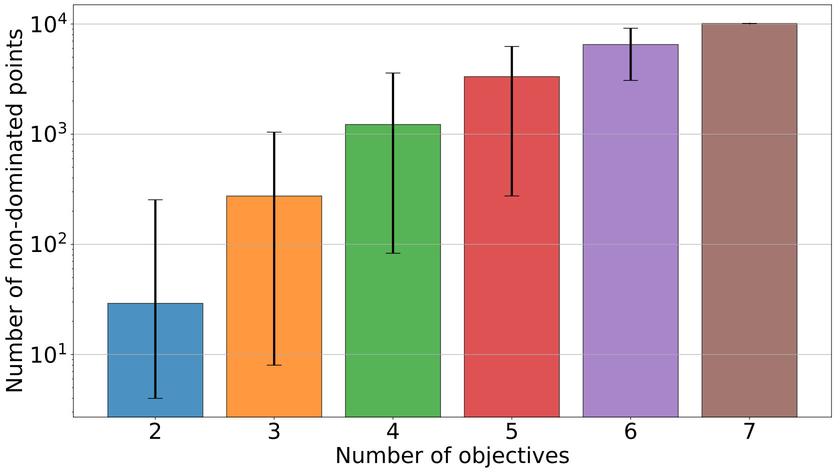

Figure 1: Number of non-dominated solutions as a function of the number of objectives.

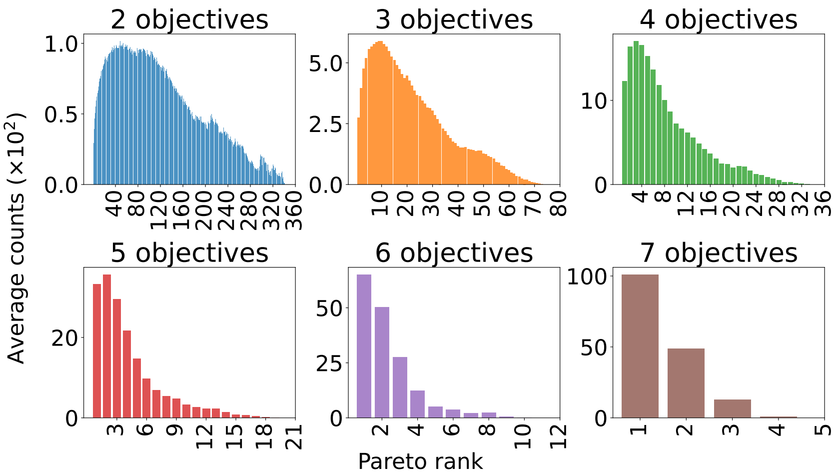

Figure 2: Distribution of solutions across Pareto ranks for increasing numbers of objectives.

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