MULTI-OBJECTIVE SIMULATION OPTIMIZATION OF THE ADHESIVE BONDING PROCESS OF MATERIALS

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ABSTRACT

Automotive companies are increasingly looking for ways to make their products lighter, using novel materials and novel bonding processes to join these materials together. Finding the optimal process parameters for such adhesive bonding process is challenging. In this research, we successfully applied Bayesian optimization using Gaussian Process Regression and Logistic Regression, to efficiently (i.e., requiring few experiments) guide the design of experiments to the Pareto-optimal process parameter settings.

1 INTRODUCTION

The adhesive bonding process we consider consists of different steps: first, plasma is applied to the materials, next glue is applied, and finally the materials are cured in an oven. The optimization problem is bi-objective: the goal is to find the plasma process settings that maximize break strength, while minimizing the associated production costs. We consider six process parameters: 1) whether the materials are pre-processed (Yes or No), 2) the power setting of the plasma torch (300W - 500W), 3) the speed at which the plasma torch moves over the sample (50 mm/s - 250 mm/s), 4) the distance between the plasma torch nozzle and the sample (0 mm - 50 mm), 5) the number of passes of the plasma torch over the sample (5-20), and 6) the time between the plasma treatment and the application of the glue (1 min - 60 min).

Real-life experiments involve the application of a stress test to the joined components: the break strength at which the components come apart is measured, as well as the type of breach (substrate breach, cohesive breach, or adhesive breach) and the occurrence of visual damage. Importantly, process settings that lead to a substrate or cohesive breach or that imply visual damage should be avoided. The break strength is noisy: a given set of process parameters may yield different values in different experiments. As real-life physical process experiments are time expensive (requiring hours for a single replication), a computer simulator of the adhesive bonding process was developed by the Joining & Materials Lab of Flanders Make (flandersmake.be/en) to facilitate the development and assess the efficiency of the algorithm. All results presented here are thus obtained with this simulator.

2 METHOD

We start with an initial latin hypercube sample consisting of n_0 parameter sets, which we evaluate using the simulator. We use augmented Tchebycheff scalarization to transform the two objectives into a single objective, and apply Gaussian Process Regression (GPR) with heteroscedastic noise (Ankenman, Nelson, and Staum 2008) to model this function. Next, the algorithm iteratively selects a single new design (referred to as "infill point") to evaluate, by maximizing an infill criterion (using the Particle Swarm optimization algorithm). Our infill criterion consists (for any arbitrary point) of the Modified Expected Improvement (Gonzalez, Jalali, and Van Nieuwenhuyse 2020) multiplied with the Probability of Feasibility of the point (estimated by a Logistic Regression Classifier, LRC (Friedman, Hastie, Tibshirani, et al. 2009)). The simulation results of the infill point are then used to update the GPR and LRC models, and the algorithm continues to iterate until a stopping criterion is reached.

3 RESULTS AND CONCLUSIONS

We applied a Latin Hypercube sampling of $n_0 = 30$ initial design points. Figure 1a shows the Pareto optimal solutions obtained with our algorithm (after 180 iterations). To assess the quality of the solutions, we compare the results to those obtained with NSGA-II (using a population size of 30, and allowing for 180 generations). As shown in Figure 1b, our algorithm converges to a hypervolume that is superior to the one obtained with NSGA-II, requiring only a fraction of the function evaluations (210 vs. 5400); in fact, as evident from the figure, the hypervolume stabilizes already after +/- 50 infill points.
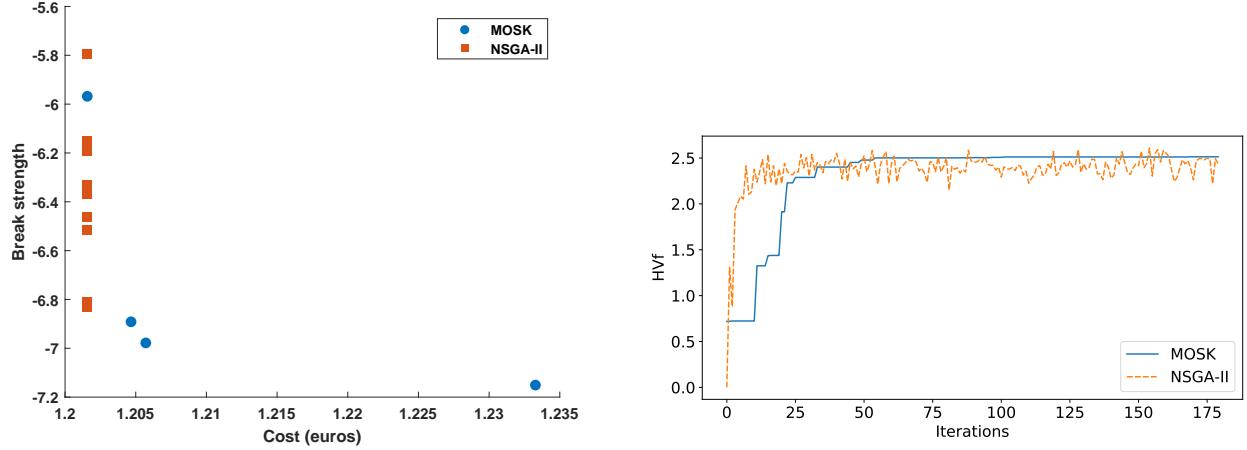
(a) Break strength and cost of the adhesive bonding process.

(b) Evolution of the hypervolume of the feasible solutions in the Pareto front.

Figure 1: Multi-objective optimization results (only feasible Pareto solutions are considered).

Our results show that the use of machine learning techniques holds great promise in solving complex and expensive optimization problems. In this case, the use of the infill criterion allows the algorithm to efficiently search for the Pareto-optimal plasma settings, exploiting the information that has been learned from the already observed process settings through the GPR and LRC models. Future research will focus on the development of a generic tool, allowing lab experts to apply this type of algorithm to other process optimization problems.

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