Construction Of An Integrated Mold Design And Manufacturing Framework Based On Digital Twins

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Injection molding is widely used for manufacturing high-precision plastic components, but complex interactions between material properties and process parameters often lead to defects such as warpage, shrinkage, and incomplete filling. Traditional optimization approaches have limited adaptability to dynamic manufacturing environments. This study proposes an integrated digital twin-driven framework combined with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) for injection molding optimization. This study contributes to Industry 4.0 by integrating digital twin technology and AI-based optimization for real-time, data-driven decision-making in smart manufacturing systems. The proposed AI-driven digital twin framework also enables predictive maintenance by continuously monitoring process conditions and identifying potential equipment and process anomalies before defects occur. The framework integrates CAD-based mold design, multi-physics simulation, and virtual–physical synchronization to monitor material flow, predict thermal and pressure distributions, and identify potential defects. NSGA-II optimizes key process parameters, including melt temperature, injection pressure, injection speed, and cooling time, to simultaneously minimize cycle time, warpage, and defect rate. Experimental results demonstrate significant improvements, reducing cycle time from 40 s to 26 s, warpage from 1.83 mm to 1.12 mm, and defect rate from 15% to 7%. Validation results show prediction errors below 5%, confirming the effectiveness and reliability of the proposed framework.

Keywords: Digital Twin; Injection Molding; Multi-Objective Optimization; NSGA-II; Process Simulation; Warpage Reduction; Cycle Time Optimization; Intelligent Manufacturing

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1. Introduction

The manufacturing process known as injection molding serves an essential function because it creates intricate plastic parts that multiple industries including automotive and aerospace and medical devices and consumer electronics require [1]. As manufacturers continue to respond to an increasing consumer demand for high-quality products and decreased production time, manufacturers also look for additional advanced computational and intelligent manufacturing technologies to increase their production capabilities [2]. Many manufacturers today have modern smart manufacturing environments that use advanced digital technologies to perform simulation-based monitoring, predictive analysis, and optimization of processes [3]. Digital twin technology has emerged as a breakthrough technology that enables the creation of a virtual representation of a physical system to improve design accuracy, operational efficiency, and lifecycle management [4].

The injection molding process has been widely accepted as an industrial manufacturing method by the plastics industry for a long time [5]. This process is very sensitive to various process parameters as well as to material properties (e.g., viscosity) [6]. The amount and type of material used will affect the quality and consistency of the finished product being manufactured [7]. The melt temperature, injection pressure, cooling time, and mold temperature are all affected by the amount of material being introduced for injection, and once the material is in the mold, it will have different flow patterns depending upon the properties of that specific material [8]. The viscosity of the material being injected along with the density, thermal conductivity, and specific heat of the material will make the overall process more complex. Defects result in an increase in production costs, longer production cycle times, and less reliable products.

This study presents a framework using digital twins and NSGA-II for mold design and fabrication. Recent research has increasingly focused on integrating digital twin technology with data-driven optimization techniques to enable intelligent monitoring, prediction, and control of injection molding processes. Furthermore, AI-driven predictive maintenance enables continuous equipment health monitoring and early fault prediction, reducing unplanned downtime and improving manufacturing reliability within smart manufacturing systems. It integrates geometry, material, and process data to monitor performance, detect defects, and optimize warpage, cycle time, and quality for smart manufacturing. The study attributes its main contributions to,

- Implements dynamic virtual–physical synchronization to model and predict flow, thermal, and pressure behaviours.
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- Applies the NSGA-II multi-objective optimization approach to effectively handle trade-offs among process parameters influencing product quality and manufacturing efficiency.
- Validates the proposed framework through experimental analysis, demonstrating reliable prediction capability and consistency between simulated results.
- Enhances intelligent manufacturing by enabling data-driven decision-making, adaptive control, and scalable optimization within advanced industrial environments.

The structure of this paper as follows, the Section 1 presents the introduction and problem motivation. Section 2 reviews related literature on digital twin and injection molding optimization. Section 3 describes the proposed methodology, including CAD modeling, digital twin development, simulation, and optimization. Section 4 presents the experimental setup and parameter configuration. Section 5 discusses results and performance evaluation. The study ends with Section 6, which presents research findings and future research directions.

Kariminejad et al. [9] The digital twin model improves cooling prediction accuracy in injection molding using Dynamic Mode Decomposition and Kalman Filter, but focuses only on cooling systems and lacks multi-objective optimization capabilities. Huang et al. [10] hybrid learning-based digital twin framework improves prediction accuracy and system performance, but has not yet been applied to optimize injection molding processes. Hung et al. [11] explored Digital Twins for intelligent manufacturing but did not investigate NSGA-II-based optimization. Nasiri et al. [12] developed a Digital Twin framework for smart injection molding to improve process monitoring and quality control. Polezi Munhoz et al. [13] introduced an AI-enabled Digital Twin framework that employs generative AI for intelligent manufacturing; however, it has not been applied to injection molding process optimization. The new digital twin framework uses generative AI to enhance design efficiency and adaptability, but has not yet been applied to injection molding manufacturing processes. The digital twin model improves manufacturing flexibility and reduces modeling time but lacks process parameter optimization. Van Dyck et al. [14] The Delphi study identifies key trends in interconnected digital twins, including interoperability, scalability, and data-driven decision-making, but lacks experimental proof and technical implementation details for manufacturing systems. The AI-driven ontology-based digital twin improves smart building maintenance but is limited to building systems. Gotlih et al. [15] The research optimizes cooling efficiency, cycle time, and warpage using Pareto-based simulation but lacks real-time digital twin adaptation.

2. Material and methods

The research applies digital twin technology in injection molding through modeling, simulation, and validation to reduce defects, optimize processes, and support data-driven manufacturing decisions. Figure 1 illustrates the interaction among CAD modeling, digital twin simulation, process simulation, optimization, and performance evaluation within the proposed framework.

The mold cavity is designed based on the required product geometry while incorporating material shrinkage effects. The cavity volume is calculated as Eq. (1):

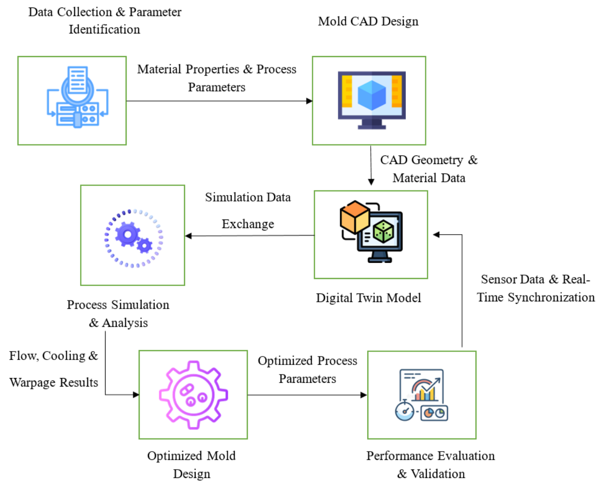

Fig. 1. Proposed Digital Twin-Based Workflow for Injection Molding Optimization

$$V_c = V_p\,(1 + S_r) \tag{1}$$

where V_c is the mold cavity volume, V_p is the product volume, and S_r is the shrinkage rate of the material. For 100 cm^3 product with 2% shrinkage, mold cavity volume is increased to 102 cm^3 to compensate cooling shrinkage and maintain dimensional accuracy.

Digital twin mirrors injection molding using CAD data, enabling simulation, monitoring, and prediction of temperature, pressure, and cooling conditions. Figure 2 shows digital twin linking simulation, sensors, and optimization.

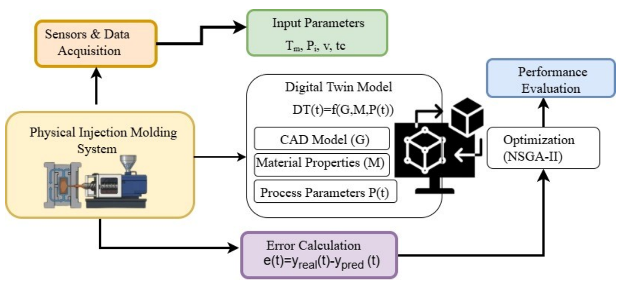

Fig. 2. Digital Twin-Based Architecture for Monitoring and Optimization in Injection Molding

A Kalman filter-based data assimilation mechanism is employed to integrate sensor measurements with simulation outputs. The approach improves estimation accuracy while reducing measurement noise and uncertainty. Real-time process data maintain digital twin synchronization. Sensor measurements are affected by measurement noise, which may reduce synchronization accuracy between the physical system and the digital twin. The Kalman filter minimizes these effects, improving synchronization accuracy and ensuring reliable and robust digital twin operation.

During the injection molding operation, the digital twin continuously exchanges process information with the physical injection molding system through sensor measurements and simulation updates. Secure communication and data integrity ensure reliable synchronization between the physical system and the digital twin. These considerations support trustworthy industrial digital twin deployment.

The digital twin system establishes a mapping between the physical system and its virtual counterpart. This relationship can be expressed as Eq. (2):

$$DT(t) = f(G, M, P(t)) \tag{2}$$

Were, $DT(t)$ = digital twin state at time t, G = geometric parameters (CAD model), M = material properties, $P(t)$ = time-dependent process parameters, $f(\cdot)$ = system mapping function. The mapping function $f(G, M, P(t))$is implemented through Autodesk Moldflow simulations integrated with the digital twin framework. System behavior is predicted using physics-based simulations and NSGA-II optimization without surrogate models.

The digital twin models flow, heat, and pressure to detect defects and optimize injection molding with AI-driven intelligence. The proposed framework advances smart manufacturing through AI-driven techniques that support predictive maintenance and intelligent process monitoring. The proposed digital twin framework accommodates different polymer material grades by updating the corresponding material properties. This enables consistent process prediction and optimization under diverse material conditions.

Figure 3 illustrates the interactions among the flow, thermal, and structural domains within the proposed digital twin framework, highlighting the multi-physics coupling used for process simulation and optimization. The flow of molten polymer inside the mold cavity is governed by the principles of fluid dynamics.The continuity equation is expressed as Eq. (3):

$$\nabla \cdot v = 0 \tag{3}$$

where V represents the velocity field of the molten material. Momentum conservation is defined using the Navier-Stokes is given by Eq. (4):

$$\rho\left(\frac{\partial v}{\partial t} + v \cdot \nabla v\right) = -\nabla P + \mu \nabla^2 v \tag{4}$$

Where, ρ is the material density,P is the pressure, and μ is the dynamic viscosity.

The Cross-WLF model is selected because it accurately represents the temperature- and shear-rate-dependent vis-

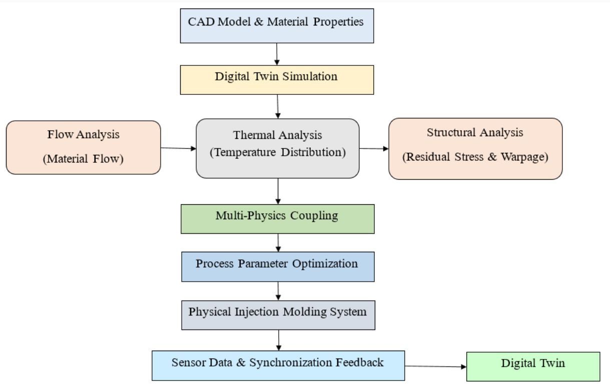

Fig. 3. Multi-physics coupling interactions in the proposed digital twin framework.

cosity of polymer melts during injection molding. This improves the accuracy of melt flow prediction and enhances the reliability of process simulation.

A partitioned solver architecture is adopted to couple the Navier-Stokes and thermal energy equations within the simulation framework. Flow, pressure, and temperature fields are iteratively solved to ensure multi-physics consistency.

Thermal Analysis and Heat Transfer

The temperature distribution within the mold is critical for controlling solidification and product quality. The heat transfer process is governed by the energy is denoted by Eq. (5):

$$\rho c_p \frac{\partial T}{\partial t} = k \nabla^2 T \tag{5}$$

Where, c_p is the specific heat capacity, k is thermal conductivity, and T is temperature.

Multi-objective optimization balances warpage, cycle time, and defects using digital twin simulations.

The optimization problem is defined in terms of a decision variable vector representing key process parameters is expressed by Eq. (6):

$$\mathbf{x} = [T_m, P_i, v, t_c] \tag{6}$$

Where, T_{m}, P_{i}, v, and t_{c} represent melt temperature, injection pressure, speed, and cooling time.

The multi-objective optimization problem is formulated as Eq. (7):

$$\min F(x) = \{f_1(x), f_2(x), f_3(x)\} \tag{7}$$

Were, $F(x)$: Multi-objective function vector representing overall system performance, $f_1(x)$: Warpage function, $f_2(x)$: Cycle time function, $f_3(x)$: Defect rate function.

The consolidated symbol definitions improve consistency and facilitate easier interpretation of the equations as shown in Table 1.

Table 1. Unified Notation Used in Mathematical Formulations

Symbol	Description	Unit
V_c	Mold cavity volume	cm^3
V_p	Product volume	cm^3
S_r	Material shrinkage rate	%
$DT(t)$	Digital twin state	-
G	Geometric parameters	-
M	Material properties	-
$P(t)$	Process parameters	-
V	Velocity field	m/s
ρ	Material density	kg/m^3
P	Pressure	MPa
μ	Dynamic viscosity	Pa·s
C_p	Specific heat capacity	J/kg-K
$\mathbf{k}$	Thermal conductivity	W/m·K
T	Temperature	°C
X	Decision variable vector	-
$F(X)$	Multi-objective function	-

Algorithm 1 iteratively updates the population through non-dominated sorting and genetic operators to obtain Pareto-optimal process parameters. The computational complexity of NSGA-II is primarily associated with the non-dominated sorting procedure and depends on the population size and number of objectives. The NSGA-II algorithm generates a Pareto-optimal set of non-dominated solutions representing different trade-offs among the optimization objectives. The final solution is selected from the Pareto set based on the best overall balance between cycle time, warpage, and defect reduction.

The performance gain percentage was calculated by comparing the proposed digital twin framework with the conventional manufacturing approach using the relative percentage improvement. The performance gain is expressed as Eq. (8):

$$\text{Performance Gain (\%)} = \frac{\text{Conventional Value} - \text{Proposed Value}}{\text{Conventional Value}} \times 100\% \tag{8}$$

where the Conventional Value represents the performance of the conventional manufacturing approach, and the Proposed Value represents the performance of the proposed digital twin framework. For example, the cycle time improvement was calculated as $(40 - 26)/40 \times 100 = 35.0\%$. The same procedure calculated improvement percentages for warpage and defect rate.

Algorithm 1. Digital Twin-Based Multi-Objective Optimization Using NSGA-II

Require: Population size N, maximum generations G, process parameter bounds $(T_{\mathrm{m}}, P_{\mathrm{i}}, v, t_{\mathrm{c}})$
Ensure: Pareto-optimal set of process parameters P^*

Initialize population P_0 with N random solutions
Evaluate each solution using Digital Twin:
for each solution $x_i \in P_0$ **do**
  $F_i = DT(x_i)$
Set generation counter $g = 0$
while $g < G$ **do**
  Perform non-dominated sorting on P_g
  Calculate crowding distance
  Selection: Apply tournament selection to choose parent population
  Crossover:
  for $i = 1$ **to** $N/2$ **do**
    Generate offspring using SBX crossover
  Mutation:
  for each offspring x_i **do**
    Apply polynomial mutation
  Evaluate offspring using Digital Twin:
  for each x_i in offspring **do**
    $F_i = DT(x_i)$
  Create combined population: $R_t = P_g \cup Q_g$
  Perform non-dominated sorting on R_t
  Select best N solutions based on rank and crowding distance $\rightarrow P_{g+1}$
  Update generation counter: $g = g + 1$
return final Pareto optimal solution set P^*

Table 2 presents optimal parameters: melt temperature (220.57°C), mold temperature (50°C), pressure (119.39 MPa), and speed (55 mm/s), reducing cooling time by 15 seconds. The process parameter bounds were selected based on industrial injection molding operating conditions and polymer material processing requirements, ensuring practical applicability during optimization. The selected ranges are consistent with standard industrial practices.

The hyperparameter configuration used for the multi-objective optimization process is summarized in.

A mutation distribution index of 20 is adopted for the polynomial mutation operator to maintain population diversity while supporting stable convergence throughout the evolutionary search process.

Table 2. Optimized Process Parameters Obtained from Digital Twin-Based NSGA-II Optimization

Parameter	Value	Unit
Melt Temperature	220.57	°C
Mold Temperature	50	°C
Injection Pressure	119.39	MPa
Injection Speed	55	mm/s
Cooling Time	15.00	s
Packing Pressure	55	MPa
Material Density	1100	kg/m^3
Material Viscosity	1250	Pa·s
Thermal Conductivity	0.20	W/m·K
Specific Heat	1750	J/kg·K
Cavity Thickness	3.5	mm
Runner Diameter	7.5	mm
Gate Size	3.40	mm

Table 3. NSGA-II Hyperparameter Configuration for Multi-Objective Optimization

Hyperparameter	Value / Type
Optimization Algorithm	NSGA-II
Population Size	40
Maximum Generations	50
Crossover Rate	0.9
Mutation Rate	0.1
Encoding Method	Real-Valued Encoding
Selection Operator	Tournament Selection (size = 2)
Crossover Operator	Simulated Binary Crossover (SBX)
Mutation Operator	Polynomial Mutation

3. Results and discussion

The process of molten polymer flow through the mold cavity during injection operation.

Figure 4 shows symmetric cavity filling, faster injection point flow, and stable digital twin simulation with smooth gradient distribution.

Figure 5 shows that the proposed method achieves faster cooling, reaching ~20°C in 40 seconds, compared to the conventional approach's gradual decrease to 75°C.

Figure 6 shows increased computational time and resource cost with complexity. The reduction in cooling duration is reflected in shorter cycle times, indicating the contribution of thermal performance to overall manufacturing productivity and process efficiency.

Figure 7 shows reduced residual stress with increasing cooling time, with the proposed method achieving lower values. The reduced residual stress contributes to improved long-term component reliability by minimizing the risk of deformation, cracking, and dimensional instability while enhancing the structural performance of the molded component.

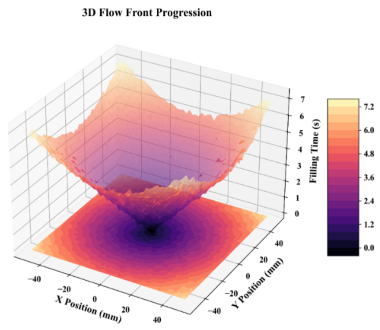

Fig. 4. Flow Front Advancement Analysis in Injection Molding

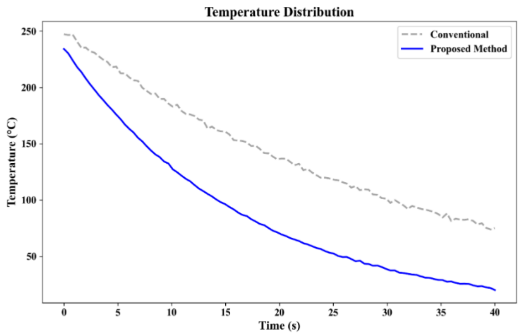

Fig. 5. Temperature Distribution and Cooling Performance Analysis

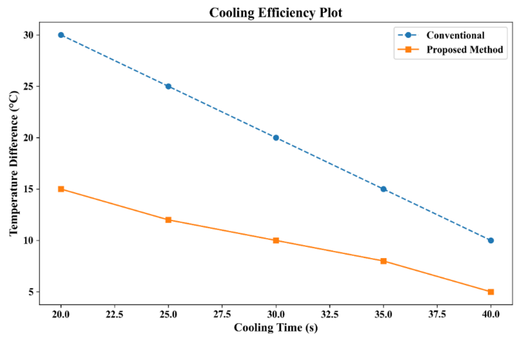

Fig. 6. Cooling Efficiency Comparison

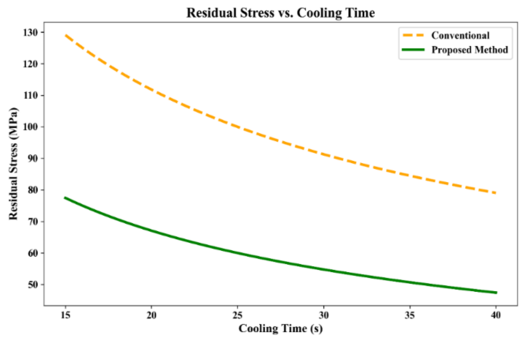

Fig. 7. Residual Stress Reduction with Respect to Cooling Time

Figure 8 shows a sensitivity analysis of process parameters on warpage, including melt temperature, injection pressure, cooling time, and injection speed.

Figure 9 shows objective value rapidly decreasing from 23.7 to 21.2, stabilizing at 21.18, confirming optimization convergence and final solution.

Table 4 shows that the Hypervolume (HV) increases progressively from 0.680 to 0.936, while the Generational Distance (GD) decreases from 0.145 to 0.014, indicating continuous improvement in Pareto solution quality. Both metrics stabilized after 40 generations, demonstrating NSGA-II's reliable Pareto convergence.

The experimental conditions included a melt temperature of 220.57 °C, mold temperature of 50 °C, injection pressure of 119.39 MPa, injection speed of 55 mm/s, and cooling time of 15 s, which were consistently maintained during both simulation and experimental validation. The validation dataset comprised process parameters and key quality metrics.

The validation results comparing the digital twin simulation with experimental measurements are presented in Table 5.

Figure 10 shows digital twin optimization reduces defect rate to 7%, outperforming traditional methods and improving product quality.

Figure 11 shows computational time rising from 0.5 to 12.5 hours and resource cost increasing from 5 to 90 due to higher model complexity and simulation accuracy. The proposed framework supports complex mold designs and large-scale manufacturing environments; its computational requirements increase with system complexity.

Table 6 shows NSGA-II achieves best performance with 26 s cycle time, 1.12 mm warpage, 7% defects, and 35% improvement over baseline.

Table 7 shows NSGA-II digital twin method outperforms others with 26 s cycle time, 1.12 mm warpage, and 7% defects.

Table 8 compares the proposed framework with the future machine learning-enhanced framework. The comparison highlights the pathway toward adaptive smart manufacturing.

Table 4. NSGA-II Convergence Performance Evaluation using Hypervolume (HV) and Generational Distance (GD)

Generation	Hypervolume (HV) ↑	Generational Distance (GD) ↓
5	0.680	0.145
10	0.760	0.101
15	0.820	0.073
20	0.860	0.051
25	0.890	0.039
30	0.910	0.028
35	0.920	0.021
40	0.930	0.017
45	0.934	0.015
50	0.936	0.014

Table 5. Validation of Digital Twin Model with Experimental Results

Metric	Unit	DigitalTwin (Simulation)	Experimental (Real)	Error (%)
Cycle Time	s	26.0	26.4	1.52
Warpage	mm	1.12	1.18	5.08
Average Temperature	°C	52.4	54.1	3.14
Maximum Pressure	MPa	98.5	102.3	3.71

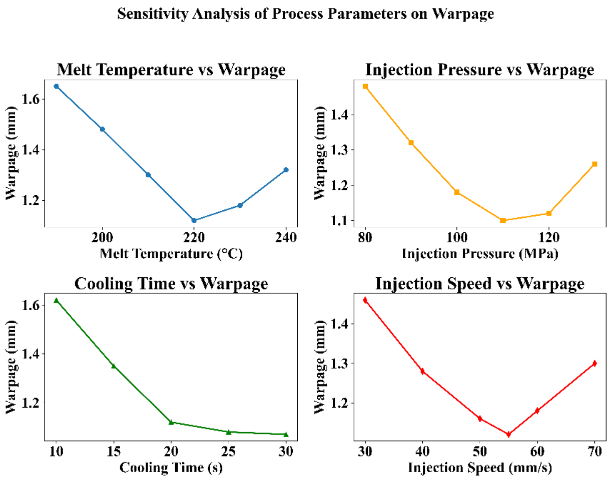

Fig. 8. Sensitivity Analysis of Injection Molding Process Parameters on Part Warpage

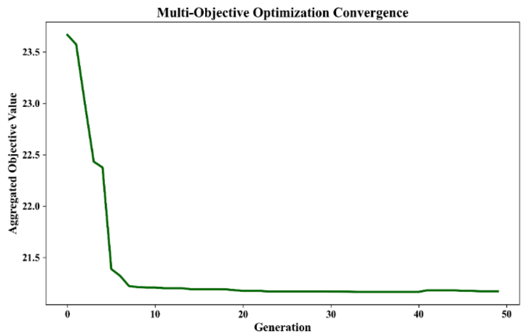

Fig. 9. Optimization Algorithm Convergence Behavior

4. Conclusion

This study proposes a digital twin-based NSGA-II injection molding framework that improves cooling, product quality, and efficiency while reducing cycle time, warpage, and defects, despite computational limitations. Future work includes integrating machine learning for adaptive digital twins, IoT-based real-time monitoring, and predictive maintenance. Despite its promising performance, deploying the proposed Digital Twin framework in large-scale industrial environments may face challenges related to computational cost, real-time data synchronization, and system scalability. Future work will also explore energy-efficient and sustainable optimization methods, support complex geometries and multi-material molding, and require validation in Industry 4.0 industrial smart manufacturing environments. Future work may integrate machine learning with the proposed digital twin framework to enable adaptive process control, intelligent prediction, and autonomous manufacturing decision-making. This integration has the potential to further support smart manufacturing environments.

Acknowledgement

Data availability:

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Table 6. Ablation Study of the Proposed Digital Twin-Based Optimization Framework

Configuration	Cycle Time (s)	Warpage (mm)	Defect Rate (%)	Performance Gain (%)
Baseline (Manual Design)	40.0	1.83	15.0	0.00
+ Simulation Module	38.5	1.65	12.5	3.75
+ Digital Twin Integration	36.2	1.42	10.2	9.50
+ NSGA-II Optimization (Full Model)	26.0	1.12	7.0	35.00

Table 7. Quantitative comparison of the proposed framework with existing studies

Study	Method	Cycle Time (s)	Warpage (mm)	Defect Rate (%)
Gotlih et al. [15]	Non-dominated sorting–based optimization	30–45	1.3–1.8	10–18
Gim et al. [16]	Machine learning–based multi-objective optimization	28–35	1.2–1.5	8–12
Li et al. [17]	Simulation-based process optimization with in-mold sensing	32–38	1.4–1.7	9–14
Proposed Method	Digital Twin + NSGA-II multi-objective optimization	26	1.12	7

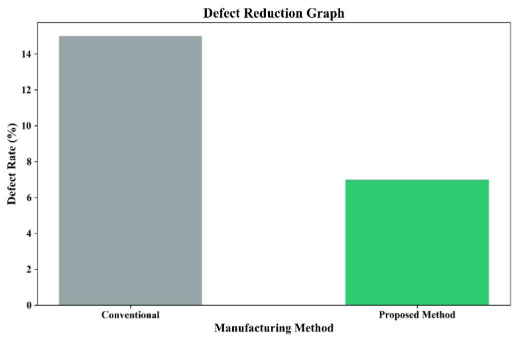

Fig. 10. Comparative Defect Rate Analysis Between Conventional Manufacturing and the Proposed Digital Twin–Based Optimization Framework

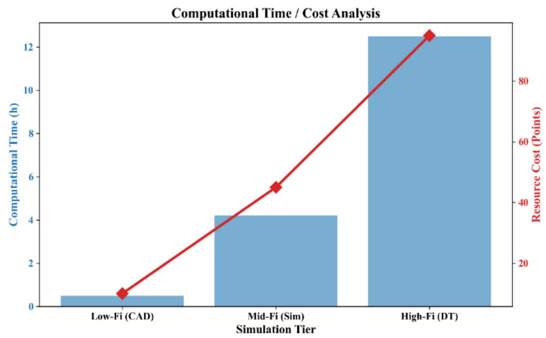

Fig. 11. Computational Cost Across Simulation Fidelity Levels

Conflicts of interest:

The author declares that there are no conflicts of interest regarding the publication of this paper.

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Author contribution:

Ruimei Ci contributed solely to all aspects of this work, including conceptualization, methodology design, digital twin framework development, simulation analysis, optimization using NSGA-II, result interpretation, and manuscript preparation.

Ethical approval:

This study does not involve human participants, animal studies, or any ethical concerns requiring institutional approval.

Consent to participate:

Not applicable, as this study does not involve human participants.

Competing interests:

The author declares that there are no competing interests.

References

[1] W. Wang et al., (2022) *"BIM Information Integration Based VR Modeling in Digital Twins in Industry 5.0"* **Journal of Industrial Information Integration** *28*: 100351. DOI: 10.1016/j.jii.2022.100351.

Table 8. Comparison of the Proposed Digital Twin–NSGA-II Framework and the Future Machine Learning–Enhanced Framework

Feature	Proposed Digital Twin–NSGA-II	Future ML-Enhanced Digital Twin
Process Control	Rule-based optimization	Adaptive process control
Prediction	Simulation-based prediction	Intelligent predictive prediction
Decision Making	Operator-assisted	Autonomous decision-making
Framework Capability	Multi-objective optimization	Self-learning and adaptive optimization

[2] Y. Zhao, N. Wang, Z. Liu, and E. Mu, (2022) *"Construction Theory for a Building Intelligent Operation and Maintenance System Based on Digital Twins and Machine Learning"* **Buildings** ***12***(2): 87. DOI: 10.3390/buildings12020087.

[3] L. Wang et al., (2025) *"The Development of Prefabricated Buildings and Intelligent Construction Based on Digital Twins"* **Journal of Intelligent Construction** ***3***(1): 1–25. DOI: 10.26599/JIC.2025.9180080.

[4] H. Qu, L. Fang, and J. Tan, (2026) *"An embodied intelligence-based online optimization methodology for injection molding process using multi-cavity hot-runner"* **Journal of Industrial Information Integration** ***49***: 101009. DOI: 10.1016/j.jii.2025.101009.

[5] I. Khan, A. Al Rashid, and M. Koç, (2025) *"Integration of machine learning and digital twin in additive manufacturing of polymeric-based materials and products"* **Progress in Additive Manufacturing** ***10***(12): 10685–10737. DOI: 10.1007/s40964-025-01257-4.

[6] M. Abed, A. Mohammad, D. Axinte, A. Gameros, and D. Askew, (2026) *"Digital-twin-assisted multi-stage machining of thin-wall structures using interchangeable robotic and human-assisted automation"* **Robotics and Computer-Integrated Manufacturing** ***97***: 103077. DOI: 10.1016/j.rcim.2025.103077.

[7] J. Kombaya Touckia, N. Hamani, and L. Kermad, (2022) *"Digital twin framework for reconfigurable manufacturing systems (RMSs): design and simulation"* **The International Journal of Advanced Manufacturing Technology** ***120***(7): 5431–5450. DOI: 10.1007/s00170-022-09118-y.

[8] L. Zhang, L. Feng, J. Wang, and K.-Y. Lin, (2022) *"Integration of Design, Manufacturing, and Service Based on Digital Twin to Realize Intelligent Manufacturing"* **Machines** ***10***(4): 275. DOI: 10.3390/machines10040275.

[9] M. Kariminejad, D. Tormey, and M. McAfee, (2025) *"Developing a Digital Twin of part cooling in an injection moulding process through a Dynamic Mode Decomposition-Kalman Filter approach"* **Computers in Industry** ***172***: 104333. DOI: 10.1016/j.compind.2025.104333.

[10] Z. Huang, M. Fey, C. Liu, E. Beysel, X. Xu, and C. Brecher, (2023) *"Hybrid learning-based digital twin for manufacturing process: Modeling framework and implementation"* **Robotics and Computer-Integrated Manufacturing** ***82***: 102545. DOI: 10.1016/j.rcim.2023.102545.

[11] M.-H. Hung et al., (2022) *"A Novel Implementation Framework of Digital Twins for Intelligent Manufacturing Based on Container Technology and Cloud Manufacturing Services"* **IEEE Transactions on Automation Science and Engineering** ***19***(3): 1614–1630. DOI: 10.1109/TASE.2022.3143832.

[12] S. Nasiri, M. R. Khosravani, T. Reinicke, and J. Ovtcharova, (2024) *"Digital Twin Modeling for Smart Injection Molding"* **Journal of Manufacturing and Materials Processing** ***8***(3): 102. DOI: 10.3390/jmmp8030102.

[13] I. Polezi Munhoz et al., (2026) *"Integrating artificial intelligence and digital twins into a data architecture for small-batch manufacturing"* **The International Journal of Advanced Manufacturing Technology** ***144***(7): 4667–4686. DOI: 10.1007/s00170-026-18133-2.

[14] M. van Dyck, D. Lüttgens, F. T. Piller, and S. Brenk, (2023) *"Interconnected digital twins and the future of digital manufacturing: Insights from a Delphi study"* **Journal of Product Innovation Management** ***40***(4): 475–505. DOI: 10.1111/jpim.12685.

[15] J. Gotlih, M. Brezocnik, S. Pal, I. Drstvensek, T. Karner, and T. Brajlih, (2022) *"A Holistic Approach to Cooling System Selection and Injection Molding Process Optimization Based on Non-Dominated Sorting"* **Polymers** ***14***(22): 4842. DOI: 10.3390/polym14224842.

[16] J. Gim, H. Yang, and L.-S. Turng, (2023) *"Transfer learning of machine learning models for multi-objective process optimization of a transferred mold to ensure efficient and robust injection molding of high surface quality parts"* **Journal of Manufacturing Processes** ***87***: 11–24. DOI: 10.1016/j.jmapro.2022.12.055.

[17] Y. Li, J. C. Chen, and W. M. Ali, (2022) *"Process optimization and in-mold sensing enabled dimensional prediction for high precision injection molding"* **The International Journal of Advanced Manufacturing Technology** ***16***(3): 997–1013. DOI: 10.1007/s12008-021-00800-1.