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Data-Driven Multi-Objective Optimization of Conformal Cooling Channels for Energy-Efficient Injection Molding

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Abstract

Injection molding is widely used for plastic parts, but its performance is limited by the cooling stage, which dominates cycle time and affects dimensional stability and energy consumption. Conformal cooling channels, which can be manufactured using additive technologies, improve thermal efficiency but introduce a high-dimensional design problem. This work proposes an integrated methodology for optimizing injection molds with conformal cooling channels that combines parametric CAD (Computer-Aided Drawing), simulation, non-linear principal component analysis, artificial neural network, and multi-objective evolutionary optimization. The workflow is applied to a case study with five cooling layouts. An initial set of 36 metrics related to temperature gradients, warpage, shrinkage, and energy is reduced to a small number of latent objectives, simplifying the search space while preserving the main physical trends. Artificial neural networks surrogates accurately reproduce numerical results, enabling exploration of the design space at a fraction of the computational cost. The optimization yields diverse Pareto-optimal solutions that balance cycle time, dimensional stability, and energy consumption, assisting the design of more sustainable injection molds. Sensitivity analysis identifies mold temperature and channel position/diameter as key design levers. The proposed methodology reduces dependence on expensive simulations and is readily transferable to industrial mold design.

Keywords: injection molding; conformal cooling channels; objectives selection; surrogate models; multi-objective optimization

MSC: 68T01; 68T07



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1. Introduction

Injection molding is a dominant manufacturing process for producing polymer parts (and, through Metal Injection Molding (MIM), small complex metal components), widely used in sectors such as automotive, electronics, packaging, and consumer goods, due to its high productivity, precision, and ability to produce complex geometries with excellent repeatability. The overall performance of the process, however, is strongly conditioned by the cooling stage, which typically accounts for more than 50% of the total cycle time and has a critical impact on dimensional stability, residual stresses, shrinkage, and energy consumption [1–3]. Non-uniform heat extraction leads to heterogeneous solidification, warpage, and internal defects, often requiring conservative processing conditions and longer cycles to ensure quality.

Besides processing parameters, the mold is a decisive element for thermal control and defect mitigation; complementary strategies such as nozzle heating, hot-runner systems,

and local inserts are often used to stabilize melt delivery and improve part quality. Cooling-rate non-uniformity generates temperature gradients that promote residual stresses and warpage, and the magnitude of these effects depends on material thermophysical properties and part thickness distribution.

Conventional cooling systems are typically manufactured through drilling and milling operations, restricting channels to straight or smoothly curved paths that cannot closely follow part geometry. This limitation often creates hot spots and steep temperature gradients, particularly in regions with variable thickness or complex features. Conformal cooling channels (CCCs) overcome these drawbacks by following the part's contour, enabling placement closer to critical areas and a more uniform temperature distribution. Several studies have shown that CCCs can reduce the cycle time while improving dimensional quality, with reported reductions in several tens of percent under favorable conditions [1,4]. The increasing availability of metal additive manufacturing (AM) has made CCC feasible, enabling intricate three-dimensional geometries and additional mold functionalities [3,5,6].

Despite these advantages, CCC design remains challenging. The problem is intrinsically multi-objective and high-dimensional, combining geometric variables (e.g., channel diameter, spacing, distance to the cavity surface, topology) with processing variables (melt and mold temperatures, injection velocity, packing pressure and time, and cooling time). AM also introduces constraints on minimum feature size, projections, powder removal, and mold structural integrity. Designers must balance conflicting targets such as cycle time, temperature uniformity, warpage, residual stress, and energy consumption while ensuring manufacturability [3–5]. Classical trial-and-error or single-objective approaches are insufficient to explore this design space.

Simulation-based optimization, supported by three-dimensional injection-molding software, provides a systematic approach to addressing this problem. However, directly coupling high-fidelity simulations with multi-objective evolutionary algorithms (MOEAs) can be computationally prohibitive when many variables and performance indicators are considered. This difficulty is well-documented in injection molding and extrusion, where MOEAs such as NSGA-II have been applied to optimize processing conditions and conventional cooling layouts [5]. Surrogate models provide an attractive alternative: once trained on a suitably designed set of simulations, they can replace expensive evaluations during optimization, reducing cost while preserving the richness of the Pareto solutions.

A further complication arises from the objective space. In injection molding, quality and performance indicators are often strongly correlated; different measures of warpage, temperature non-uniformity, and residual stresses may convey similar information. Treating them as independent objectives can produce redundant search directions, unnecessarily complex Pareto fronts, and difficulties in interpretation and decision-making. Linear Principal Component Analysis (PCA) has been used to select objectives or construct composite quality indices, but the relationships among objectives are frequently non-linear. In this context, Nonlinear PCA (NL-PCA) provides a more flexible method for extracting latent variables that capture the dominant variability of the original objectives [7].

Recent studies increasingly combine simulation, machine learning, and optimization to enhance injection-molding quality and efficiency, including ML-aided CCC design and AI-driven energy-oriented process optimization [4].

To address these challenges, we implement a surrogate-assisted multi-objective optimization workflow combining NL-PCA, artificial neural network (ANN) metamodels, and a state-of-the-art MOEA. First, NL-PCA is applied to the original performance indicators to identify a compact set of latent objectives, reducing redundancy and simplifying the objective space. Second, ANN models are trained to map design variables, CCC geometric parameters, and process conditions onto these latent objectives, enabling rapid predictions

that replace time-consuming simulations during optimization. Finally, NSGA-III [8] is employed to identify a diverse set of Pareto-optimal solutions in the reduced objective space, ensuring a good spread of trade-offs among productivity, quality, and energy-related metrics while preserving convergence properties.

Simultaneously, the use of multiple objectives supports the development of molds that contribute to sustainability in injection molding. Minimizing cycle time, defects, and energy consumption contributes decisively to this desideratum.

Within this framework, the primary objective of the present work is to design molds incorporating CCCs for sustainable injection-molding. For that, the secondary objectives are (i) to apply and extend an existing optimization methodology to different processing conditions and CCC configurations, evaluating its robustness under distinct thermal and mechanical scenarios; (ii) to validate ANN-based metamodels for the considered case study, assessing accuracy and generalization across the design space; (iii) to demonstrate, through an industrially relevant example, that the methodology can generate CCC designs that improve cycle time, dimensional quality, and energy consumption while respecting AM constraints; and (iv) to discuss tool integration and workflow automation, strengthening the connection between CAD/CAE environments, data-driven modeling, and multi-objective optimization in industrial practice. In this way, the work provides a unified framework for jointly optimizing CCC geometry and injection molding processing conditions, with guidelines extendable to other polymer processing operations.

The main contributions of this work are as follows. First, a systematically integrated framework combining dimensionality reduction (NL-PCA), surrogate modeling (ANNs), and many-objective evolutionary optimization (NSGA-III) for simultaneous CCC geometry and processing-condition design; based on a previous revision made by the authors [4], this combination has not yet been explored in a unified manner for CCC design. Second, it provides an analysis of the injection-molding objective space with CCCs, clarifying how correlated quality indices and energy-related metrics can be mapped onto a small number of latent objectives, facilitating both search and post-optimization decisions. Third, the study quantifies benefits in cycle time reduction, dimensional quality, and energy consumption relative to baseline conventional cooling layouts, generating Pareto-optimal solutions that can serve as benchmarks for future research in sustainable mold design. Finally, by discussing implementation aspects, sampling strategies, ANN training procedures, and practical handling of AM-related constraints, the work provides methodological guidelines of broad interest for researchers and practitioners at the intersection of digitalization, optimization, and advanced mold manufacturing.

The remainder of the paper is organized as follows. Section 2 presents the relevant background on injection molding and CCC design, summarizing the main concepts underlying the proposed methodology, including NL-PCA, ANN-based surrogates, and NSGA-III. Section 3 describes the case study, the decision variables, the objectives, and the experimental plan used to generate the training and validation data. Section 4 discusses the optimization results, focusing on the structure of the reduced objective space, the quality of the ANN models, and the characteristics of the obtained Pareto fronts. Finally, Section 5 presents the main conclusions and outlines directions for future work.

2. State-of-the-Art

2.1. The IM Process

Figure 1 schematically represents the stages of the injection-molding process: plasticizing, filling, packing, cooling, and ejection. Each stage can significantly influence the final quality of the molded part [1–4,9].

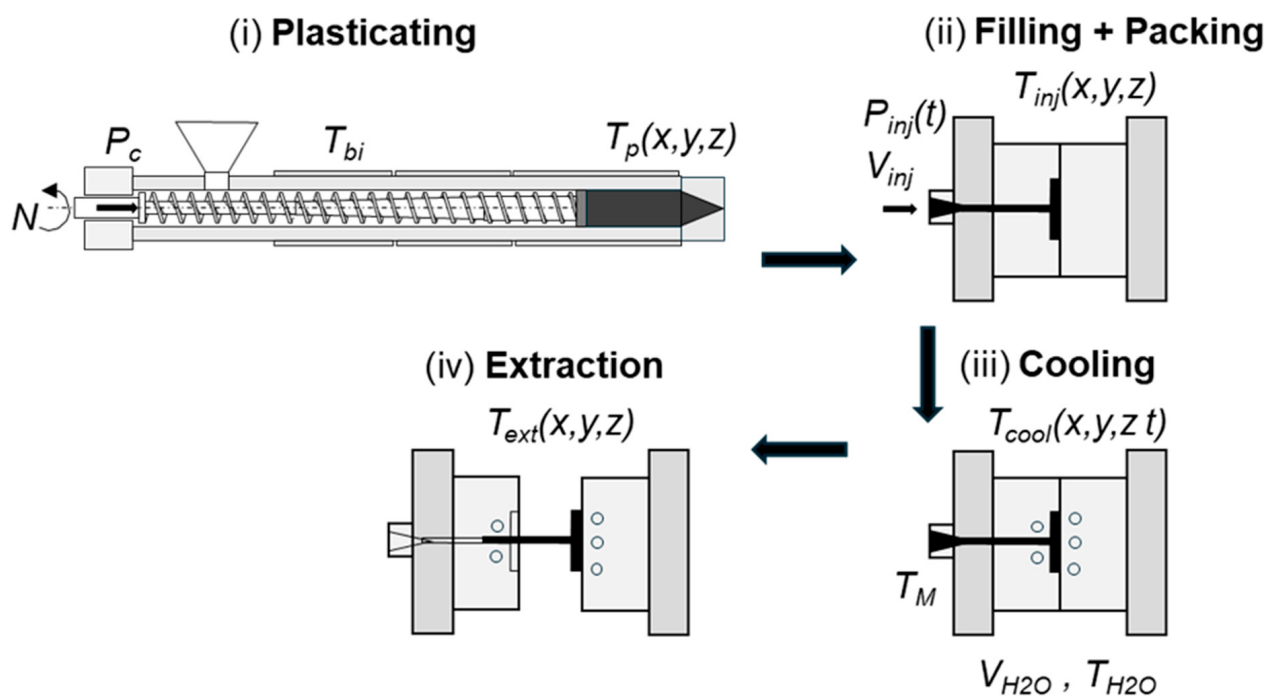


Figure 1. Stages of the injection-molding process.

During plasticizing (i), pellets melt in the barrel. Temperature and screw speed are critical: improper heating can cause poor melting or degradation, while higher screw speed increases shear and improves melt uniformity. These factors control melt flow during injection [1,3]. In the filling phase (ii), the melt enters the mold cavity. Runner and gate design affect flow and pressure loss. Injection pressure and speed must be balanced, since too fast or too slow filling can cause defects. Melt temperature again controls viscosity. During packing (iii), pressure is applied to offset shrinkage. Packing time and pressure ensure full cavity filling, while mold temperature controls solidification and internal stresses. During cooling (iv), the polymer solidifies in the mold. Mold and coolant temperatures control heat transfer, while cooling time must be balanced to avoid deformation or long cycles. In the ejection phase (v), the part is removed after sufficient solidification. Proper draft angles and surface finish help ensure smooth ejection [1,3].

Overall, process optimization and an efficient cooling system are essential for minimizing cycle time and ensuring part quality, with mold design as a key determinant [3].

2.2. Process Optimization

The integration of numerical modeling tools with multi-objective optimization requires dimensionality reduction techniques and metamodels, given the high computational cost of full three-dimensional simulations [10]. As summarized in Figure 2, the optimization loop is driven by a multi-objective evolutionary algorithm (MOEA), which controls candidate generation, evaluation, and evolution. The main phases are (i) population initialization; (ii) evaluation via numerical modeling or metamodels; (iii) fitness calculation; (iv) selection, recombination, and mutation; and (v) creation of a new population, iterated until convergence or a stopping criterion is met [11].

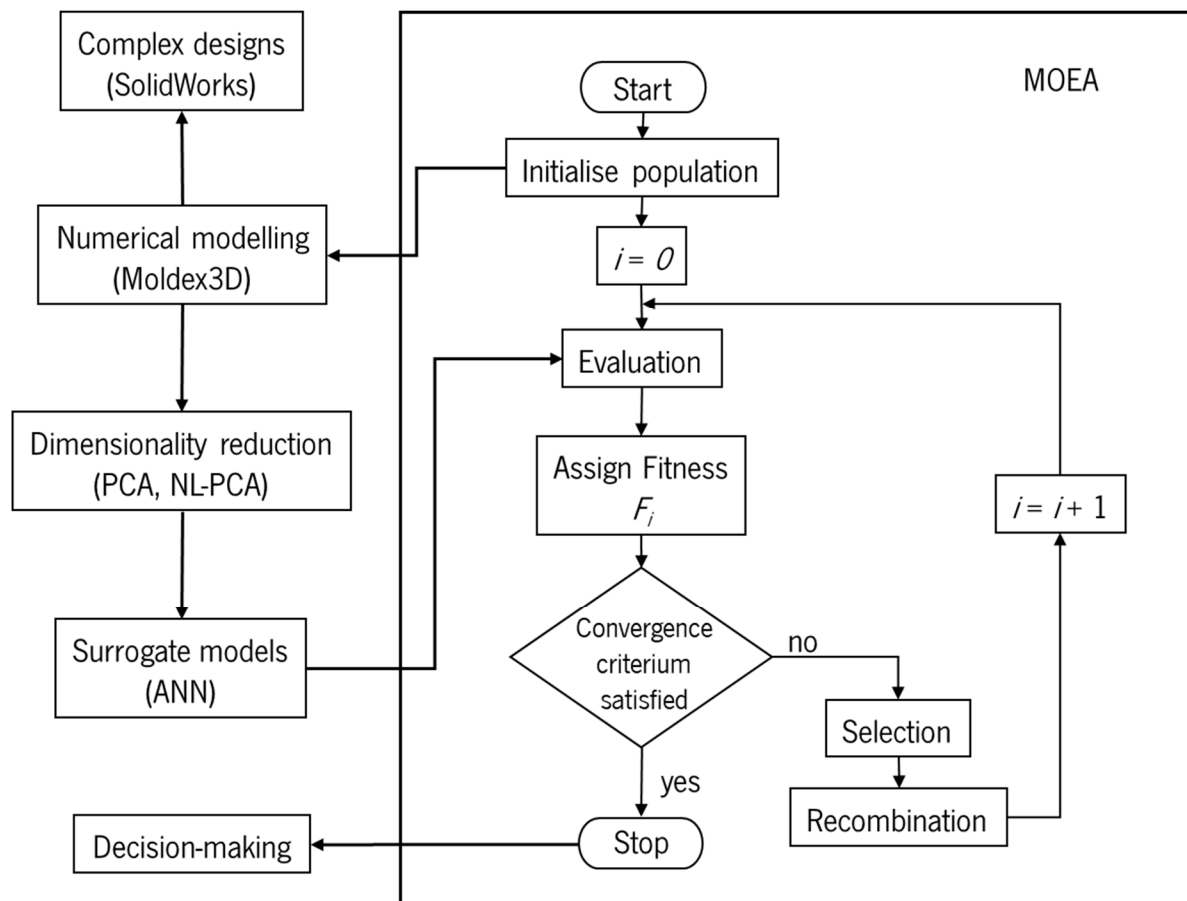


Figure 2. Workflow methodology.

In the present work, the proposed methodology combines numerical simulation, artificial intelligence, and MOEAs in a structured workflow (Figure 2):

- (i) Generation of parameterized geometries: automatic creation of mold and CCC configurations using Python scripts and, when required, the SolidWorks 2024 API;
- (ii) Numerical simulation: thermal–mechanical analysis with Moldex3D 2023, obtaining information on temperature evolution, cycle time, warpage, and related metrics;
- (iii) Dimensionality reduction: application of NL-PCA to retain the most informative objectives, reducing redundancy;
- (iv) Metamodel development using ANNs: training ANN-based surrogate models to emulate simulations and provide fast predictions;
- (v) Multi-objective optimization with MOEAs: use of evolutionary algorithms (e.g., NSGA-II and NSGA-III) to explore the design space and construct Pareto fronts [11,12];
- (vi) Analysis and selection of solutions: post-processing of the Pareto set, selection of representative solutions, and experimental or detailed numerical validation.

Candidate generation starts with Python 3.12.4 scripts that define decision variables, including CCC geometry, processing conditions, and, when needed, feeding-system parameters. Python supports systematic sampling and communication with SolidWorks, where parameterized 3D geometries are automatically generated via the API. This automation enables the exploration of many CCC designs while respecting design and AM constraints. The geometries are then analyzed in Moldex3D.

Moldex3D predicts thermal and mechanical behavior during injection molding, providing results such as filling, pressure, temperature, shrinkage, and warpage. These

outputs help identify defects and define optimization objectives, but they typically create a high-dimensional objective space.

To reduce this complexity, objectives are selected using NL-PCA [7,13]. An initial set of 36 metrics is reduced to three or four latent objectives based on eigenvalues and variance retention, preserving the main performance trends. Linear PCA captures only linear correlations, whereas NL-PCA captures non-linear redundancies among objectives, which is relevant in injection molding, where thermal, deformation, and energy-related criteria can be coupled nonlinearly. Therefore, NL-PCA is used here as a more general objective-selection mechanism.

Non-linear PCA (NL-PCA) was implemented using a distance-based approach. After standardizing the objectives (zero mean, unit variance), we compute a pairwise Euclidean dissimilarity matrix for all samples and apply metric multidimensional scaling (MDS; SMACOF optimization) using the precomputed dissimilarities to obtain an unfolded low-dimensional representation that better reflects the non-linear manifold structure. Conventional PCA is then performed on this unfolded representation to obtain principal components, explained-variance ratios, and the corresponding non-linear principal scores. Compared with classical PCA in the original space, this approach can better capture curved manifolds and non-linear correlations among objectives, which are common in injection molding due to interactions among thermal, geometric, and cycle-time variables [7,14].

ANNs are then trained as surrogate models using Moldex3D data, linking design and process variables to the reduced objectives. Once trained, ANNs rapidly predict objective values for new designs, allowing the evaluation of thousands of candidates with low computational cost [15].

MOEAs, such as NSGA-II and NSGA-III, are applied to the surrogate model to identify trade-offs among conflicting objectives [8]. NSGA-II is effective for a few-objective problems, whereas NSGA-III handles many-objective problems using reference points [11,12]. Together with NL-PCA and ANNs, these methods efficiently explore the design space and identify high-performance CCC solutions.

The evolutionary process starts with a diverse population, evaluates individuals using ANN predictions, and applies selection, crossover, and mutation to generate new solutions. This cycle repeats until convergence or a stopping criterion is met [11].

Finally, objectives and decision variables must be clearly distinguished. Objectives measure performance, while decision variables define geometry and processing conditions. The ANN-based mapping between them, combined with NL-PCA, is central to the optimization approach used in Sections 4 and 5.

In Gaspar-Cunha et al. [10], a multi-objective methodology combining PCA-based dimensionality reduction, ANNs, and MOEAs was proposed for CCC design, thereby simplifying the problem and improving thermal efficiency, as demonstrated through numerical and practical case studies. The present work builds on this strategy by adopting NL-PCA, explicitly integrating AM-compatible geometric constraints, and applying the framework to an industrially relevant case study.

2.3. Heat Transfer in Injection Molds

Injection molds work as heat exchangers with shape control: they must (1) fill a cavity with molten polymer, (2) keep the melt pressurized while it packs, and (3) remove heat fast and uniformly so the part solidifies with minimal warpage, sink marks, or residual stresses. From a heat-transfer viewpoint, the cycle time is often dominated by cooling, because the polymer's thermal diffusivity is low compared with steel.

Heat leaves the polymer primarily by conduction to the mold wall, then conducts through the mold steel, and is finally carried away by the coolant via convection within the

cooling channels. At steady conditions, the heat flux through the polymer–mold interface can be approximated by Fourier’s law:

$$q'' = -k \frac{\partial T}{\partial n} \quad (1)$$

where q'' is the heat flux (heat flow per unit area), $\partial T / \partial n$ is the temperature gradient in the normal direction, and n is the coordinate measured along the outward normal direction (not the vector $\mathbf{n}$). This equation explains two practical mold rules: increase the temperature gradient (coolant colder than the part) and reduce the thermal conduction path (place channels closer to the cavity) to enhance heat removal [16].

In real molds, the cooling problem is a thermal-resistance network. A simple 1D approximation is [17]

$$q = \frac{\Delta T}{R_{\text{poly}} + R_{\text{contact}} + R_{\text{steel}} + R_{\text{conv}}} \quad (2)$$

with $R_{\text{conv}} = 1/(hA)$, where h is the convective heat-transfer coefficient between the wall and the coolant, A is the area, q is the heat-transfer rate, ΔT is the driving temperature difference across the whole path, R_{poly} is the resistance to heat conduction through the polymer layer between the hot core of the melt and the cavity surface, R_{contact} is the l interfacial resistance at the polymer–mold wall due to imperfect contact, gaps, or an air layer, R_{steel} is the resistance to heat conduction through the mold steel from the cavity surface to the cooling-channel wall, and R_{conv} is the convective heat-transfer resistance from the channel wall to the coolant. Higher coolant flow rate and turbulent flow raise h , lowering R_{conv} . Good surface contact and proper clamping reduce R_{contact} .

Uniform cooling is as important as fast cooling: if one region cools more slowly, it shrinks later and pulls the part, causing warpage. That is why cooling layout (channel spacing, depth, baffles, conformal channels) and mold temperature control are central to mold design.

In Moldex3D, mold cooling is modeled by solving the transient heat-conduction equation in the polymer and mold inserts and coupling it with convection boundary conditions on cooling-channel walls, typically written as [18]

$$-k \nabla T \cdot \mathbf{n} = h (T_{\text{wall}} - T_{\text{cool}}) \quad (3)$$

where T is the temperature field (depends on position and time), ∇T is the temperature gradient vector, $\mathbf{n}$ is the outward unit normal vector at the boundary (cooling-channel wall), $\nabla T \cdot \mathbf{n}$ is the normal temperature gradient at the wall, $(-k \nabla T \cdot \mathbf{n})$ is the conductive heat flux leaving the solid through the wall, T_{wall} is the temperature of the channel wall surface, and T_{cool} is the bulk (mean) coolant temperature.

The resulting temperature field $T(\mathbf{x}, t)$ feeds the flow/packing analysis through temperature-dependent viscosity and solidification, while the local heat flux follows Fourier’s law, enabling prediction of cooling time, non-uniform shrinkage, and warpage.

3. Case Study

All simulations were performed using virgin material properties from the Moldex3D material database to ensure consistent rheological and thermophysical inputs; the effect of recycled-content variability is outside the scope of this study.

3.1. Decision Variables

As noted above, the decision variables to be optimized fall into two categories: processing conditions and CCC geometry. Figure 3 shows the geometry of the plastic part

to be studied, a cup, and illustrates the five different CCCs system designs, including conventional channels, circular ring channels (with 2–3 rings), spiral channels (with the number of turns defined by the user), and zigzag channels. Table 1 presents the geometric parameters to be optimized, as identified in Figure 3, along with their corresponding ranges of variation.

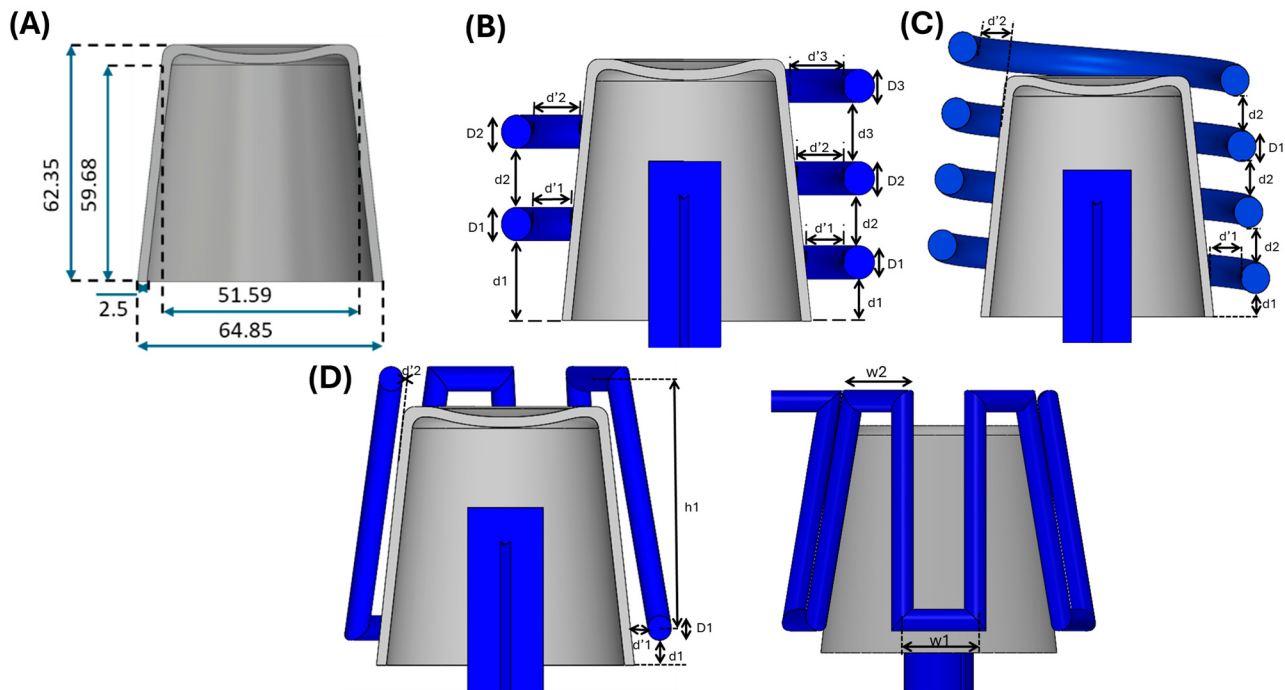


Figure 3. System to be optimized: (A) part geometry; (B) CCC system parameters for conventional and two rings (left) and three rings (right); (C) CCC system parameters for spiral; and (D) CCC system parameters for zigzag.

Table 1. Decision variables and their range of variation for the CCC geometries considered (the meaning of the decision variables is identified in Figure 3).

Decision Variables	Conventional Channels (mm)	2 Rings (mm)	3 Rings (mm)	Spiral (mm)	Zigzag (mm)
d1	[8, 25]	[8, 25]	[8, 10]	[8, 25]	[8, 25]
d2	[8, 20]	[8, 20]	[8, 20]	[8, 20]	-
d3	-	-	[8, 20]	-	-
d_1	[8, 20]	[8, 20]	[8, 20]	[8, 20]	[8, 20]
d_2	[8, 20]	[8, 20]	[8, 20]	[8, 20]	[8, 20]
d_3	-	-	[8, 20]	-	-
D1	[6, 15]	[6, 15]	[6, 12]	[6, 12]	[6, 15]
D2	[6, 15]	[6, 15]	[6, 12]	-	-
D3	-	-	[6, 12]	-	-
h1	-	-	-	-	[30, 50]
w1	-	-	-	-	[15, 30]
w2	-	-	-	-	[15, 30]

The total length of the CCC is not a key factor in its design and operation. As already stressed in the introduction, the aims are more closely related to cooling efficiency and effectiveness: the energy required and the uniformity of cooling to avoid defects, respectively. Thus, it does not affect the operation of the cooling system. Also, this length may be important for conventional channels due to manufacturing constraints, but it is not for CCCs, which are manufactured via AM. The lengths of 2 rings, 3 rings, spiral, and zigzag are approximately 610, 920, 700, and 930 mm, respectively, which corroborate our hypothesis, since the better results are not for the zigzag geometry, which has the longest length.

The processing conditions to be optimized are presented in Table 2, and Table 3 outlines the other processing conditions considered in the numerical modeling that are held constant. The switch-over from volume to pressure is represented by the 98% threshold and the cooling-fluid temperature.

Table 2. Processing conditions to be optimized.

Parameter	Designation	Range	Units
Injection pressure	PiMax	[120, 160]	MPa
Packing pressure	PpMax	[120, 160]	MPa
Melt temperature	Tmelt	[220, 260]	°C
Mold temperature	Tmold	[30, 50]	°C

Table 3. Unmodified processing conditions.

Parameter	Designation	Reference Value	Units
Injection time	tfill	1.13	s
Packing time	tpack	7.09	s
Switch-over from volume to pressure	vpswit	98	%
Volumetric flow rate of the cooling system	Qcoolt	120	cm ³ ·s ^{−1}
Cooling fluid temperature	Tcoolt	Tmold	°C
Ambient temperature	Tair	25	°C
Ejection temperature	Teje	115	°C
Cooling time	tcool	16.5	s
Mold opening time	tmopen	5	s

3.2. Objectives to Be Optimized

To capture the complex variations arising from changes to the cooling system, the objectives were organized into six categories to optimize thermal performance and minimize defects. Table 4 summarizes the objectives considered. All these objectives are evaluated using Moldex3D numerical modeling software. These objectives are selected to validate the methodology in a real-world environment, where it is not possible to determine in advance the objectives necessary for the specific problem under study. In some cases, they appear redundant, but our experience indicates that selecting performance measures for complex problems is not straightforward.

Table 4. Objectives considered.

	Name	Description
Temperature profiles	aDTsm	Average temperature difference between the inner and outer surfaces and the core
	sDTsm	Standard deviation of aDTsm
	aDTsmH	Average temperature difference between the inner and outer surfaces and the core for the 20% of points with the highest temperature
	sDTsmH	Standard deviation of aDTsmH
	aDTms	Average temperature difference between the core and the outer surface
	sDTms	Standard deviation of aDTms
	aDTmsH	Average temperature difference between the core and the outer surface for the 20% of points with the highest temperature
	sDTmsH	Standard deviation of aDTmsH
	aDTss	Average temperature difference between the outer and inner surfaces
	sDTss	Standard deviation of aDTss
	aDTssH	Average temperature difference between the outer and inner surfaces for the 20% of points with the highest temperature
	sDTssH	Standard deviation of aDTssH
Warpage	maxWaT	Maximum total warpage
	maxWaX	Maximum warpage in the X direction
	maxWaY	Maximum warpage in the Y direction
	maxWaZ	Maximum warpage in the Z direction
	minWaT	Minimum total warpage
	minWaX	Minimum warpage in the X direction
	minWaY	Minimum warpage in the Y direction
	minWaZ	Minimum warpage in the Z direction
Shrinkage	maxSrT	Maximum total shrinkage
	maxSrX	Maximum shrinkage in the X direction
	maxSrY	Maximum shrinkage in the Y direction
	maxSrZ	Maximum shrinkage in the Z direction
	minSrT	Minimum total shrinkage
	minSrX	Minimum shrinkage in the X direction
	minSrY	Minimum shrinkage in the Y direction
	minSrZ	Minimum shrinkage in the Z direction
Time	tcycle	Minimum cycle time predicted by Moldex3D Studio in which all regions of the part reach the ejection temperature
Density, thermal efficiency	sdDens	Standard deviation of density
	coolef	Difference in heat flux transfer between the baffle cooling system and the cavity cooling systems
Von Mises stresses	maxVMS	Maximum Von Mises stress
	aVMS	Average Von Mises stress
	sdVMS	Standard deviation of Von Mises stress
Energy	energconsumpt	Process energy consumption
	deltaenerg	Thermal energy balance

- (A) Temperature profile-based objectives: Temperature gradients within molded parts have a significant impact on the final product quality. To control these gradients, objectives were established based on temperature variations across the part thickness:
 1. Surface–Core Variations: Measure the average and standard deviation of temperature differences between the surface and the core of the part.
 2. Surface–Surface Variations: Analyze the temperature difference between opposite surfaces.
 3. Core–Opposite Surface Variations: Evaluate temperature differences through the core and between opposite surfaces. These objectives, measured at the end of the cooling phase, ensure uniform cooling, reducing the risk of residual stresses and warpage. Furthermore, by focusing the analysis on the 20% of regions with the highest thermal gradients, the optimization targets the most critical areas, improving the overall cooling performance.
- (B) Defect-based objectives: Minimizing defects is essential to ensure final product quality. Sixteen objectives were defined to assess the following phenomena:
 1. Warpage: Determination of maximum and minimum displacements along the X, Y, and Z axes, as well as total deformation.
 2. Volumetric Shrinkage: Evaluation of part shrinkage, expressed as the percentage variation in linear dimensions along the X, Y, and Z axes (linear shrinkage is calculated as the percentage difference between the molded part dimension and the nominal mold dimension), as well as total linear shrinkage. The separation between maximum and minimum values enables the identification of asymmetries in deformation. For symmetric parts, this approach ensures consistency and highlights areas that require process adjustments. The analysis of warpage, for instance, enables understanding of the impact of flow direction on deformation and guides improvements in product design.
- (C) Time-related objective: Cycle time has a direct influence on production efficiency:
 1. Cycle Time: Total cycle time calculated by Moldex3D.
- (D) Objectives related to density and thermal efficiency: A uniform density distribution in molded parts is essential to avoid defects such as uneven shrinkage and internal stresses. The density standard deviation was used as a metric to evaluate and minimize variability, ensuring structural integrity and compliance with design specifications. Thermal efficiency objectives focus on the dynamics of heat transfer between the molded parts and the cooling channels. By analyzing efficiency differences across the cooling channels, it is possible to maximize heat removal while maintaining thermal uniformity. This balance improves energy use and reduces cycle times without compromising quality.
- (E) Von Mises stress-based objectives: The mechanical integrity of the parts is assessed using the Von Mises stress metric, which includes the following parameters:
 1. Maximum Stress: Identification of regions with a higher risk of structural failure.
 2. Average Stress: Analysis of the overall material behavior.
 3. Standard Deviation: Evaluation of the uniformity of stress distribution. Reducing stress concentrations improves part durability and prevents structural failure. This comprehensive assessment enables the identification of areas that require reinforcement in the design or adjustments to the manufacturing process, thereby contributing to greater long-term reliability.
- (F) Energy-based objectives: The analysis of energy consumption during the injection-molding process is essential to ensure the sustainability and efficiency of the production process. To this end, two main energy-related objectives were developed:

1. **Total Energy Consumption:** This objective aggregates the different forms of energy used throughout the injection cycle, including plasticization energy (energy required to melt and homogenize the thermoplastic material), viscous dissipation energy (associated with internal friction losses during material flow), hydraulic energy (consumed by the machine's hydraulic systems responsible for mechanical movements such as screw advance, mold closing and opening, and part ejection), and coolant pumping energy (required to circulate the cooling fluid through the channels).
2. **Residual Thermal Energy in the Part:** This objective quantifies the thermal energy that remains accumulated in the part at the end of the cooling phase. The presence of residual thermal energy may indicate insufficient or uneven cooling, increasing the risk of warpage, internal stresses, and dimensional defects. Its minimization improves the part's dimensional stability and optimizes cycle time without compromising final product quality.

3.3. Experimental Plan

To evaluate and optimize the thermal performance of different conformal cooling channel (CCC) geometries and ensure the robustness of the proposed solutions, the experimental plan was structured into two distinct studies, as shown in Table 5.

Table 5. Experimental plan (OC—operating conditions; and CC—cooling channels).

Study	Description	Number of DVs
1st study	Conventional cooling channels (OC + CC)	10
	2 rings (OC + CC)	10
	3 rings (OC + CC)	13
	Spiral (OC + CC)	9
	Zigzag (OC + CC)	11
2nd study	2 rings (CC)	6
	2 rings (OC + CC: $T_{\text{mold}} = \text{constant}$)	9
	2 rings (CC: $d_i = \text{constant}$, $d_o = \text{constant}$)	4
	2 rings (CC: $D_i = \text{constant}$)	2
	2 rings (OC + CC: spiral vs. baffle)	10

The first study aims to compare the performance of conventional channels with different CCC geometries for the same objectives, and decision variables, i.e., operating conditions (OC), and cooling channel (CC) geometry and location. For that, the potential of CCC solutions is evaluated by evaluating critical objectives, including thermal efficiency, part quality, and cycle time, and ultimately selecting the best-performing solutions from the most promising geometry.

The second study focuses on evaluating the impact of optimizing certain decision variables on the injection process performance of the two-ring geometry by optimizing (i) the CC location and geometry; (ii) the OC and CC with mold temperature constant; (iii) the CC with d_i and d_o constant; (iv) the CC with D_i constant; and (v) OC and CC by changing the baffle by a spiral in the fix part of the mold. This study allowed us to assess the influence of the variables that were changed.

An ANN surrogate model was built using the selected objectives and 200 Moldex3D initial solutions randomly generated in the search space. The dataset size (200) was selected based on prior testing by the authors: smaller designs (e.g., 60 and 160 solutions) did not capture the design-space complexity well enough, resulting in weaker generalization and less stable predictions.

To tune the ANN, Bayesian optimization was performed with 5-fold cross-validation using the Tree-structured Parzen Estimator (TPE) implemented in Hyperopt [19]. Com-

pared with grid or random search, this approach typically reaches better configurations with fewer trials and improves robustness. The search was run for 1000 evaluations, and the hyperparameter set with the lowest cross-validated loss was selected. Model training used mean squared error (MSE) as the loss function. Overfitting was mitigated through early stopping and regularization, improving the surrogate model's generalization across the design space. The hyperparameters used for training are number of hidden layers, number of neurons, dropout rate, activation functions, optimizers, number of epochs, batch size, and learning rate.

4. Results and Discussion

4.1. A Simple Practical Example

To provide a more precise understanding, the overall methodology is explained below using a simple example of optimizing two-ring circular cooling channels for four objectives. All results reported in Table 5 are presented in this section and in the Data Repository [20].

4.1.1. NL-PCA for the Selection of Objectives

As previously mentioned, dimensionality reduction (i.e., reduction in the number of objectives) was performed using NL-PCA based on numerical modeling data. Table 6 presents the results obtained when the selected objectives are 4 and 3. In both cases, the explained variance was 95%.

Table 6. NL-PCA results for two-ring circular channels.

3 objectives	sdVMS	sDTms	energconsumpt	
4 objectives	sdVMS	sDTms	energconsumpt	maxWaT

4.1.2. ANN Model Performance

Figure 4 compares predicted and observed values and summarizes the model error. For this case, the training NMAE (normalized mean absolute error) was 0.0243. For the remaining cases, the NMAE values fall within the interval [0.0151, 0.0318]. In all cases, cross-validation is made, with the dataset being split into training and validation subsets. However, the final optimization results must be analyzed with care, since as the population of solutions approaches the Pareto front, the ANN accuracy can decrease. In Section 4, the differences between ANN and Moldex3D values on the Pareto front are compared.

NMAE is defined as the mean absolute difference between predicted and measured values, normalized by the range of each variable. This yields a dimensionless metric that enables direct comparison across objectives with different scales. As shown in Figure 4, the error is low, with most points clustering near the 1:1 (diagonal) line, indicating strong agreement between predictions and observations.

4.1.3. Multi-Objective Optimization Results

Multi-objective optimization was performed using NSGA-III with a population size of 100 and 50 generations. For the case with four NL-PCA-selected objectives (sdVMS, maxWaT, sDTms, and energconsumpt) and two-ring circular channels, Figure 5 shows the Pareto fronts obtained from the 50th generation. Cross markers indicate the initial ANN solutions. The figure also highlights the selected designs and their corresponding channel geometries, providing a physical interpretation of the results.

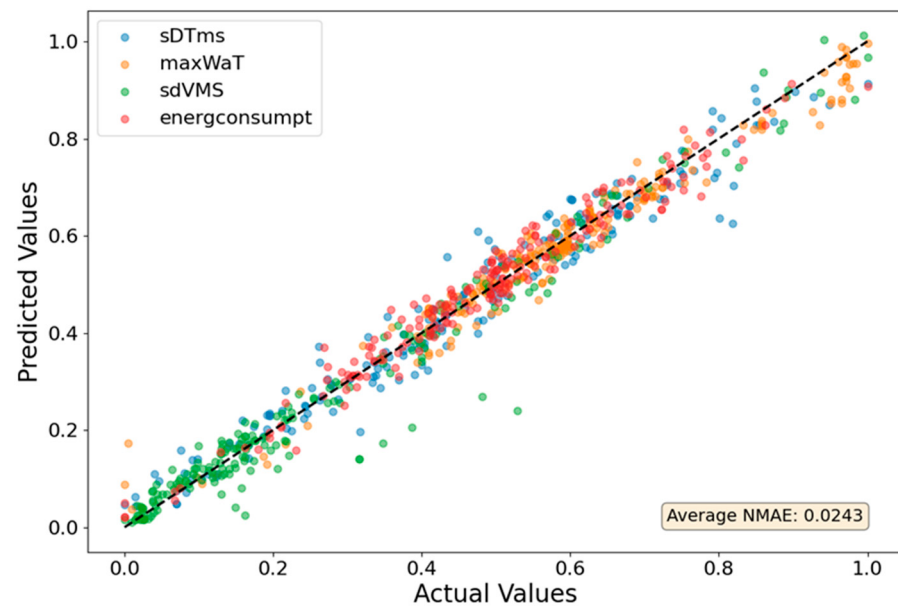


Figure 4. ANN error: predicted vs. actual values.

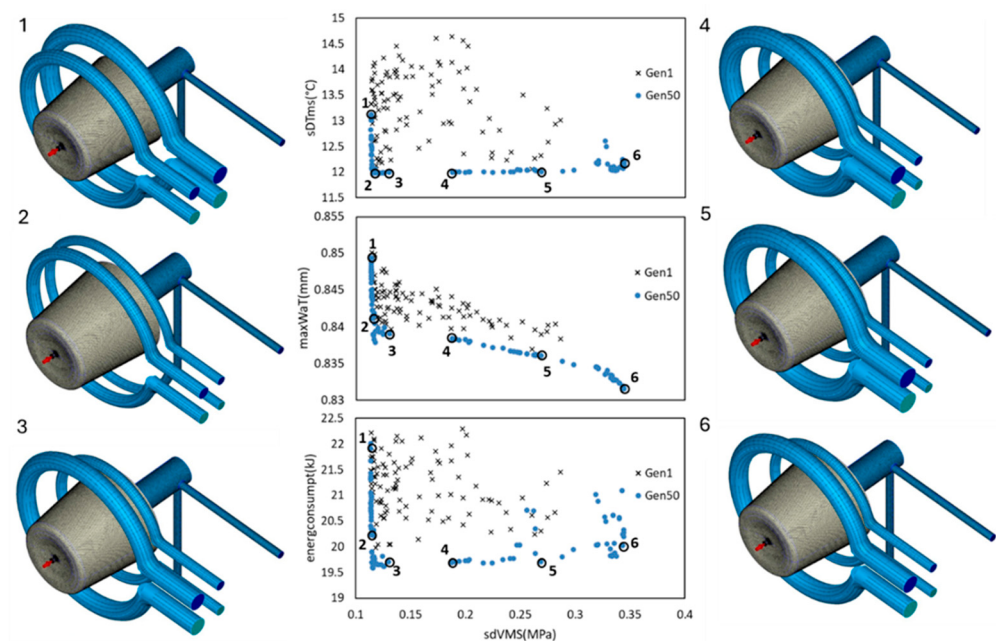


Figure 5. Optimization of two-ring circular channels for four objectives ($sDTms$, $maxWaT$, $sdVMS$, and $energconsumpt$).

Table 7 reports the processing conditions and geometric parameters of the solutions in Figure 5, and Table 8 lists the associated objective values. As all objectives are minimized, preferred solutions lie toward the lower-left of each plot. However, because the objectives conflict, some solutions that appear dominated in one 2D projection remain non-dominated in another. Then, to characterize both trade-off limits and near-ideal compromises, solutions at the curve extremes and representative intermediate points were selected. Table 7 further clarifies how decision variables influence performance.

Table 7. Solutions identified in Figure 5—processing conditions and geometric parameters of the channels.

Solution	d1 (mm)	d2 (mm)	d_1 (mm)	d_2 (mm)	D1 (mm)	D2 (mm)	PiMax (MPa)	PpMax (MPa)	Tmelt (°C)	Tmold (°C)
1	8.2	11.8	19.6	19.9	12.9	9.9	126.2	156.2	255.9	49.9
2	8.1	8.2	19.9	19.9	6.2	8.4	155.7	158.6	220.1	49.8
3	8.4	10.7	8.7	19.4	6.9	12.1	121.4	122.9	220.0	47.9
4	8.2	8.0	8.4	19.9	7.4	13.7	121.4	131.6	220.1	43.2
5	8.2	8.0	8.5	19.8	6.7	14.5	120.2	156.7	220.3	38.8
6	8.0	11.2	8.6	19.9	6.4	12.2	124.5	158.4	220.4	30.1

Table 8. Solutions identified in Figure 5—objective values (EnergyC—energyconsumpt).

Solution	ANN				Moldex3D			
	sdVMS (MPa)	sDTms (°C)	maxWaT (mm)	EC (kJ)	sdVMS (MPa)	sDTms (°C)	maxWaT (mm)	EnergyC (kJ)
1	0.113	13.108	0.849	21.837	0.130	13.172	0.846	21.639
2	0.115	11.990	0.841	20.314	0.181	10.876	0.832	20.899
3	0.130	11.992	0.839	19.704	0.188	10.812	0.829	19.596
4	0.187	11.997	0.838	19.694	0.195	10.951	0.826	19.603
5	0.268	12.005	0.836	19.707	0.208	11.217	0.823	19.670
6	0.343	12.076	0.831	20.022	0.250	11.750	0.816	20.071

The simultaneous analysis of Figure 5 and Tables 7 and 8 indicates that reducing PiMax to approximately 120 MPa is beneficial for the process, as it promotes greater thermal uniformity, reduces the probability of thermal defects, and lowers energy consumption, as observed in solutions 1–6. For PpMax, no consistent trend could be identified. Finally, both reducing Tmelt toward its lower limit and decreasing Tmold result in lower energy consumption, with the mold temperature showing an approximately linear relationship with energy. Regarding the geometric parameters, d1 tends to approach its lower limit, while for d2, no clear conclusion can be drawn. For d_1, approaching the lower limit reduces maxWaT, although this effect is not statistically significant, whereas d_2 tends to approach the upper limit. For the D1 parameter, values near the lower bound are generally associated with reduced energy consumption, provided that D2 approaches its upper bound.

To assess the ANN's ability to calculate objective values as the optimization evolves towards the Pareto front, solutions 1 to 6 were also simulated using Moldex3D. As shown, the differences are not significant and follow the same trend as those obtained with the ANN.

4.2. Optimization of Different Cooling Channel Geometries

4.2.1. Optimization Conditions

In this section, the performance of the conventional channel geometry with various CCC geometries developed is evaluated, i.e., the first study identified in Table 5. For this purpose, critical parameters, including thermal efficiency, part quality, and cycle time, are evaluated, and the best-performing solutions are ultimately selected from the most promising geometries. Tables 9 and 10 present the characteristics and runs for the different types of cooling channels for the objectives selected by the DM and by NL-PCA, respectively.

Table 9. Characteristics of the optimization runs with objectives selected by the DM: cc—conventional channels; 2r—2 circular rings; 3r—3 circular rings; sp—spiral; zz—zigzag.

Run ID	N. Objs.	Objectives	cc	2r	3r	sp	zz
(I)	3	tcycle, maxWaT, energconsumpt	Yes	Yes	Yes	Yes	Yes
(II)	3	tcycle, maxSrT, energconsumpt	Yes	Yes	No	No	No
(III)	3	tcycle, maxWaT, deltaenerg	Yes	Yes	Yes	Yes	Yes
(IV)	3	tcycle, maxSrT, deltaenerg	Yes	Yes	No	No	No
(V)	4	tcycle, maxWaT, maxSrT, energconsumpt	Yes	Yes	Yes	Yes	Yes
(VI)	4	tcycle, maxWaT, maxSrT, deltaenerg	Yes	Yes	No	No	No

Table 10. Characteristics of the optimization runs with objectives selected by NL-PCA: cc—conventional channels; 2r—2 circular rings; 3r—3 circular rings; sp—spiral; zz—zigzag.

Type	3 Objectives: Run ID—(VII)	4 Objectives: Run ID—(VIII)
cc	sDTmsH, aDTss, minSrT	aDTss, tcycle, maxWaT, minSrT
2r	sdVMS, sDTms, energconsumpt	sdVMS, sDTms, energconsumpt, maxWaT
3r	aVMS, minSrZ, maxWaZ	aVMS, minSrZ, maxWaZ, maxVMS
sp	maxSrY, sDTss, aVMS	maxSrY, sDTss, aVMS, sdDens
zz	minWaT, aVMS, energconsumpt	minWaT, aVMS, energconsumpt, sDTssH

Figure 6 presents the Pareto fronts for the conventional channels and all CCC geometries for run I (Table 9). These results will be analyzed together at the end of this section.

4.2.2. Conventional Channels

Before detailing each case, a direct comparison is first provided to highlight the dominant performance trends across geometries and objective-selection configurations. The following subsections then report supporting results for each scenario. Convergence was assessed by tracking standard many-objective indicators (e.g., HV/IGD) over generations, confirming stabilization of the search process.

The analysis of the eight objective sets considered for the different cooling-channel geometries (runs I to VIII, Tables 9 and 10) shows that, at the lower bounds of the objectives, the differences between scenarios are generally small, indicating convergence toward similar optimal solutions regardless of the specific objective combination adopted. Nevertheless, consistent patterns can still be identified, particularly in terms of relative performance between cooling-channel topologies and in the dispersion of solutions, which is influenced by the inclusion or exclusion of specific thermal, deformation, or energy-related objectives.

Figures 6–11 illustrate the Pareto fronts and representative solutions obtained for objective set I (tcycle, maxWaT, and energconsumpt), which was selected as a reference because it captures the main trade-offs between productivity, dimensional stability, and energy efficiency. The remaining objective sets (runs II–VIII) lead to similar qualitative conclusions, as shown in [20] for brevity. Complete optimization results, including Pareto fronts, selected solutions, and corresponding decision-variable values for all objective combinations and cooling geometries, are provided in the Data Repository [20].

For conventional cooling channels the conclusions obtained, regarding the processing conditions, remain consistent with those previously discussed in the application example of the methodology, with no relevant changes observed in the trends associated with the maximum injection pressure or the thermal parameters (Tmold and Tmelt), except that the mold temperature does not exhibit a linear relationship with energy consumption. As for PpMax, it continues to show no conclusive trend. The main divergence relative to the

first topic arises in the analysis of the geometric parameters (d_1 and d_2). Contrary to prior observations, an inversion in the trend of these parameters is identified, indicating different behavior as they approach the admissible bounds. In this case, d_1 tends toward the upper limit, while d_2 tends toward the lower limit.

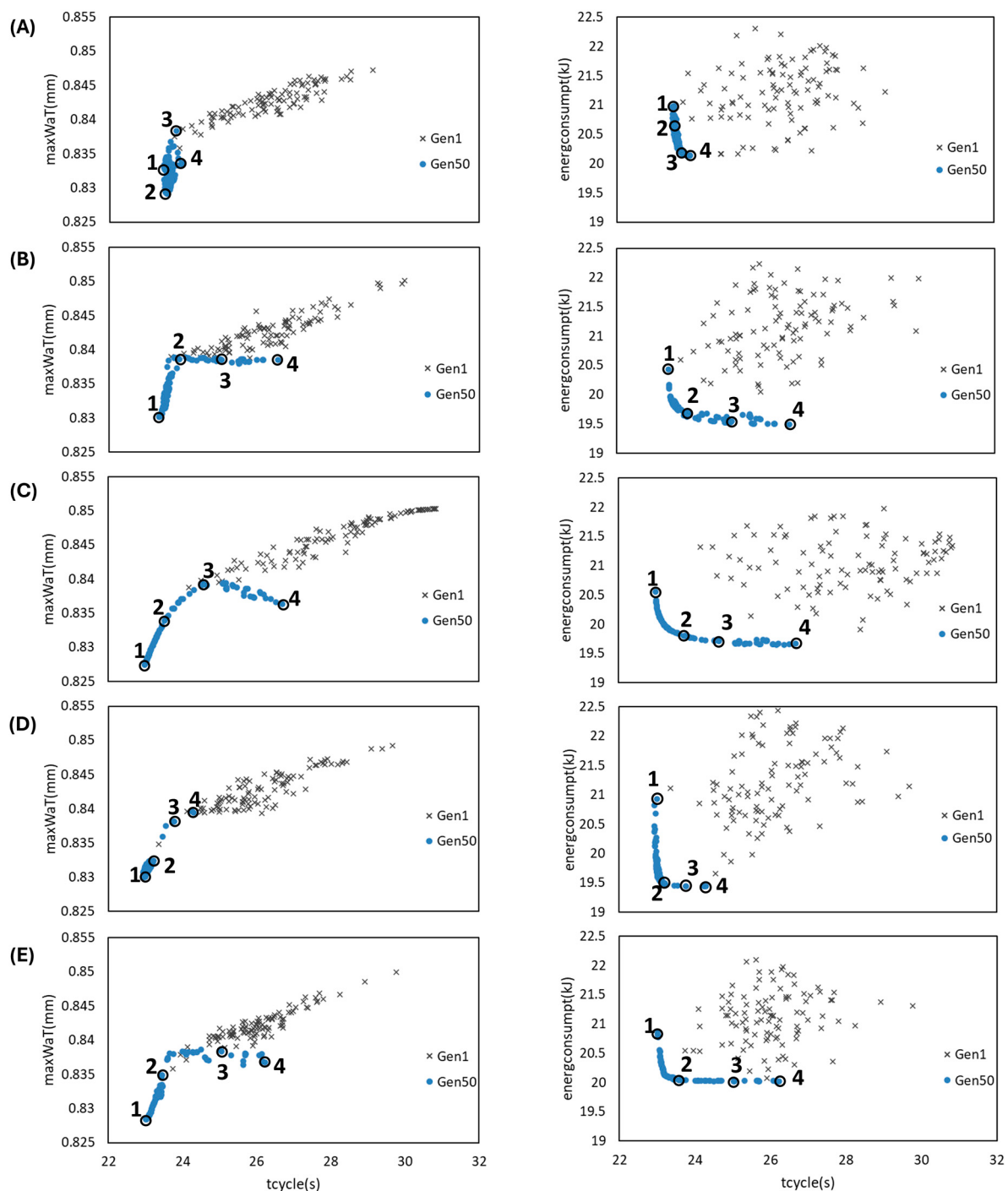


Figure 6. Optimization results using the objective set tcycle , $\max WaT$ and energconsumpt for: (A) conventional channels; (B) 2-rings; (C) 3-rings; (D) spiral channel; (E) zigzag channel.

Across the remaining runs, it was observed that replacing energconsumpt with deltaen-erg or $\max WaT$ with $\max SrT$ mainly affects convergence, but not the best achievable values. In particular, sets including $\max SrT$ showed greater dispersion in tcycle , revealing greater sensitivity of this objective to process variations.

To evaluate solution-set quality beyond visual inspection, we computed standard many-objective performance indicators, including hypervolume (HV) and IGD+, using normalized objectives. HV captures both convergence and diversity, while IGD+ measures proximity to a reference approximation set formed by the union of non-dominated solutions across experiments. For each case, we performed 11 independent NSGA-III runs. Hypervolume was computed using the nadir point as the reference point. For IGD+, the Pareto fronts from all runs (11×5) were combined, and the non-dominated solutions of this combined set were used as the reference approximation to evaluate each run. Accordingly, better performance corresponds to higher HV and lower IGD+. The mean and standard deviation of both indicators are reported in Table 11. Overall, the spiral geometry yields the best results.

Table 11. Comparison of NSGA-III results using Hypervolume and IGD+.

CCC Type	Hypervolume		IGD+	
	Average	STD	Average	STD
Conventional	0.395422	0.001767	0.319176	0.001039
2 rings	0.567118	0.001833	0.158919	0.001515
3 rings	0.703368	0.003152	0.123668	0.002194
Spiral	0.757042	0.001714	0.023854	0.000414
Zigzag	0.537706	0.004174	0.205491	0.002378

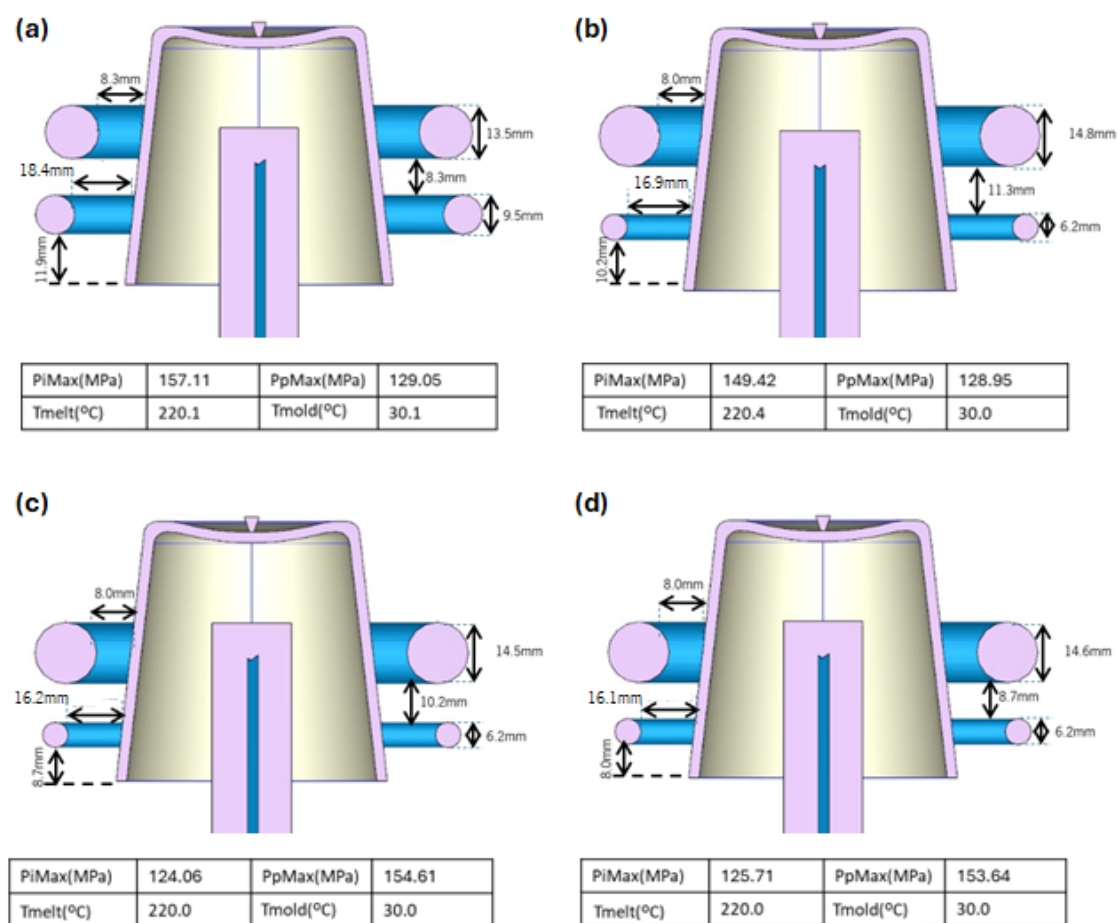


Figure 7. Selected solutions for conventional channels using the following objective set (tcycle, maxWaT, and energy consumption): (a) Solution 1; (b) Solution 2; (c) Solution 3; (d) Solution 4.

4.2.3. Two-Ring Channels

Under the processing conditions used, differences are observed in the results obtained for the 2-ring channels compared with conventional channels. PpMax tends to approach the upper limit without significantly affecting warpage. The remaining processing conditions follow the same trends as those previously obtained for conventional channels. The main divergence from conventional channels is evident in the analysis of the geometric parameters (d_1 and d_2). Unlike previously observed trends, an inversion in this parameter's trend is noted. In this case, d_1 tends toward the upper limit, while d_2 remains inconclusive. The other geometric parameters (D_1 and D_2) exhibit trends similar to those observed in the previous results.

When comparing all runs (I to VI), the 2-ring geometry showed measurable improvements over the conventional design: reduction in maxWaT, lower maximum shrinkage (maxSrT), lower energy consumption, despite t_{cycle} being nearly unchanged. Differences between runs were again slight, although scenarios V and VI showed more evident convergence when ΔE_{eng} replaced $E_{consumpt}$.

In the NL-PCA-selected sets, including maxWaT (in VIII), increased dispersion along sdVMS, highlighting greater sensitivity of the 2-ring geometry to this objective. However, the lower bounds remained similar, indicating that optimal performance is maintained.

Overall, the 2-ring geometry represents an advancement over the conventional design, particularly with respect to dimensional stability and energy efficiency.

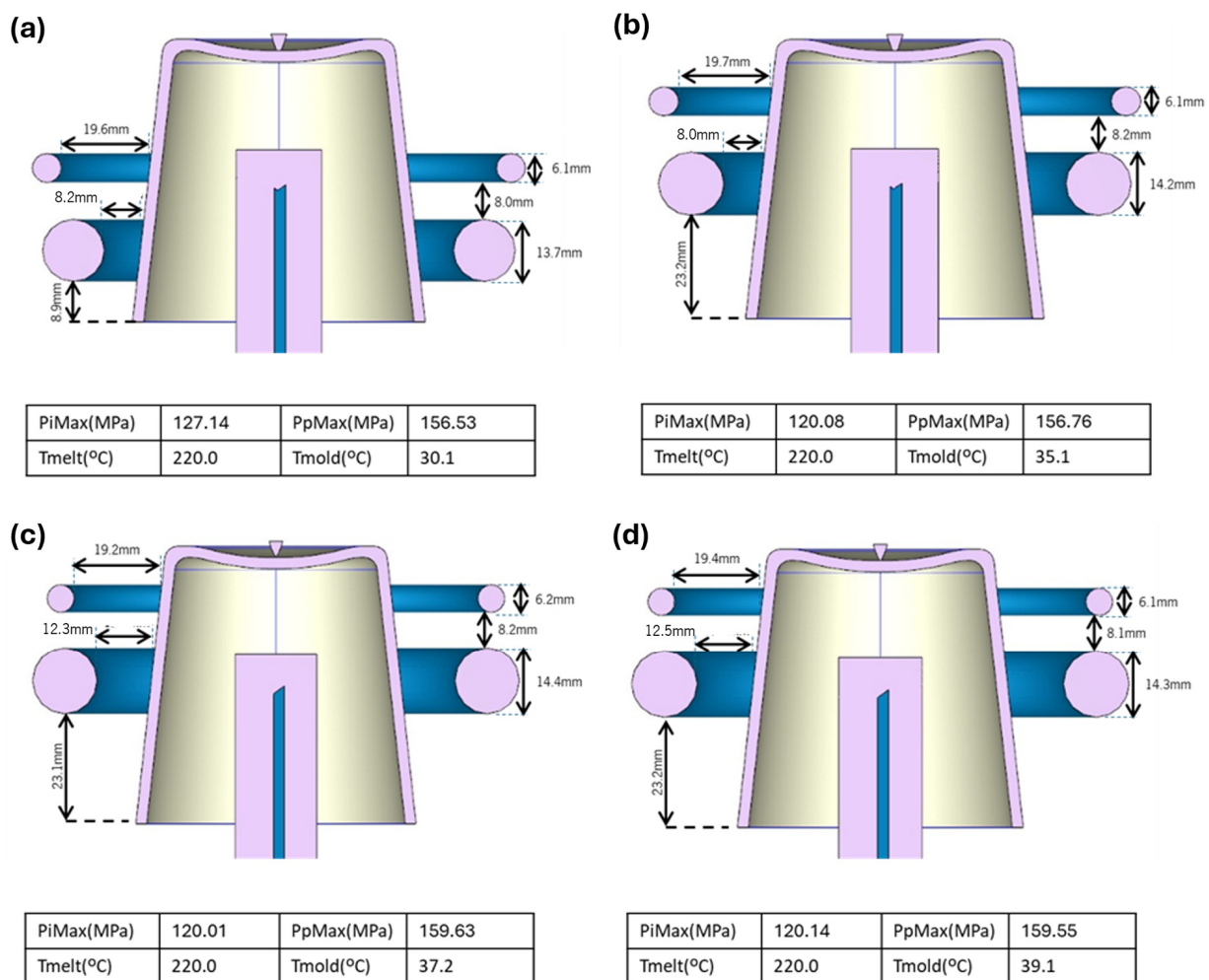


Figure 8. Selected solutions for 2-rings channels for the following objective set (t_{cycle} , maxWaT, and energy consumption): (a) Solution 1; (b) Solution 2; (c) Solution 3; (d) Solution 4.

4.2.4. 3-Ring Channels

For the processing conditions, the conclusions obtained are the same as those for conventional channels. In the analysis of the geometric parameters, the main similarity with conventional channels is observed in d_1 , d_2 , d_{-1} , and d_{-2} ; however, no clear conclusion can be drawn for d_3 , and d_{-3} tends to approach its upper bound. Regarding channel diameters, the trends observed previously are maintained; however, for at least two channels in the selected solutions (D2 and D3), the values approach the upper limit, whereas the third channel (D1) approaches the lower limit.

The three-ring geometry proved to be one of the most consistent throughout the study. Comparing runs I, III, and V, the addition of maxSrT (run V) did not affect energyconsumpt, while replacing it with deltaenerg (run III) resulted in greater convergence, particularly in tcycle. In runs VII and VIII (NL-PCA), including maxVMS significantly increased dispersion, confirming that this objective is strongly correlated with the others and thus validating the automatic selection via NL-PCA. In terms of performance, the 3-ring geometry exhibited lower warpage than the 2-ring design, slightly reduced shrinkage, and maintained low energy consumption. Overall, the 3-ring geometry stood out as one of the most balanced solutions in terms of deformation, cycle time, and energy efficiency.

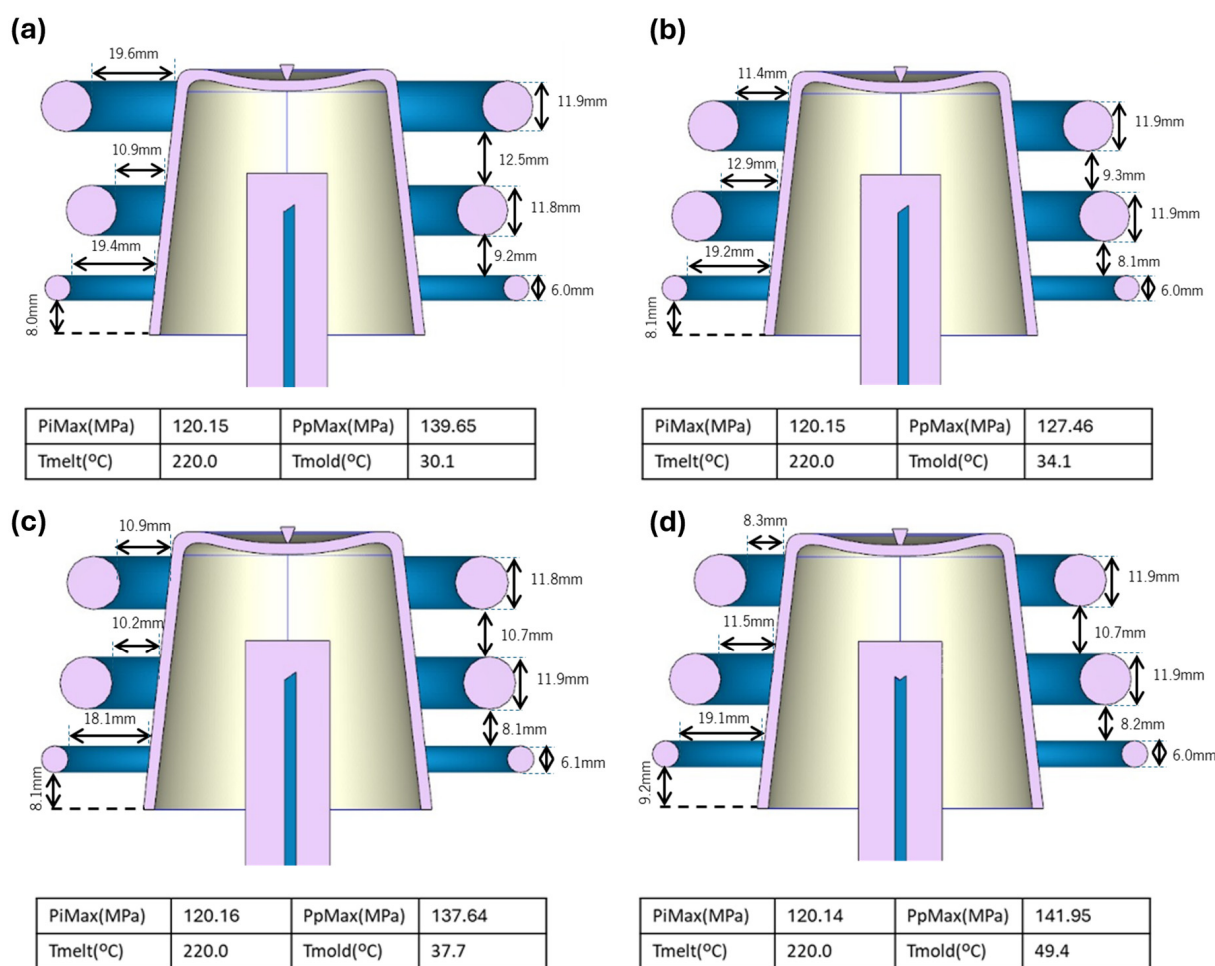


Figure 9. Selected solutions for 3-rings channels for the following objective set (tcycle, maxWaT, and energy consumption): (a) Solution 1; (b) Solution 2; (c) Solution 3; (d) Solution 4.

4.2.5. Optimization of Spiral Channel

The only difference observed in the processing conditions relative to the other geometries is that PpMax tends to approach the lower limit, thereby reducing warpage and other thermal defects. The remaining processing conditions exhibit the same trends as those previously observed. Regarding geometric parameters, d2 and d_2 follow the same logic as in the previous cases, whereas d1 is inconclusive and d_1 approaches the lower limit, which does not occur in the previous geometries. Regarding the channel diameter D1, since there is only one channel, it tends toward the upper limit, thereby reducing process energy consumption.

The spiral geometry showed highly competitive results, with low warpage (maxWaT) comparable to the 3-ring design, controlled shrinkage (maxSrT), and energy and tcycle values very close to those of the other geometries. The most significant differences appeared in the NL-PCA sets: the introduction of sdDens increased dispersion in aVMS, maxSrY, and sDTss, indicating that the spiral is particularly sensitive to density variations. Even so, the spiral maintained stable minimum values, exhibiting robust behavior comparable to that of the 3-ring geometry.

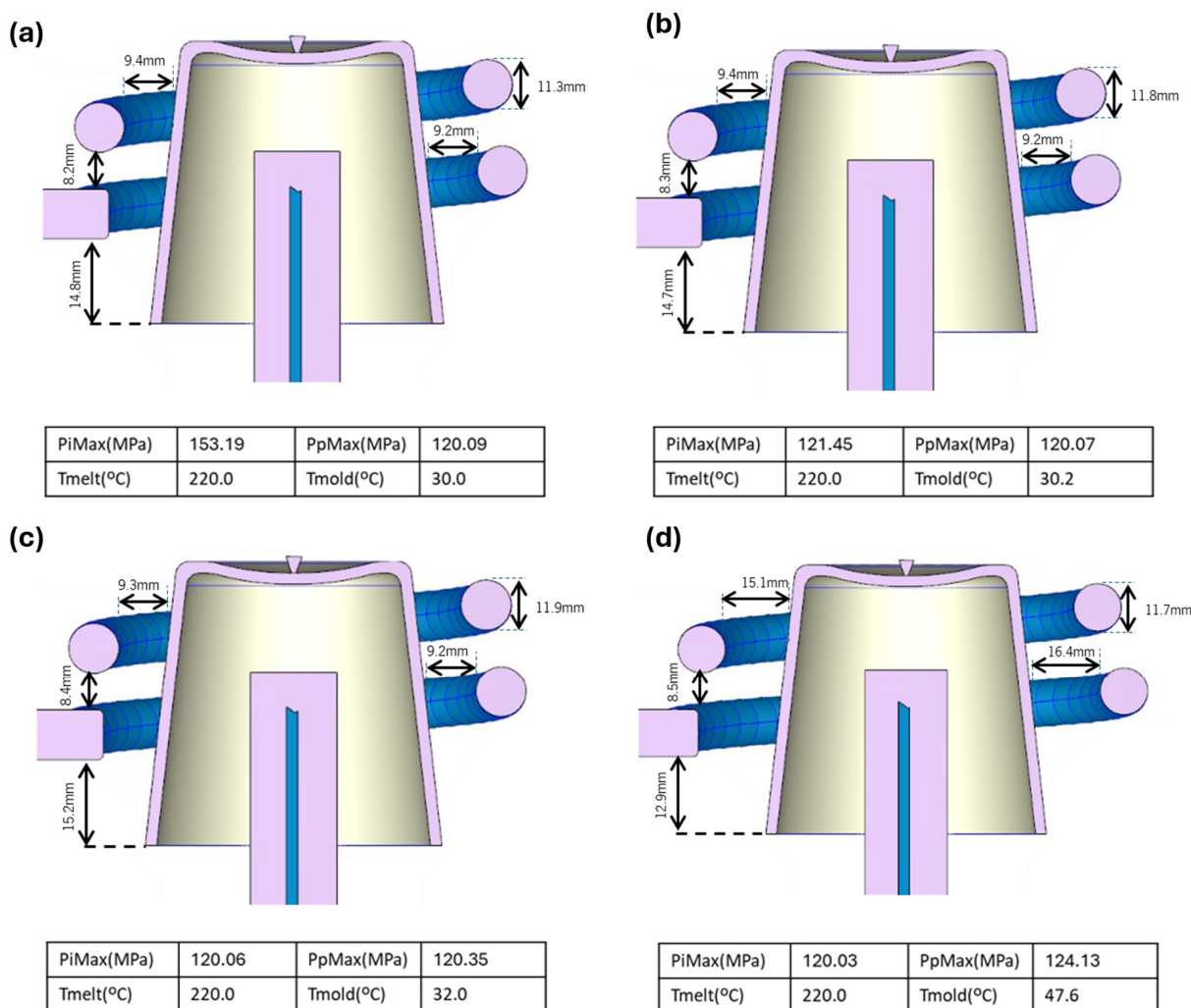


Figure 10. Selected solutions for a spiral channel using the following objective set (tcycle, maxWaT, and energy consumption): (a) Solution 1; (b) Solution 2; (c) Solution 3; (d) Solution 4.

4.2.6. Optimization of Zigzag Channel

Regarding processing conditions, the conclusions are consistent with those obtained for the 2-ring channels. Regarding the geometric parameters, d_1 , d_2 , and d_3 continue to follow the same trends as in previous cases, except in the spiral configuration. For the channel diameter D_1 , the results are similar to those observed in the earlier spiral-channel scenario. For h values, the lower bound is preferred, which reduces energy consumption; however, it slightly increases warpage, though not in a globally significant way. Similarly, w_1 approaches values near its upper bound, while w_2 moves toward values close to its lower bound.

The zigzag geometry demonstrated the best performance in t_{cycle} , thanks to its shorter flow pattern, and exhibited lower energy consumption, standing out as one of the most energy-efficient designs. Its $maxWaT$ values were slightly higher than those of the spiral and 3-ring geometries, but still competitive. The inclusion of sDT_{ssH} led to a marked increase in dispersion, highlighting the zigzag geometry's high sensitivity to local thermal variations. Geometrically, lower crossover heights and shorter distances to critical points were observed to yield better thermal performance. Overall, the zigzag design did not outperform the spiral in overall performance, but it was equivalent for specific objectives and superior in energy efficiency and cycle time.

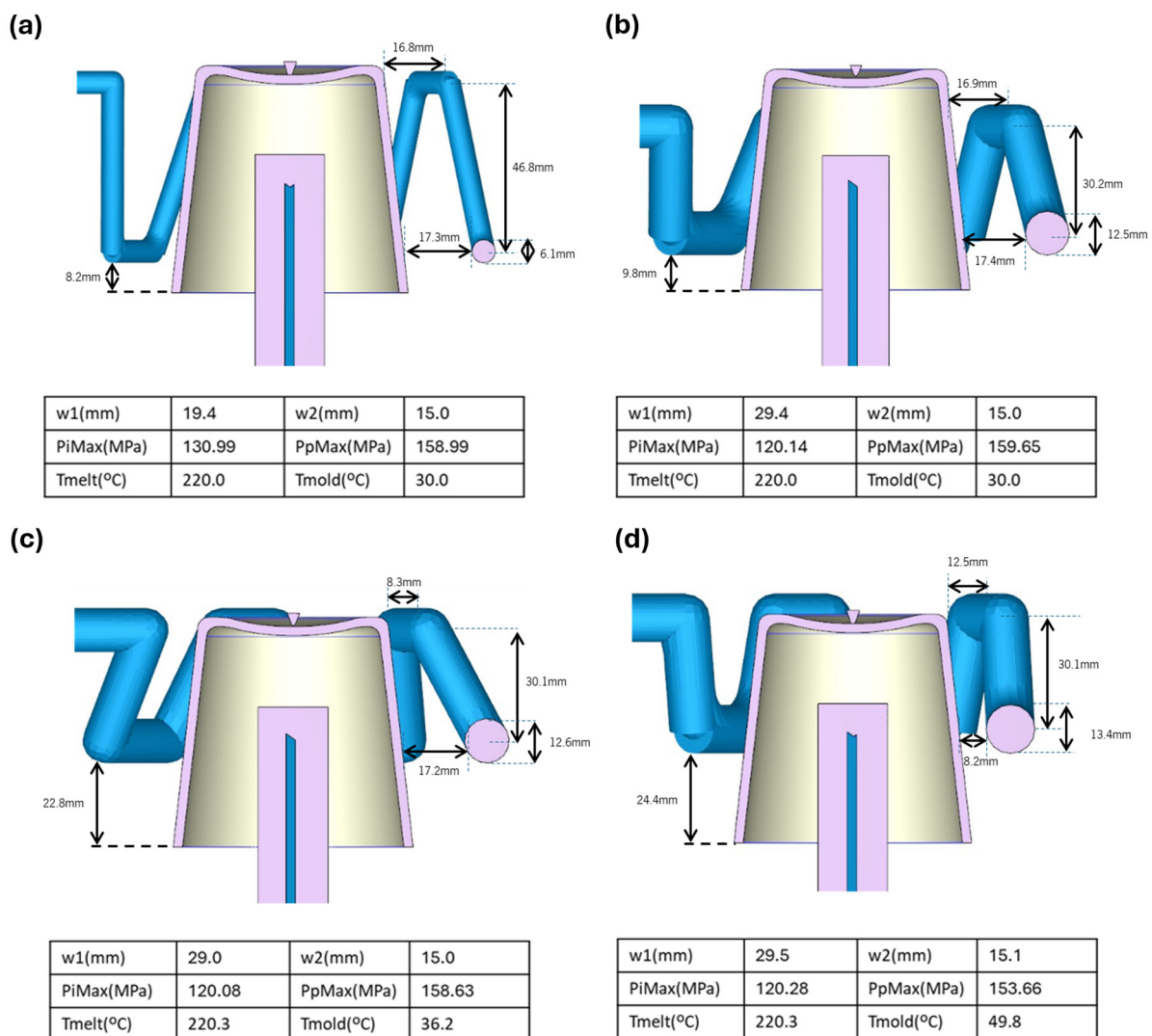


Figure 11. Selected solutions for zigzag channel for the following objective set (t_{cycle} , $maxWaT$, and energy consumption): (a) Solution 1; (b) Solution 2; (c) Solution 3; (d) Solution 4.

4.3. Global Comparative Analysis

These comparative trends are consistent with the literature, where conformal cooling is repeatedly reported to improve mold-temperature uniformity and reduce thermally driven defects, while enabling reductions in cooling time and, consequently, lower energy demand. Recent works also emphasize that data-driven workflows combining simulation, surrogate models, and Pareto-based search provide practical decision support for CCC design by efficiently exploring trade-offs between energy efficiency and dimensional quality.

All cooling channel geometries were evaluated using universal objective sets applicable to all scenarios (runs I, III and V, Table 9):

- *tcycle*, *maxWaT*, *energconsumpt*;
- *tcycle*, *maxWaT*, *deltaenerg*;
- *tcycle*, *maxWaT*, *maxSrT*, *energconsumpt*.

Regarding maximum warpage (*maxWaT*), all geometries exhibited very similar convergence, with values in the range of 0.83–0.84 mm. However, the three-ring circular (3-ring), zigzag, and conventional geometries recorded slightly lower values, which is noteworthy in this parameter.

With respect to energy consumption (*energconsumpt*), more significant differences between geometries were observed. While the zigzag and conventional configurations showed consumption between 20 and 21 kJ, the two-ring (2-ring), three-ring (3-ring), and spiral geometries were more efficient, with values ranging from 19.5 to 20.5 kJ. Within this group, the 3-ring and spiral designs were the most economical.

When analyzing energy variation (*deltaenerg*), the three-ring (3-ring) geometry showed the best performance, with values between 2 and 3.5 kJ. The two-ring (2-ring) geometries fell within the range of 2.5–3.5 kJ, whereas zigzag, spiral, and conventional designs yielded the highest values, between 3 and 4.5 kJ.

Regarding maximum shrinkage (*maxSrT*), the spiral geometry exhibited the narrowest and most stable range of values. However, in multi-objective scenarios with additional parameters, the three-ring (3-ring) geometry achieved lower or better values, indicating greater optimization capability.

4.4. Selection of a Representative Compromise Solution

From the obtained Pareto-optimal set, a single representative design was selected as the closest point to the utopia solution, computed in normalized objective space (minimum Euclidean distance to the ideal vector). This provides an explicit, reproducible multi-criteria decision criterion rather than a subjective visual selection.

The final selection required a thorough analysis of the trade-offs between objectives, as metrics such as warpage, energy, and cycle time exhibit opposing correlations. In such cases, there is no single global optimum, but rather a set of compromise solutions located on the Pareto front. The final selection considered not only the relative positions of solutions on the Pareto front but also engineering criteria such as thermal uniformity, manufacturability, dimensional stability, and industrial feasibility. After this integrated analysis, it was concluded that the objective combination based on (*tcycle*, *maxWaT*, *deltaenerg*) produced the most robust compromise solutions. Within this set, Solution 2 (Figure 12) demonstrated the best balance between reduced cycle time, moderate deformation, and optimized energy, and was therefore selected as the compromised solution of the study.

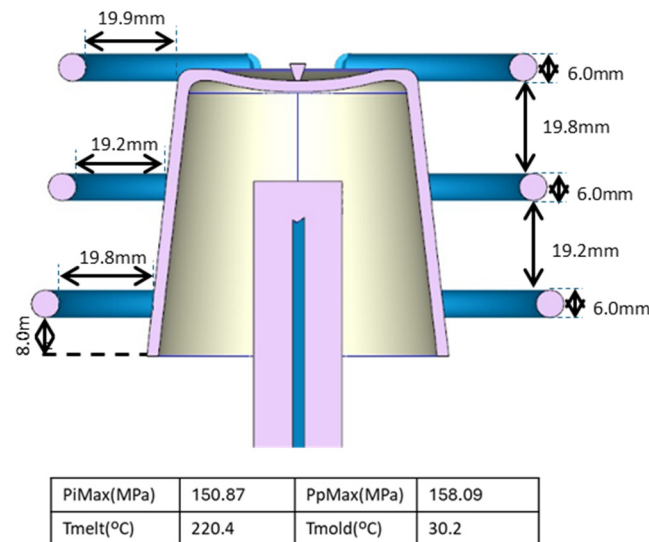


Figure 12. Selected solution.

4.5. Impact of Certain Decision Variables

The second study evaluates the impact of optimizing selected decision variables on injection process performance for the 2-ring CCC configuration, specifically by keeping certain variables constant (e.g., T_{mold} , d_i , d_o , D_i) and by replacing the internal baffle with a spiral.

The results demonstrate that optimizing processing conditions (OC) plays a decisive role in expanding the solution space and improving the quality of the final part. When processing parameters were allowed to vary, the Pareto fronts obtained showed greater dispersion and lower objective values, reflecting enhanced exploration capability of the search algorithm and superior achievable solutions. Conversely, when processing conditions were held constant, the solution space became significantly narrower and more constrained, with higher lower bounds and lower upper bounds across objectives, confirming that fixing these variables restricts optimization potential.

Overall, the study concludes that certain decision variables, especially processing conditions, channel location, and channel diameter, strongly influence the solution space, and that optimizing them is essential to maximizing the performance of CCC systems. The spiral baffle also demonstrated a measurable effect, indicating its potential as an alternative internal cooling feature. The optimization results are provided in the Data Repository [20].

5. Conclusions

This work proposed a surrogate-assisted, many-objective framework to design and optimize conformal cooling channels (CCCs) in injection molds, integrating simulation data, objective reduction (NL-PCA), ANN surrogates, and evolutionary optimization. The study demonstrated (i) the impact of objective selection on the resulting Pareto trade-offs, (ii) the importance of sampling density for stable surrogate-assisted optimization, and (iii) the ability to simultaneously improve energy-related indicators and part-quality proxies (warpage/shrinkage) by targeting more uniform heat extraction and shorter cycles.

The three-ring (3-ring) geometry proved to be the most balanced and robust among the configurations studied. With consistently strong performance across all evaluated objectives (low warpage, reduced energy consumption, excellent control of energy variation, and effective shrinkage management), this configuration emerges as the most recommendable

solution for additive manufacturing of molds when comprehensive optimization of the cooling system in injection molding is desired.

Overall, the study confirms that the combination of AI, numerical modeling, and MOEAs is a powerful and scalable tool for advanced injection mold design.

Compared with prior CCC optimization workflows, the proposed framework reduces reliance on exhaustive simulation by leveraging surrogates and provides quantitative indicators of many-objective solution quality (HV/IGD), enabling objective comparisons across objective sets and sampling densities.

Despite the positive results, the proposed methodology has several limitations that must be acknowledged. First, the objective selection was based on NL-PCA, which, although effective, does not explicitly account for mutual information or relevance–redundancy trade-offs between objectives; more advanced feature selection strategies could further improve the reduced objective set. Second, although the ANN metamodels exhibited low global error, discrepancies between predicted and simulated values tend to increase near the Pareto front, precisely where greater accuracy is required for final decision-making; therefore, improvements in network architectures, training strategies, and local refinement mechanisms are needed. Third, the optimization procedure was tested on a specific class of CCC layouts and a limited set of objectives; extending the approach to more complex design spaces, additional materials, and a larger set of constraints will require more efficient, scalable MOEAs. Finally, solution selection at the end of the optimization remains a largely manual step; the development of systematic decision-support tools to rank and select Pareto-optimal solutions according to industrial priorities is an important topic for future work, together with the experimental validation of the most promising designs and the comparison with alternative layouts, such as three-turn spiral configurations.

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Conflicts of Interest: The authors declare no conflict of interest.

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