Multi-Objective Optimization and Decision Support for Conformal Cooling in Injection Molding

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***Abstract*—The design of conformal cooling channels (CCC) in injection molding is a complex, multi-objective engineering task in which geometric, thermal, and mechanical constraints interact in nonlinear ways. Although evolutionary multi-objective optimization (EMO) algorithms, such as NSGA-II, have been successfully applied to this domain, the interpretation of large Pareto-optimal sets often relies on manual visual inspection, which limits knowledge transfer and decision reproducibility. This paper examines how interactive knowledge discovery, facilitated by the Mimer platform, can enable the systematic interpretation of EMO results in the injection molding process. Four bi-objective CCC optimization problems were solved using high-fidelity simulations accelerated by an Artificial Neural Network surrogate model based on Moldex3D data. Mimer was then used to analyze the resulting solution sets through linked visualizations, region-of-interest-based preference articulation, and flexible pattern mining for rule extraction. The generated knowledge was compared against the independent assessment of an expert in mold design. Results show that Mimer consistently complements expert insights, identifies the most influential geometric variables, and uncovers additional non-obvious relations across runs, including stable structural rules governing channel diameter, distance to the cavity surface, and gate-dependent performance. These findings demonstrate that Mimer can act as a semi-automatic analyst in EMO-based CCC design, increasing transparency, supporting informed decision-making, and improving the reusability of optimization knowledge in industrial injection molding.**

***Index Terms*—Injection molding, Multi-objective optimization, Knowledge discovery, Decision support, Pattern mining**

I. Introduction

Injection molding (IM) is one of the most essential methods for producing polymer parts, facing increasing demands to achieve shorter cycle times, tighter tolerances, and improved sustainability. The cooling phase often accounts for 50–80% of the cycle time. Therefore, the design of the cooling system, including its topology, distance to critical regions, and thermal behavior, has a significant impact on productivity, quality, and energy consumption. Additionally, additively manufactured CCCs enable coolant paths that follow part geometry, improving heat extraction and temperature uniformity over conventional drilled layouts. To exploit this flexibility, recent work has combined high-fidelity simulation with EMO. However, industrial applications often end with the visual inspection of Pareto fronts and ad hoc design choices, which limit knowledge transfer and reproducibility [1]–[3].

This gap between 'computed Pareto-optimal sets' and 'knowledge gained' is increasingly recognized in the EMO community. Decision-makers require interpretable connections between objectives and design variables, discernible patterns that explain high-performing design regions, and transparent justification for final solutions. Data-driven post-optimality techniques, such as clustering, rule extraction, or variable importance analysis, demonstrate that such knowledge can be obtained [4], [5]. However, they are rarely integrated into coherent, user-oriented workflows or systematically compared with expert reasoning in complex engineering problems, such as injection molding.

Mimer [6] addresses this challenge as an interactive, web-based environment for analyzing multi-objective optimization results. It couples solution visualization with interactive knowledge discovery tools, such as flexible pattern mining and influence scores, to connect preferred regions in objective space to actionable prescriptions in decision space. Prior applications in other manufacturing-related domains [7]–[9] suggest that such platforms can reveal nontrivial relations and support both decision-making and knowledge-driven optimization. However, their potential for polymer processing, and specifically for CCC design in injection molding, remains underexplored. This work applies Mimer for the post-optimality analysis of a simulation-based evolutionary framework for designing CCCs in IM [10], [11]. Seven geometric and positional decision variables describe the real-world problem. Four bi-objective cases are studied, each combining two performance criteria (e.g., cooling efficiency and temperature uniformity, or thermal and stress-related indicators), and solved using NSGA-II [12] to generate representative Pareto-optimal designs. It is essential to note that the analysis provided by Mimer was also extended to the same problem, but with four objectives, optimized using the NSGA-II algorithm. However, due to a lack of space, we will not report those results here.

Our working hypothesis is that systematic exploration with Mimer can (i) discover patterns that an experienced mold design expert would derive from the same Pareto-optimal sets, and (ii) uncover additional, non-obvious relationships that are difficult to identify via manual inspection alone. We therefore view Mimer as a candidate "semi-automatic analyst" for multi-objective evolutionary algorithm (MOEA) studies in injection molding – agreement with expert reasoning would support integrating interactive knowledge discovery into standard design workflows, while discrepancies would highlight hidden modeling assumptions or unexplored design opportunities.

The contributions of this paper are threefold. First, we demonstrate Mimer's use on a realistic injection molding CCC optimization problem. Second, we provide a structured comparison between Mimer-based interpretations and those of an independent domain expert, assessing consistency, coverage, and added practical value. Third, by examining four bi-objective problem formulations, we demonstrate how different objective pairs affect both the optimization results and their interpretability within Mimer.

The remainder of this paper is organized as follows: Section II presents a background on designing CCC, multi-objective optimization, and knowledge discovery based on Mimer. Next, Section III describes the problem formulation and optimization workflow. Section IV presents and discusses the results obtained, and finally, Section V concludes the paper.

II. Background

A. CCC Design in IM

With the adoption of conformal cooling channels (CCCs), the design of cooling systems in injection molding shifts from a simple drilled layout problem to a tightly constrained geometric and thermomechanical optimization task. Metal additive manufacturing enables channels to be routed in three dimensions with controlled distances to the cavity and critical regions [1], [10], [11]. Fig. 1 shows the visual comparison between traditional drilled cooling channels and the CCC. The distance of the conventional drilled channels to the part surface is not constant, which results in non-uniform part cooling, whereas the CCC follows the part shape, enabling more uniform cooling.

To assess candidate layouts, 3D numerical simulation tools (e.g., Moldex3D or equivalent) provide a set of performance indicators that extend beyond cycle time, including:

- average and local cavity temperatures,
- temperature uniformity indices and maximum temperature differences between critical locations,
- stress- and deformation-related representations,
- warpage and shrinkage measures.

Even with a relatively compact parameterization, such as the seven decision variables used in this work to control channel positions, orientations, diameters, and layout features, the combination of these indicators defines a nonlinear, constrained, and inherently multi-objective design space. In this setting, manual tuning or single-objective optimization is insufficient, rather a systematic multi-objective approach is needed.

B. MOEAs and Post-Optimality Analysis

MOEAs are widely used for simulation-based engineering design problems where evaluations are expensive, constraints are complex, and the Pareto-optimal front is difficult to approximate. Their population-based search naturally produces sets of non-dominated solutions representing trade-offs among multiple objectives and is compatible with parallel simulation workflows [12].

In CCC and mold design studies, MOEAs are often combined with design of experiments, surrogate models, or dimensionality reduction to manage computational cost. However, as the dimensionality of both decision and objective spaces grows, the resulting trade-off sets become difficult to interpret using only scatter plots, marginal histograms, and expert-driven visual inspection. Important patterns, such as robust intervals for key variables, conditional relations between objectives, or recurring structural features of high-performing solutions, may remain implicit [1], [2].

To address this issue, various post-optimal analysis techniques have been proposed, including the clustering of Pareto-optimal solutions, association rule mining, regression or classification models that link objectives and decision variables, variable importance analysis, and targeted pattern extraction in regions of interest [4]. These methods aim to convert solution sets into explicit, reusable knowledge, but are typically implemented as case-specific workflows with limited interaction and weak integration into standard design processes. This is precisely the gap that this study targets.

C. Mimer for Multi-Criteria Decision Support

Mimer [6] is a unified, web-based environment that operationalizes interactive knowledge discovery from multi-objective optimization datasets to provide decision support to decision makers. It offers an integrated pipeline with:

1) Interlinked visualizations (e.g., parallel coordinates, scatter plots), which enable coordinated visual exploration of solutions in the objective and decision spaces,
2) Region-of-interest (ROI) analysis, where decision makers can articulate preferences in the objective space in various forms, including desirable ranges for the objectives, reference point, and lasso selection of desirable regions by mouse/finger input,
3) Flexible Pattern Mining (FPM) [13], for generating compact, human-readable decision rules (e.g., intervals or conditional relations) associated with preferred solutions, together with metrics for checking their significance (support) in the selected and remaining solutions.

In this paper, Mimer's web-based environment (available at https://assar.his.se/mimer/html/) is used as part of a structured workflow to analyze the four bi-objective NSGA-II runs for CCC design. It enables a systematic comparison between algorithmic findings and expert reasoning, providing the mechanisms through which the hypotheses stated in the introduction, regarding knowledge extraction, validation, and interpretability, are empirically examined in the context of IM.

III. Problem Definition, Optimization Setup, and Decision Support Workflow

A. Case Study and Design Variables

The study revisits a real injection mold insert equipped with an additively manufactured conformal cooling system. The baseline concept features a two-ring CCC layout surrounding

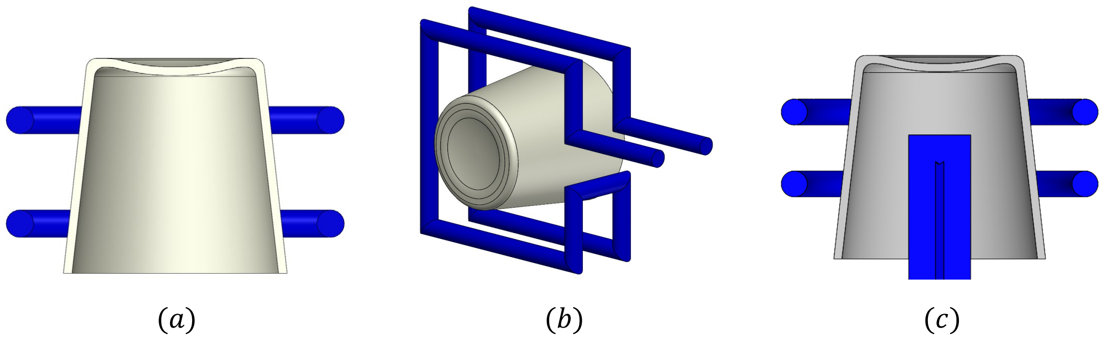

Fig. 1. Conventional versus CCC designs: (a) conventional drilled channel, (b) conventional drilled channel perspective, and (c) CCC.

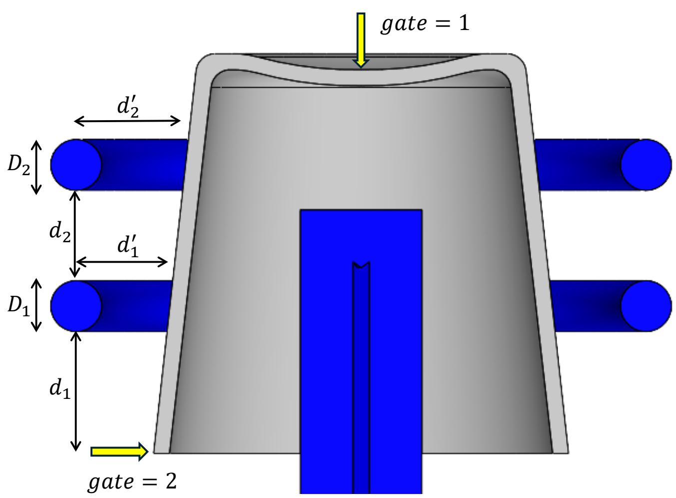

Fig. 2. Cup geometry and CCC general layout.

the gate region, constrained by minimum distances to the cavity and between channels, as well as manufacturability limits on diameters and curvatures, and fixed coolant boundary conditions. The geometric details and constraints are summarized in Fig. 2. Simultaneously, this figure illustrates the two possible locations for injecting the polymer inside the cavity, designated as $gate = 1$ and $gate = 2$. This discrete design variable enables the identification of more variations in performance criteria, allowing for more flexible designs.

The design is parameterized by seven decision variables that control the position, size, and orientation of the rings and their connections, as well as the choice between two feasible gate configurations. This parametrization offers sufficient flexibility to shape the heat extraction pattern in critical regions, while remaining compatible with industrial additive manufacturing practices and previous optimization studies on the same mold. The design variables and their corresponding ranges are:

- Distances between the centers of the channels and the part wall, $d'_1 \in [8, 20]$ mm and $d'_2 \in [8, 20]$ mm,
- Distance of channel 1 to the part border and that of channel 2 to channel 1, $d_1 \in [0, 25]$ mm and $d_2 \in [8, 20]$ mm,
- Channel diameters, $D_1, D_2 \in [6, 15]$ mm, and
- Gate location, $gate \in \{1, 2\}$.

B. Performance Indicators and Bi-objective Formulations

Thermal and mechanical responses are evaluated using 3D numerical simulations (Moldex3D), from which we extract a set of physically interpretable indicators, namely, (i) cooling efficiency, (ii) measures of temperature deviation and maximum temperature differences between critical locations, (iii) stress-related indicators (e.g., von Mises-based), (iv) warpage and shrinkage metrics, and (v) cycle time. Using these we define the following five optimization objectives:

1) *coolef* - cooling efficiency measured as the difference between heat flux transfer from the core cooling system and cavity cooling systems,
2) *sDTms* - standard deviation of the average difference in temperature between the center and outer surface,
3) *sDTsmH* - standard deviation of the average difference of 20% higher variation temperatures between the inner and outer surfaces and the center,
4) *sdVMS* - standard deviation of von Mises Stress, and
5) *tcycle* - the cycle time.

All objectives are to be minimized, except *coolef*, which must be maximized. Next, we define four bi-objective problem formulations, namely:

- Run 1: *coolef* vs. *sDTms*,
- Run 2: *coolef* vs. *sDTsmH*,
- Run 3: *coolef* vs. *sdVMS*, and
- Run 4: *coolef* vs. *tcycle*.

C. Optimization Setup and Generated Datasets

Each of the four formulations is solved using NSGA-II with a population size of 100 evolved over 50 generations. All settings are consistent across runs and in line with established EMO practice for simulation-based problems. For each run, we retain the final population (both non-dominated and dominated solutions), resulting in datasets with the seven decision variables, the two objective values, and constraint satisfaction information.

Candidate solutions are evaluated using an artificial neural network (ANN) trained on 160 randomly generated solutions within the search space, which were modeled using Moldex3D numerical modeling software. The hyperparameters of the ANN were optimized using Bayesian optimization. For more details, the reader is referred to [10], [11].

D. Mimer Configuration and Decision Support Workflow

Mimer is used for multi-criteria decision support in these four runs. The workflow comprises:

Interlinked Visualization: First, the trade-off dataset from each run is visually explored using 2D/3D scatter plots, parallel coordinates plot (PCP) and t-SNE projections. As t-SNE can be sensitive to its parameters, Mimer automatically shows nine projections using different parameter settings. Because all plots are interlinked, any selection or filtering performed in one visualization is instantly reflected across all others, thus providing a coordinated view of decision and objective spaces.
ROI Analysis: Next, the preferences are articulated through the "Filter & Highlight" interface, which offers both rule-based selections or reference-point-based filtering. Solution ranks are regenerated using the built-in non-dominated sorting function, and the rule $nds\_rank = 0$ is used to highlight the non-dominated front. We also highlight the solutions corresponding to $gate = 1$ as the categorical nature of this variable means that its relationship with the objective space is easy to interpret.
Pattern Mining: Finally, we use Mimer's Flexible Pattern Mining (FPM [13]) implementation to extract knowledge in the form of decision rules for each of the four datasets. The highlighted non-dominated solutions in ROI analysis are assigned as the `selected set`. The rest of the solutions automatically form the so-called `unselected set`. FPM is an extension of the popular Apriori algorithm. It extracts association rules that distinguish between the selected and unselected sets. The rules are ranked by their Positive Likelihood Ratio, which is the ratio of support in the selected set to the support in the unselected set. See [13] for more details.

E. Expert Assessment and Evaluation Criteria

In parallel, an experienced injection molding and CCC design expert independently analyzes the NSGA-II results (scatter plots and representative designs) without access to Mimer's outputs. The expert identifies key variables, selects preferred solutions, and articulates qualitative design rules.

The rules obtained using Mimer are then compared against this expert knowledge along four criteria:

- Agreement – consistency in key variables, recommended ranges, and preferred trade-off regions,
- Coverage – extent to which Mimer captures relevant patterns identified by the expert,
- Novelty – presence of plausible, non-obvious relations revealed by Mimer but not initially stated by the expert,
- Transparency – clarity and reproducibility of the reasoning provided by Mimer's visualizations and rules.

This combined setup is the basis for evaluating Mimer as a semi-automatic analyst for MOEA-based CCC design in IM.

IV. Results and Discussion

A. Complete Analysis of a Single Run

To explain the aforementioned methodology in detail, we first present the analysis on a single run (Run 1).

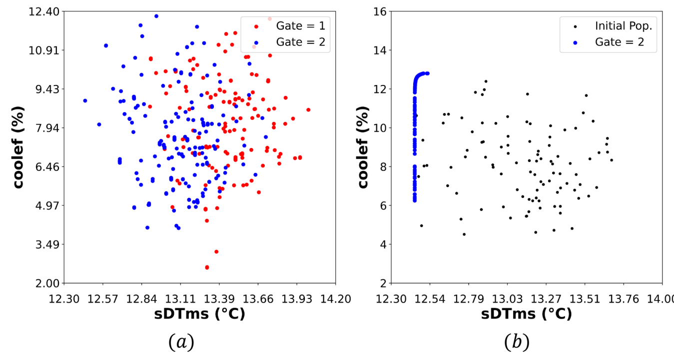

Fig. 3. Scatter plot of objective values for run 1: (a) set of solutions for training ANN, (b) trade-off front and initial solutions.

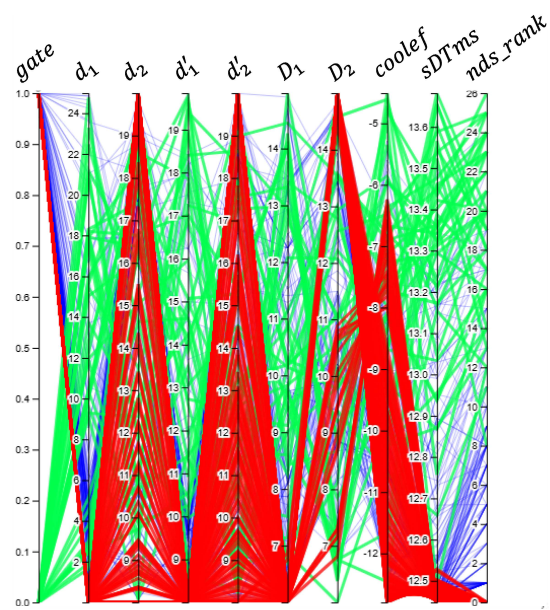

Fig. 4. Parallel coordinates plot for run 1 (Note that $gate$ is offset by 1).

1) Mimer Analysis: Fig. 3 shows objective space scatter plots of the 400 solutions used to train the ANN surrogate (left) and the trade-off front obtained after 50 generations for run 1, i.e., *coolef* versus *sDTms*. The scatter plot shows a separation between the solutions obtained for the two gates, but with some overlap. For $gate = 1$, the solutions are located in the top-right corner, while for $gate = 2$, the solutions are located in the bottom-left and top-left corners. As expected, since *coolef* is to be maximized and *sDTms* minimized, the trade-off front is located in the region where the solutions for $gate = 2$ prevail, mainly at the top-left corner.

Fig. 4 presents the parallel coordinates plot for the trade-off solutions, color-coded so that: (i) red represents the non-dominated solutions, (ii) blue are the dominated solutions representing $gate = 1$, and (iii) green are the dominated solutions representing $gate = 2$. This enabled clear identification of the relevant solutions for ROI analysis.

Fig. 5 presents the nine t-SNE projections of the decision space for different hyperparameters, clearly showing distinct

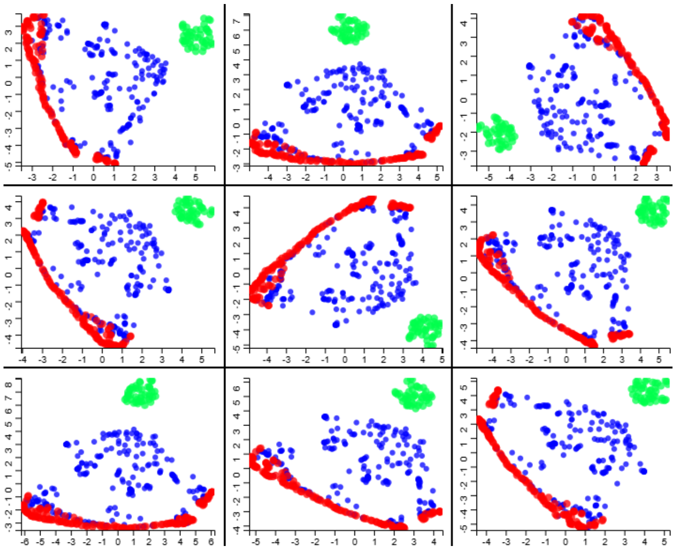

Fig. 5. t-SNE projections for run 1 with different hyperparameter settings.

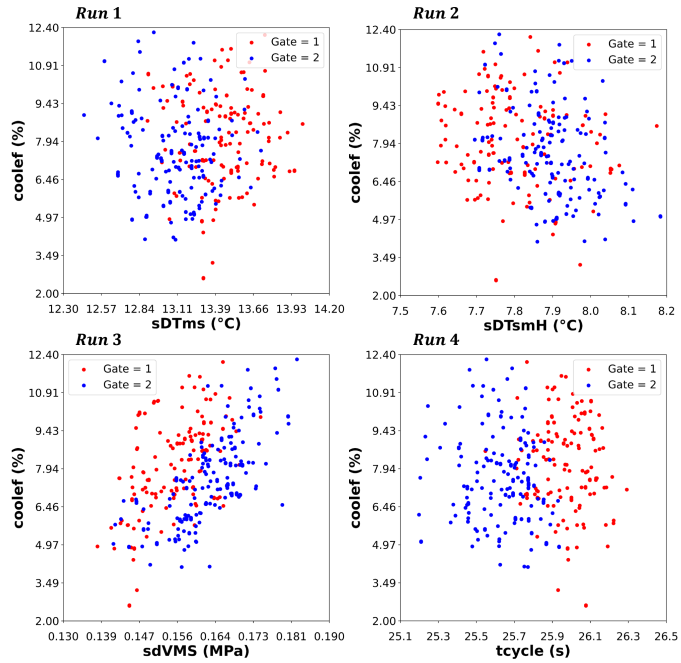

Fig. 6. Scatter plots of objective values used for training ANN in runs 1 to 4.

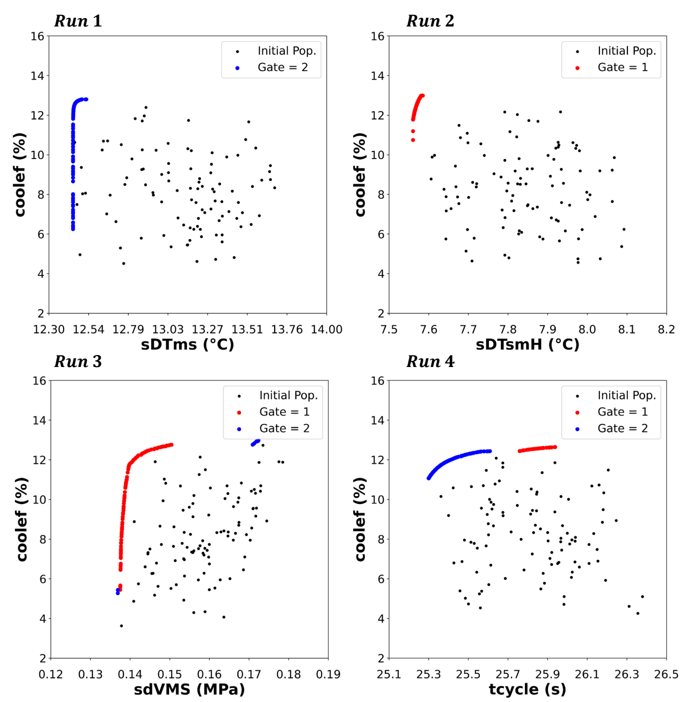

Fig. 7. Trade-off fronts and initial solutions for runs 1 to 4.

regions. The trade-off solutions (in red) are located at the boundary of region representing $gate = 2$, while $gate = 1$ solutions form an isolated region. The consistency of these projections confirms the hidden structure of the decision space.

Finally, using FPM, Mimer infers rules that reflect the trade-off solutions in the decision space. For the present run, a single rule is obtained, $0.00 < d_1 < 0.016$ mm, with a support of 54.81% in the trade-off set and 3.62% in the dominated set.

2) Expert Assessment: The expert assessment is based on the scatter plot of objectives (Fig. 3), parallel coordinates plot (Fig. 4), the trade-off fronts, and their knowledge of the process, as well as the numerical modeling results, specifically the thermomechanical behavior during the IM phases. The starting point in assessing Fig. 3 is the location of the solutions for both gates in the objective space, as mentioned before, and the location of the Pareto front.

Finally, the expert receives an explanation of the solutions obtained from the thermomechanical behavior, i.e., the dynamics of the polymer flow and the temperature profiles, primarily during the cooling phase (the most extended phase), as well as the mathematical differential equations involved, including the energy and momentum equations.

From this perspective, the cooling efficiency increases from 6% to 13%, and the temperature standard deviation converges to lower values (12.30 °C to 12.54 °C) when the distance between channel 1 and the part wall (d_1') is minimal (≈ 8 mm), and the distance between channel 1 and the part border (d_1) is also minimal (≈ 0 mm). The diameter of channel 1 (D_1) is likewise close to its minimum allowed value (≈ 6 mm). This behavior is physically consistent: when the gate is positioned at $gate = 2$, the system must remove heat more rapidly from the injection region, which exhibits the highest temperature.

B. Complete Analysis of the Bi-objective Runs

For the bi-objective problem formulations, Figs. 6 and 7 show the solutions used to train the ANN surrogate and the obtained trade-off fronts, respectively. The varying effect of the gate location can clearly be seen in these plots.

Key observations from Mimer and expert assessment are:

- The trade-off fronts support expert intuition regarding the conflict between the objectives. However, Mimer also discovers tight ranges for some variables in the runs:

Run 2:	$d_1' < 8.047 \wedge d_1 < 0.038$	$(64.00\%, 0.00\%)$
Run 3:	$D_1 > 14.874$	$(74.04\%, 2.28\%)$
Run 4:	$D_1 > 14.937$	$(63.76\%, 7.10\%)$

- Less influential variables show weak or inconsistent contributions, suggesting opportunities for dimensionality reduction in future design studies.
- Several high-support rules constrain combinations of D_1, D_2, d_1, d_2, e.g., upper bounds on ring distances from the cavity and moderate channel diameters, associated with uniform cooling without excessive stress.

Across runs 1 to 4, Mimer's variable-importance scores consistently rank a small subset of geometric variables as the dominant influencing performance, effectively reducing the perceived decision space dimensionality of the problem.

C. Cross-run Patterns and Robustness

By comparing the results of Mimer's analysis across all runs, several robust insights emerge:

1) **Important variables:** A small set of decision variables repeatedly appears in high-support rules that explain all four trade-off sets.
2) **Consistent design rules:** Many rules across different objective formulations share overlapping bounds for $D_1, D_2, d_1,$ and d_2, indicating that (i) channels should stay within defined distance corridors from the part wall, (ii) larger diameters or excessive offsets are systematically associated with dominated solutions. This supports their validity as generalized CCC design principles.
3) **Gate dependence:** The visualization and rules show that one gate configuration tends to dominate the other on the trade-off fronts, reinforcing the coupling between gating and efficient cooling already recognized by the expert.

These findings collectively support the working hypothesis that an interactive knowledge discovery environment like Mimer can (i) reproduce the main insights that an expert would derive from the MOEA results and (ii) articulate them as explicit, reusable, and verifiable design knowledge.

V. Conclusions

This work demonstrates that Mimer effectively supports the interpretation of multi-objective optimization results for conformal cooling design. Across four bi-objective runs, Mimer consistently identified the most influential variables, generated clear design rules, and aligned well with expert reasoning, while also uncovering additional patterns. These results confirm its value as a semi-automatic analytical tool that enhances transparency and facilitates informed decision-making in injection molding optimization. Future work will extend this approach to many-objective problems and explore how extracted rules can guide the setup and design-space reduction of MOEAs.

Acknowledgements

The authors acknowledge funding from FEDER (COMPETE 2020) and FCT under projects UID-B/05256/2020 and UID-P/05256/2020, as well as "Agendas para a Inovação Empresarial" (PRR/49/INOV.AM/EE), supported by the RRP and Next Generation EU. The last author acknowledges the financial support received from KK-Stiftelsen (The Knowledge Foundation, Stockholm, Sweden) through the research profile VF-KDO: Virtual factories with knowledge-driven optimization at the University of Skövde (2018-0011).

Part of this work was conducted by the first author as a Visiting Professor at University of Skövde, Sweden during a short-term scientific mission. This mission was funded by COST Action CA22137 "Randomised Optimisation Algorithms Research Network" (ROAR-NET), supported by COST (European Cooperation in Science and Technology).

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