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Using physical and simulated data to improve injection molding performance

María G. Villarreal-Marroquín, Po-Hsu Chen, Rachmat Mulyana, Thomas J. Santner, Angela M. Dean, and José M. Castro

A novel, calibrated-predictor-based optimization methodology is used to identify the best compromises between competing processing conditions.

Injection molding (IM) is one of the primary manufacturing processes for the mass production of plastic components. Indeed, the fabrication of many products (e.g., automobile components and appliances) is currently reliant on the IM technology of polymer companies. To ensure success, it is thus important for these companies to deliver high-quality products at the lowest possible cost. One approach for identifiying the correct processing conditions for optimizing relevant performance measures (PMs) is to use advanced computer simulations. An ongoing problem in the optimization of manufacturing processes, however, is that different PMs usually exhibit conflicting behavior. For example, the processing conditions that provide the best quality product may not correspond to the lowest production cost.

Optimizing a single PM for IM manufacturing is therefore not recommended. Instead, it is better to consider all the PMs simultaneously, i.e., in a practice known as multiple objective optimization (MOO) or Pareto optimization. MOO methods have previously been applied to find optimal processes, based on simulator output.[1–3] In principle, to identify the best solutions with MOO methods, the evaluation of the PMs at a large number of combinations of the controllable process variables (CPVs) is required. In the case of IM, this means that for each evaluation either an experimental run or a computer simulation must be performed. The high cost and long evaluation times of these approaches, however, means that they can be prohibitive in IM optimization.

In our work, we have thus proposed an alternative methodology in which we combine simulator runs with observations from a designed manufacturing process experiment to construct calibrated predictors for the mean of the PMs, (i.e., the most relevant quantities for improving the IM process).[4] These statistical tools—known as 'calibrated' predictors[5]—relate the CPVs (inputs) to the PMs (outputs) and are based on a relatively small amount of data. Our predictors are thus much faster and less costly than running a physical experiment or computing a simulation model. In previous work,[2,3,6] predictors based on physical or simulated data (but not both) have been used for IM.

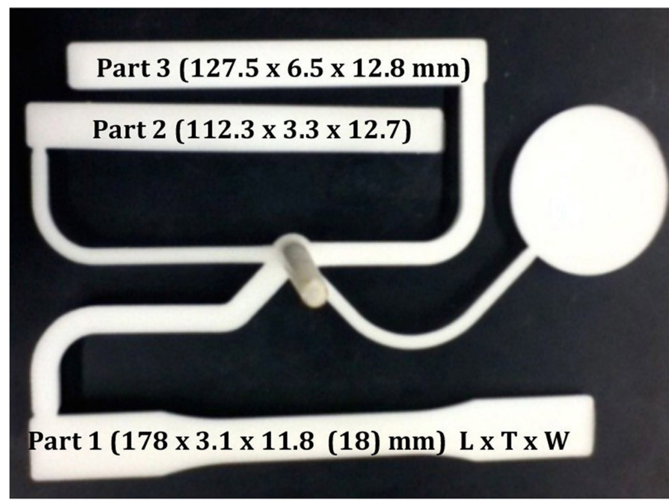

Figure 1. *Photograph of the thermoplastic polyolefin ASTM physical test sample, with the length (L), thickness (T), and width (W) of its three parts shown.*

After the predictors are built in our methodology, the values of the selected PMs are estimated on a grid of CPVs. We also use non-dominance criteria to identify a set of predicted Pareto solutions. A solution is 'non-dominated' (or Pareto) if there are no other solutions for which the values of the PMs are better/equal than it, and it is strictly better for at least one PM. We can then refine the original Pareto solutions by predicting the PMs on a finer CPV grid (i.e., close to the resolution of the original Pareto set). A more detailed description of our technique is provided in our recent paper.[4]

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We have also used a case study, with three PMs, to show how the calibrated predictors allow an IM manufacturer to identify the optimal processing conditions for competing objectives.[4] Our goal for this case study was to minimize the relative shrinkage of part 3 (with length L3, thickness T3, and width W3) of a thermoplastic polyolefin ASTM test sample (see Figure 1) that was molded with the use of a Sumitomo 180 ton IM machine. The CPVs we used in these physical experiments were melt temperature (T_{melt}), packing time (t_{pack}), packing pressure (P_{pack}), and cooling time (t_{cool}). In addition, we kept the mold temperature and filling time constant. In addition to the four CPVs, the computer simulator (using the Moldex3D software) inputs include three calibration variables, i.e., the mold heat transfer coefficients during flow, packing, and cooling.

The outcome of our case study was the predicted Pareto set (inputs) and Pareto front (outputs), which we use to identify the CPV values that provide the best compromises between all the PMs. The Pareto set (with 31 solutions) is plotted in Figure 2, where each of the equally spaced rays represents one input vector and where each input is scaled to between 0 and 1. For example, solution 1 corresponds to T_{melt}, t_{pack}, P_{pack}, and t_{cool} values of 0.70 (208°C), 0.50 (20s), 0.78 (41MPa), and 0.76 (44s), respectively. We find that most of the solutions have high T_{melt} and P_{pack} values, whereas t_{pack} and t_{cool} tend to vary from

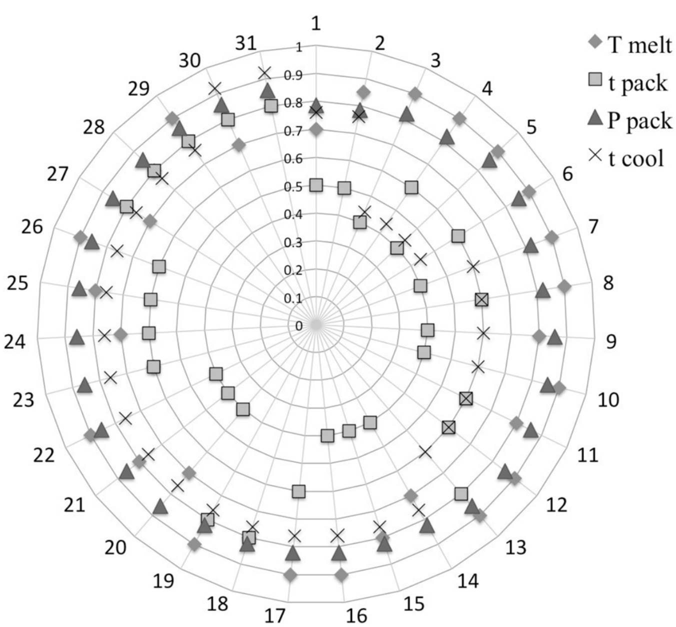

Figure 2. *The 31 predicted Pareto set solutions (normalized between 0 and 1) from the investigated case study. Each Pareto input is represented on a single axis (labeled 1–31). T_{melt}: Melt temperature. t_{pack}: Packing time. P_{pack}: Packing pressure. t_{cool}: Cooling time.*

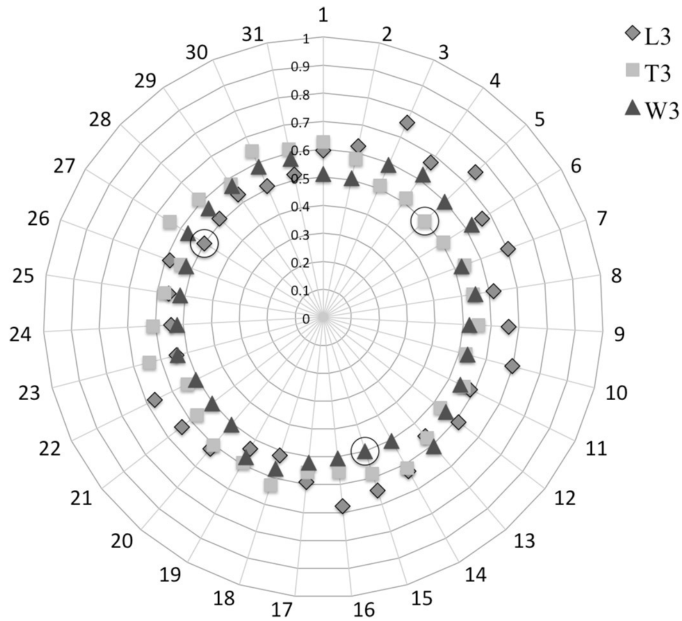

Figure 3. *The 31 predicted Pareto front solutions (normalized between 0.5 and 1). Each solution contains three outputs that are represented on each of the 31 axes. L3, T3, W3: Percentage linear shrinkage of the length, thickness, and width (respectively) of part 3 of the test sample (see Figure 1). The three circled symbols indicate the inputs that produce the minimum for each of the three outputs.*

middle to high levels. We also show the normalized (between 0.5 and 1) length, thickness, and width vectors on the estimated Pareto front in Figure 3 (where solutions closest to 0.5 are preferred). As an example, solution 27 produces the smallest L3 value. Unsurprisingly, the relative shrinkages of the thickness and width for this solution are not at their minima. Rather, we find that solutions 5 and 15 produce the lowest T3 and W3 values, respectively.

In summary, we have devised a new technique for predicting performance measures that can be used to identify optimal processing conditions in IM manufacturing (i.e., when there are competing objectives). For our approach we require both a computer simulation code and some physical experiment observations. We then use an optimization method—based on calibrated predictors—to estimate a Pareto set and front. These solutions can then be used by a plastic manufacturer to determine the ideal processing conditions (i.e., to obtain the best compromises between the different PMs involved in the process). In our future work we will introduce a sequential design methodology, in which we use a statistically calibrated simulator for Pareto optimization in IM. We will evaluate the efficiency of the sequential strategy for

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predicting the Pareto solutions, in comparison with the approach we used in this work.

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Author Information

María G. Villarreal-Marroquín
Centro de Investigación en Matemáticas
Monterrey, Mexico

María Villarreal-Marroquín is a researcher whose interests include mathematical and statistical modeling for multiple objective optimizations and simulation of manufacturing processes, as well as statistical analysis of massive and complex data sets.

Po-Hsu Chen
Battelle Memorial Institute
Columbus, OH

Po-Hsu Chen is a research statistician at Battelle, Columbus. His interests include optimization of multiobjective problems, clustering and visualization for high-dimensional data, and computer experiments.

Rachmat Mulyana and José M. Castro
Department of Integrated Systems Engineering
The Ohio State University
Columbus, OH

Rachmat Mulyana is an instructional technology specialist. His research interests include the optimization of plastic manufacturing processes.

José Castro's research focuses on modeling and optimization of industrial processes, and the development of novel environmentally friendly alternatives to current processes. His research group's areas of expertise include sheet molding compounds, compression molding, in-mold coatings, reactive liquid molding, and injection molding.

Thomas J. Santner and Angela M. Dean
Department of Statistics
The Ohio State University
Columbus, OH

Thomas Santner's research interests include the design and analysis of experiments. His most recent work involves the use of computer simulators as experimental platforms, either alone or in combination with traditional physical experiments.

Angela Dean's research is in the field of experimental design. In particular, she is interested in experiments that involve many factors but that require small budgets.

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