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Machine learning method predicting thermal performance of conformal cooling systems

Zhiqiang Zhao

The incorporation of conformal cooling systems has significantly enhanced the efficiency and quality of injection molding process. While several automated methods have been developed for creating conformal cooling channels in injection molds, the current optimization process for conformal cooling design parameters is hindered by labor-intensive iterative thermal simulation processes and the substantial reliance on empirical human knowledge. This paper presents an innovative machine learning method to assess the thermal performance of conformal cooling systems by employing a combination of a non-linear regression model and a neural network. By employing a logarithmic regression model describing the temperature graph and a neural network predicting the coefficients of the logarithmic regression model, the thermal performance of specified conformal cooling systems can be assessed and predicted precisely. This methodology empowers designers to evaluate the thermal efficiency of conformal cooling systems efficiently and effectively to further optimize the conformal cooling design parameters without relying on tedious manual thermal and fluid simulation processes.

Keywords Machine learning, Non-linear regression, Neural networks, Conformal cooling system, Thermal simulation, Cooling performance, Multiple objective optimization

Main

The cooling system plays a critical role during the injection molding process, influencing both the molding cycle time and the quality of the final product. Conformal cooling channels are intricately designed following the complex geometry of the molding profiles (Fig. 1a). The close conformity of the cooling channels over the molding profiles guarantees uniform cooling and efficient heat dissipation, ultimately leading to shortened production cycles and enhanced quality of molded products. For a given injection mold, the effectiveness of its conformal cooling system is predominantly governed by three key parameters: the diameter of cooling channel (D), the channels' distance to the molding profiles (DtP), and the total length of cooling channel (TL) as illustrated in Fig. 1b. The cooling diameter D holds a vital role directly influencing cooling efficiency. A larger diameter enhances cooling efficiency by allowing a greater volume of cooling medium to flow through the channel, effectively extracting heat energy from the molding melt. DtP is equally crucial, impacting the heat transfer efficiency between the cooling medium and the surrounding molding melt. TL determines the overall contact area and density of cooling channels over the entire molding profiles, thereby influencing the residence time of the cooling medium within the injection mold. TL also determines the stepover and pitch with respect to different conformal cooling patterns such as zigzag, periphery, and helix.

The design and optimization of conformal cooling systems is often a tough and time-consuming process involving the use of different CAD and CAE applications. The design of conformal cooling channels often requires the creation of a large number of spatial discrete points, curves, and surfaces that are offset from the molding profiles to form the 3D conformal cooling channels. The optimization process for conformal cooling design is generally an iterative process requiring meticulous fine-tuning steps to achieve the desired cooling goals. An initial conformal cooling design is crafted using CAD software based on a given mold considering relevant design parameters such as D, DtP and TL. Subsequently, it undergoes thermal simulation and analysis utilizing various Finite Element Thermal Analysis (FEA)/Computational Fluid Dynamics (CFD) applications to evaluate its thermal performance, which is often laborious and time intensive. The simulation results serve as a reference point to pinpoint design weakness for adjusting the conformal cooling design parameters. This

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Figure 1. Conformal cooling design and parameters. (**a**), Injection molds with conformal cooling design. (**b**), Key parameters of conformal cooling design.

iterative design-evaluation-redesign cycle continues until the desired goals are achieved, which require different applications and heavily empirical human knowledge.

In recent years, several research endeavors have delved into the automated design and optimization of conformal cooling, employing thermal analysis, multi-objective optimization, and machine learning techniques[1–3]. Zhao et al.[4,5] presented automated approaches to generate conformal cooling channels for given injection molds. As depicted in Fig. 2a, a 2D pattern is initially created based on the selected pattern and given molding profiles. The 3D conformal cooling channel is then generated through the projection of the 2D pattern onto the 3D molding profiles, considering the specified offset distance. Figure 2b displays several typical cooling patterns. Gao et al.[6] introduced a machine learning approach to create conformal cooling system based on specified part surface and thickness, employing three patterns: spiral, zigzag, and porous. They created a surrogate model for cooling channel topology, approximating the relationship between design parameters and surface temperature. The optimization process focused on minimizing variations in part surface temperature. Dimla et al.[1] outlined their method for determining optimal conformal cooling channels using FEA thermal analysis. Through FEA results, the optimal locations of cooling channels are identified to reduce cycle time and improve overall mold quality. Abelardo et al.[7] presented an automated design method for conformal cooling system based on a discrete multidimensional model, which first built the discrete nodes from the melt flow temperatures clusters, and then extract the geometrical parameters of conformal cooling from the discrete mesh model using genetic evolutionary algorithms. He et al.[8] introduced a response surface methodology along with a multi-objective optimization technique to generate conformal cooling channels. The optimization process involved three design parameters, cooling channel radius, distance to the mold surface, and a specific ratio through the optimal Latin hypercube experimental design method and a multi-objective approach. They aim to establish the optimal layout of cooling channels by assessing cooling performance using temperature deviation as a key metric. Jahan et al.[2] presented a design methodology for creating optimal conformal cooling channels in injection molds. They initially applied design of experiments techniques to examine the impact of critical design parameters of cooling channels. Subsequently, a trade-off technique was employed to derive optimal design configurations with the goal of achieving the best thermo-mechanical performance.

These groundbreaking studies demonstrated the potential of employing advanced techniques, including geometric topology, FEA, machine learning, and multi-objective optimization in the design and optimization of conformal cooling systems. Nonetheless, a notable gap persisted in these endeavours. Specifically, none of these studies delved into the potential efficacy of employing machine learning intelligence as a holistic optimization approach for conformal cooling systems, aimed at learning and training from massive FEA/CFD thermal simulation results of various conformal cooling molds as a foundational and experimental basis.

In response to the continuous need for design efficiency, faster cycles, enhanced consistency, and elevated quality standards, industries anticipate efficient and automated approaches for designing and optimizing conformal cooling systems. This paper introduces a machine learning approach to effectively evaluating the thermal performance of conformal cooling systems, and further enables the optimization of conformal cooling design parameters to meet specific objectives.

Methods and results

This paper presents a novel machine learning method to assess the thermal performance of conformal cooling systems. Creating a sole neural network to predict the time-series thermal behavior of conformal cooling systems is challenging. By employing a combination of a non-linear regression model and a neural network, the thermal performance of conformal cooling systems can be predicted and assessed precisely. Consequently, the determination of the optimal parameters for conformal cooling design can be attained by leveraging the thermal performance assessment results. Figure 3 describes the systematic methodology of building the machine learning

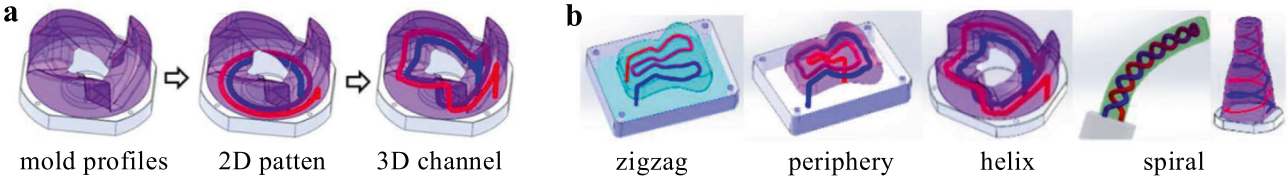


Figure 2. Conformal cooling design approach[4,5]. (**a**), Automated approach to generating conformal cooling channel. (**b**), Design patterns of conformal cooling channel.

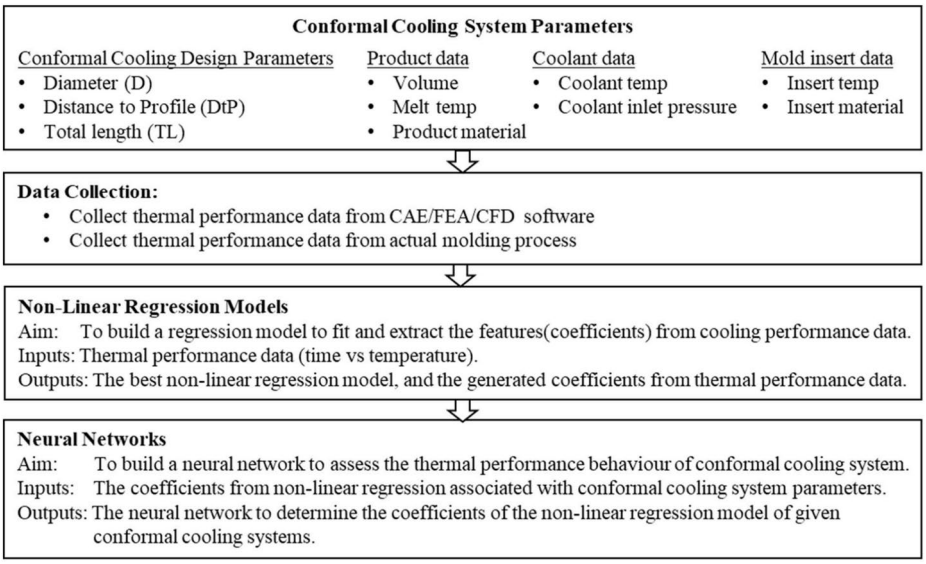


Figure 3. Systematic methodology of building machine learning methods for assessing the thermal performance of conformal cooling systems.

method for assessing the thermal performance of conformal cooling systems. It contains three main components: data collection, non-linear regression models, and neural networks, along with an introduction to the conformal cooling system parameters. Detailed explanations of each component are elaborated in the subsequent sections.

Conformal cooling system parameters

To comprehensively evaluate the thermal performance of conformal cooling molding systems, it is imperative to consider two essential sets of parameters and variables: conformal cooling design parameters and molding system parameters. The three key conformal cooling design parameters (D, DtP, and TL) play a significant role in impacting cooling performance. Additionally, molding system variables, including product data, coolant data, and mold insert data, also have a direct influence on cooling efficiency. Product data includes three key parameters (product volume, melt temperature, and product material) that define the total heat energy, melt thermal characteristics, and solidification conductivity and coefficients within the molding product. The two key coolant data are coolant temperature and inlet pressure, both exerting significant influence on cooling efficiency. The temperature and material of mold inserts are two factors influencing heat transmission rates within the metal inserts.

Data collection

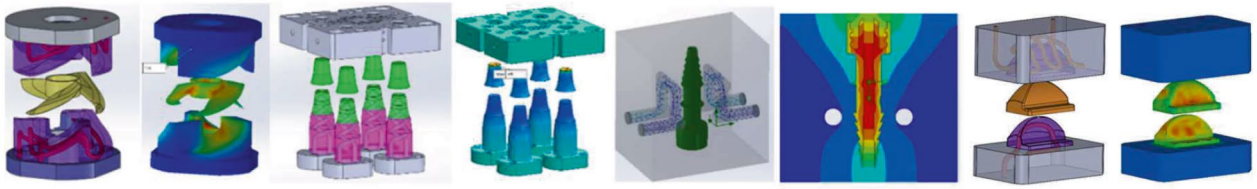
To develop robust machine learning models, a substantial volume of sample data is needed for training and validation purposes. In this study, SolidWorks' thermal simulation (FEA) and flow simulation (CFD) were employed to gather extensive cooling performance sample data from various case studies as shown in Fig. 4a. Figure 4b shows the samples of thermal records in multiple locations and conformal cooling system data. These records serve as sample datasets for the training and validation of machine learning models. Additionally, a real conformal cooling mold was integrated with thermal sensors to gather real-time thermal data during molding processes for validating the regression model and neural networks.

To compile a representative sample dataset for training regression models and neural networks, a varied set of design parameters and molding system variables is incorporated, as outlined in Table.1. These include various case studies, an appropriate range of conformal cooling parameters, diverse product materials (including ABS, nylon, PE, rubber, etc.), coolant configuration data, and mold insert materials.

Non-linear regression models

The objective of building a non-linear regression model is to identify the most effective algorithm for accurately approximating the cooling performance behavior, and extract the features, represented as coefficients, from historical cooling performance data. These coefficients reflect the relationship between cooling time and melt temperature of conformal cooling systems. The inputs for non-linear regression models are the recorded cooling performance data, with cooling time (t) and melt temperature ($Temp$) as the key variables. The outputs are the determined non-linear regression model and the coefficients (features) derived from it. Subsequently, these coefficients along with their associated conformal cooling system parameters serve as the inputs of neural networks in the subsequent phase. In this study, three non-linear regression algorithms were trained and evaluated for their effectiveness: Polynomial Regression, Logarithmic Regression and Exponential Regression.

a



fan mold recital mold nozzle mold casing mold

b

Time	Y1_Node3277	Y2_Node3396	Y3_Node3125	Y4Node1239	Y5Node9831	Y6Node9891
0.5	246.32	242.22	243.27	251.58	249.43	252.17
1	209.57	204.11	204.86	216.89	212.91	217.79
1.5	183.38	177.77	177.93	191.29	185.98	192.22
2	164	158.7	158.35	171.84	165.68	172.62
2.5	149.13	144.29	143.6	156.62	150.05	157.16
3	137.37	132.96	132.09	144.41	137.74	144.67
3.5	127.8	123.77	122.83	134.38	127.85	134.35
4	119.82	116.11	115.16	125.95	119.73	125.67
4.5	113.03	109.57	108.67	118.74	112.95	118.24
5	107.16	103.91	103.06	112.48	107.19	111.79
5.5	102.02	98.92	98.145	106.98	102.22	106.12
6	97.469	94.488	93.784	102.1	97.881	101.09
6.5	93.396	90.514	89.877	97.72	94.039	96.598
7	89.726	86.927	86.351	93.768	90.606	92.546
7.5	86.4	83.67	83.15	90.181	87.511	88.873
8	83.368	80.7	80.229	86.909	84.699	85.529
8.5	80.592	77.981	77.553	83.912	82.128	82.469

Temperature records in 6 locations

D	DtP	TL	ProdVol	MeltTer	ProdMat	CoolantT	Coolar	InsertTe	InsertMat
6	6	66.032	21.43566	300	Nylon	25	3	40	StainlessS
6	6	66.032	21.43566	300	PP	25	3	40	StainlessS
4	8	128.28	47.76223	300	Nylon	20	3	40	Carbon
5	3.5	31.599	11.56159	300	Nylon	20	2	45	StainlessS
6	9	75.12	29.52393	300	PP	25	3	40	StainlessS
7	6.5	59.323	21.43566	300	Rubber	25	3	40	StainlessS
5	7.5	160.63	89.20412	300	Rubber	18	3	45	Carbon
4	4	31.599	11.56159	300	Acrylic	20	2	45	StainlessS
6	7	49.158	10.93366	280	Rubber	20	3	45	Carbon
5	7.5	59.323	21.43566	300	Rubber	25	3	40	StainlessS
6	5	66.032	21.43566	300	PMMA	25	3	40	StainlessS
4	4	31.599	11.56159	300	ABSPC	20	2	45	StainlessS
6	8	75.12	29.52393	300	Acrylic	25	3	40	StainlessS
7	6.5	49.158	10.93366	300	Rubber	20	3	45	Carbon

Conformal cooling system data

Figure 4. Case studies for sample data collection. (**a**), Case studies of conformal cooling systems for data collection, (**b**), Samples of recorded thermal data and conformal cooling system data.

	Design parameters			Product data			Coolant data		Mold insert data	
Case studies	D	DtP	TL	Volume	Temp	Material	Temp	Pressure	Temp	Material
7	3–8 mm	2–8 mm	mm	cm^3	250–400 ℃	10 types	20–40 ℃	2,3 Bar	40–50 ℃	2 types

Table 1. The range of conformal cooling system parameters for data collection.

Algorithm 1: Polynomial regression

Polynomial regression is chosen due to its simplicity in modeling non-linear relationships. The polynomial equation is defined as follows:

$$Temp = \sum_{i=0}^{d} c_i t^i$$

where, d is the degree; c is polynomial coefficient; t is cooling time; and $Temp$ is the temperature.

As depicted in Fig. 5a, the fitting accuracy and errors of polynomial regression are sensitive to the polynomial degree. The fitting error decreases as the model degree rises. However, the fitting error still remains large (mae = 3.08) even the model degree increases to 5. It is also found that the higher-degree polynomial models introduce extra oscillations, leading to poor fitting performance. As a result, the polynomial regression model fails to precisely capture the thermal performance characteristics of conformal cooling systems.

Algorithm 2: Logarithmic regression

Logarithmic regression method is appropriate for scientific and technical scenarios, where the sample data exhibits a logarithmic pattern. The logarithmic equation is expressed as follows:

$$Temp = \sum_{i=0}^{d} c_i \log(t)^i$$

where, d is the degree; c is logarithmic coefficient; t is cooling time; and $Temp$ is the temperature.

As shown in Fig. 5b, the logarithmic regression model accurately captures the relationship between $Temp$ and t from the thermal performance data. The logarithmic model with a degree of 4 yields satisfactory fitting performance (mae = 0.46), as further increasing the model degree does not notably enhance fitting performance. Therefore, the logarithmic regression model with a degree of 4 precisely meets the goal for fitting the cooling thermal performance.

Algorithm 3: Exponential regression

The exponential regression method is applicable for scientific and technical situations, where the behavior of the sample data is exponential in nature. The exponential equation is specified as follows:

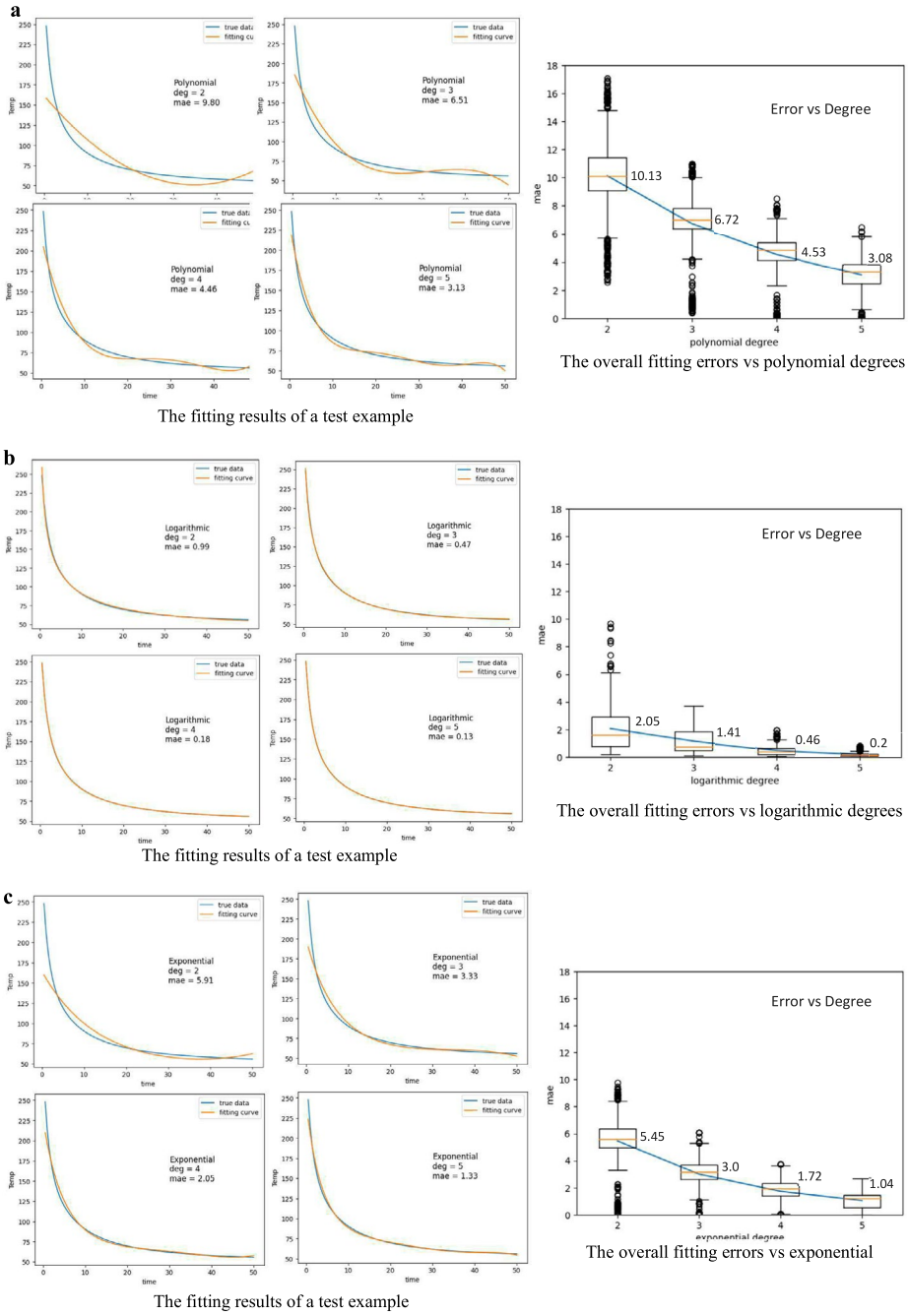


Figure 5. The fitting results of three non-linear regression models. (**a**), Polynomial regression. (**b**), Logarithmic regression. (**c**), Exponential regression.

$$Temp = \sum_{i=0}^{d} e^{c_i t^i} \; or \; Temp = \prod_{i=0}^{n} e^{c_i t^i},$$

where, d is the degree; c is exponential coefficient; t is cooling time; and $Temp$ is the temperature.

As illustrated in Fig. 5c, the fitting accuracy and errors of the exponential regression model are responsive to the degree of exponential model. A higher model degree is expected to minimize the fitting error. In contrast to the logarithmic regression model, the exponential regression model demonstrates relatively poorer fitting performance.

In conclusion, the logarithmic regression model with a degree of 4 is chosen as the preferred non-linear regression model for this study, as it exhibits the most effective fitting performance with the collected sample datasets, and successfully accomplishes the specified objectives. By employing the logarithmic regression model to process all the historical cooling performance data, the results were consolidated into a unified datasheet as

shown in Fig. 6, This dataset includes the 5 coefficients (w0, w1, w2, w3, w4) generated from non-linear logarithmic regression along with their associated conformal cooling system parameters.

Neural networks

The goal of developing a neural network is to establish the correlation between the thermal performance graph, represented by non-linear regression coefficients, and the specified conformal cooling molding system. As depicted in Fig. 6, the inputs for Neural Networks comprise the combined data of two groups: the conformal cooling system parameters as the training input features, and the coefficients generated from the logarithmic regression model as the target features. The 10 conformal cooling system parameters include 3 conformal cooling design parameters (D, DtP, TL), 3 product variables, 2 coolant configuration variables, and 2 insert variables. The 5 target features correspond to the coefficients of the logarithmic regression with a degree of 4. The output is a trained neural network to predict the thermal performance of the given 10 conformal cooling system parameters. With the given conformal cooling system parameters, the trained neural network can predict the output coefficients of the non-linear regression model. Subsequently, the cooling performance graph can be generated precisely using the non-linear regression model. Designers can easily pinpoint the optimal conformal cooling design parameters (D, DtP, TL) with a predetermined target melt cooled temperature and cooling cycle time, relying on the thermal performance results obtained through the non-linear regression model and neural network, eliminating the need for laborious CAE/FEA/CFD analysis.

In this study, three neural network architectures were developed and evaluated: Single ANN, Multiple NNs, and Branch NN.

Method 1: Single ANN

A single Artificial Neural Network (ANN) was first developed as shown in Fig. 7a. It comprises 10 input neurons, 5 hidden layers and 5 output neurons. The training results revealed that the Single ANN was effectively trained and converged within 2000 epochs, yielding low loss and error (val_mae: 3.392 ~ 4.036) with the collected sample datasets. In Fig. 7d, a comparison result for a test example was also presented between the actual cooling performance data and the cooling performance curve generated from the logarithmic regression model using the coefficients predicted by the trained neural network. The results showed that the trained Single ANN can accurately predict the thermal performance of conformal cooling systems.

Method 2: Multiple NNs

Considering the disparate value ranges of the five coefficients observed in Fig. 6, where w0 ranges in [−2.4, 2.5], w1 in [−13, 20], w2 in [−40, 30], w3 in [−111, −9.9], and w4 in [83, 380], a multiple NNs architecture (Fig. 7b) was introduced to learn each coefficient with its dedicated neural network. This strategy is expected to enhance the performance for individual coefficient. Five distinct neural networks (NN1, NN2, NN3, NN4, and NN5) were devised to independently train the coefficients (w0, w1, w2, w3, w4) respectively. Figure 7b displayed the training curves for these distinct neural networks concerning their respective coefficients. All the models exhibit successful convergence for the datasets. However, the training errors showed noticeable deviations, such as val_mae of NN5: 34.349. One possible reason could be that different capacities and configurations of neural networks should be designed and dedicated to different coefficients with distinct behaviors and value ranges. Figure 7d presented the comparison result between the actual collected cooling performance data and the cooling performance curve generated from the logarithmic regression model with coefficients predicted by multiple NNs. The results indicated that the performance of multiple NNs falls short when compared to the Single ANN in terms of the fitting accuracy and validation errors while replicating the actual cooling graph.

CoolingDesignParameters			ProductData			CoolantData		InsertData		RegressionCoefficients				
D	DtP	TL	ProdVol	MeltTemp	ProdMat	CoolantTemp	CoolantPres	InsertTemp	InsertMat	w0	w1	w2	w3	w4
8	6	128.28	47.76223	350	Nylon	30	3	40	Alloy	1.501309	-3.10808	-19.6176	-33.1816	313.554
8	6	135.771	47.76223	350	Nylon	30	3	40	Alloy	1.567131	-8.34431	-3.84152	-15.5189	328.6222
8	6	128.28	47.76223	400	Rubber	30	3	50	Carbon	1.778838	-4.15397	-21.5375	-35.5255	361.7474
8	6	135.771	47.76223	400	Rubber	30	3	50	Carbon	2.288322	-13.1544	0.418695	-14.1832	376.7735
8	6	128.28	47.76223	400	ABSPC	30	3	50	Alloy	1.706973	-3.5097	-22.5237	-38.1019	357.2438
8	6	135.771	47.76223	400	ABSPC	30	3	50	Alloy	1.769467	-9.42095	-4.39447	-17.608	375.6824
8	6	128.28	47.76223	400	Acrylic	30	3	45	Alloy	1.644728	-2.85117	-23.8329	-39.512	356.7696
8	6	135.771	47.76223	400	Acrylic	30	3	45	Alloy	1.813986	-9.63468	-4.43177	-17.9037	375.2923
8	6	75.12	29.52393	300	Rubber	25	3	40	StainlessS	-0.73757	6.041353	-6.06508	-64.7429	209.2787
8	6	59.323	21.43566	300	Rubber	25	3	40	StainlessS	-0.63251	3.80546	4.129727	-70.2221	184.0098
8	6	66.032	21.43566	300	Rubber	25	3	40	StainlessS	-0.41751	2.007312	8.153636	-69.7705	178.0977
8	6	75.965	29.52393	300	Rubber	25	3	40	StainlessS	0.078602	-0.84141	9.617936	-60.2315	173.5868
8	6	75.12	29.52393	300	PS	25	3	40	StainlessS	-0.50292	3.868311	-0.36573	-64.6764	197.3063
8	6	81.245	19.87632	300	PS	25	3	40	StainlessS	-0.34073	2.173567	0.469061	-45.6829	225.9255
8	6	76.356	19.87632	300	PS	25	3	40	StainlessS	-0.49724	3.265908	2.090288	-63.9836	196.1236
8	6	59.323	21.43566	300	PS	25	3	40	StainlessS	-0.40074	2.727183	3.336719	-65.4016	188.181
8	6	75.965	29.52393	300	PS	25	3	40	StainlessS	-0.2193	1.555553	4.751125	-63.4118	186.2402
8	6	66.032	21.43566	300	PS	25	3	40	StainlessS	-0.30891	1.208627	9.574508	-69.0654	176.0688

Figure 6. The output dataset from the logarithmic regression model associated with conformal cooling system parameters.

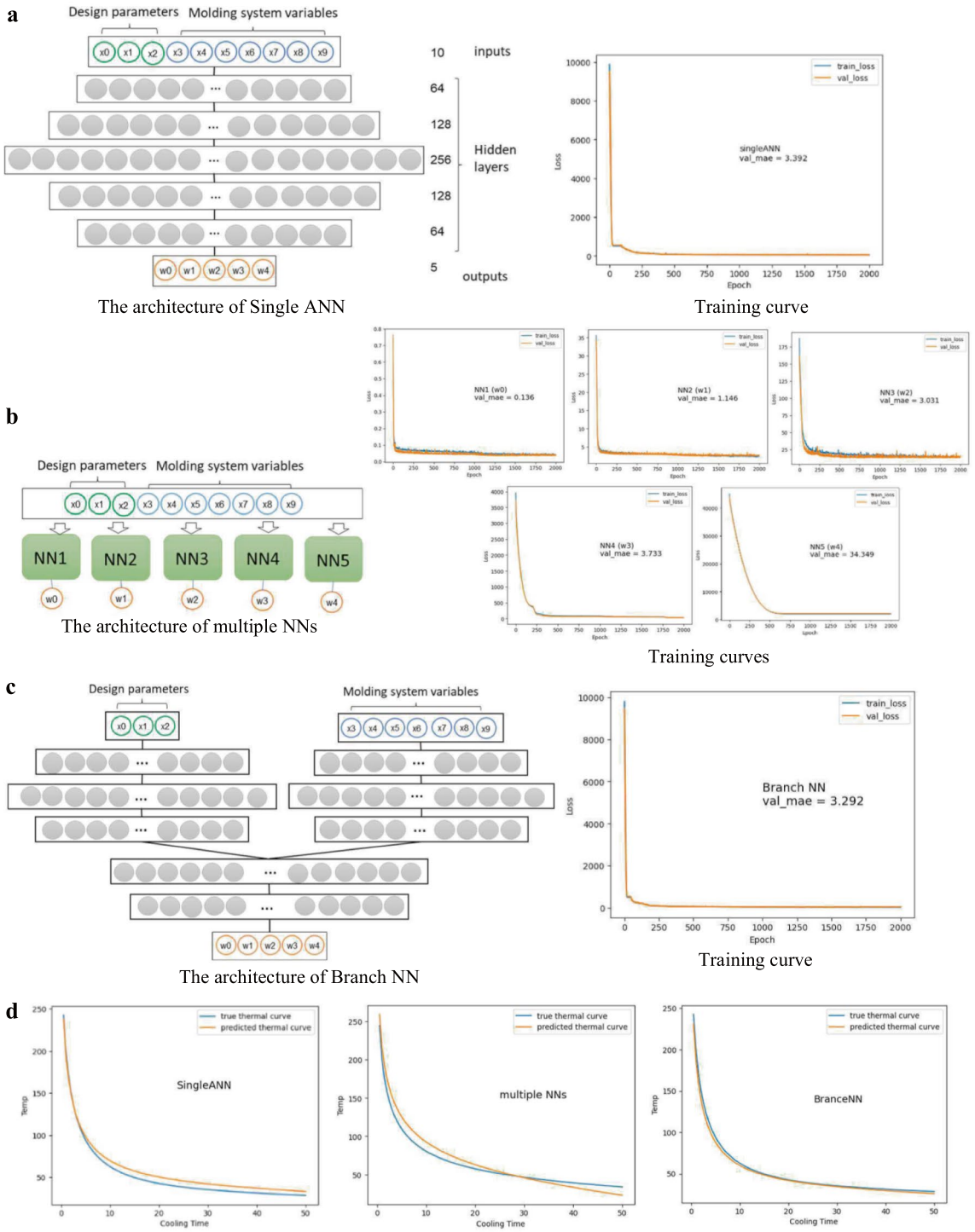


Figure 7. The architectures and training results of three neural networks. (**a**), Single ANN. (**b**), Multiple NNs. (**c**), Branch NN.

Method 3: Branch NN

The primary goal of the machine learning models is to optimize the three key conformal cooling design parameters (D, DtP, TL). Consequently, these three variables are considered more critical compared to the other seven molding system parameters. The idea was sparked by introducing a specialized branch NN to distinguish between these two sets of parameters in initial layers. This innovative approach has the potential to empower the neural network by allowing it to assign distinct weights separately to the design parameters and other molding system parameters, thereby enhancing overall effectiveness. As depicted in Fig. 7c, the three design parameters are interconnected within one branch of neurons, while the remaining seven parameters constitute the other

branch. Following three distinct layers, these two branches are merged into a dense layer, ultimately producing the five coefficients as a unified output.

Figure 7c showed the training curve of the branch NN, which exhibits an accurate convergence with very low error (val_mae = 3.057 ~ 3.568). A comparative result was presented between the actual cooling performance data and the cooling performance curve generated from the logarithmic regression model with the coefficients derived from the branch NN in Fig. 7d. The results demonstrated that the branch NN can accurately simulate the cooling performance graph for conformal cooling systems.

It was observed that the performance of the branch NN surpasses that of the Single ANN and multiple NNs. The branch NN is therefore chosen as the preferred neural network for this research due to its superior fitting and validation performance in replicating the actual cooling behavior for the collected sample datasets, effectively achieving the specified objectives. Regarding the other two models, the multiple NNs and Single ANN, additional refinements to their architectures, including neurons, activation functions, and layers, may enhance their overall performance.

Evaluation with real molding cycle data

In this study, the presented machine learning models were evaluated using a real molding cycle data. Figure 8 displayed a partial set of the thermal data recorded through thermal sensors from actual molding cycles, in which a single segment of molding cycle data was extracted for model validation. The comparative results were presented between the actual molding cycle data and the predicted outcomes generated from the branch NN and the logarithmic regression model. The result affirmed the effectiveness of the presented methods in this case study despite the fitting accuracy not reaching perfect. It is anticipated that greater accuracy and performance can be attained by expanding the size of the collected sample data and further optimizing the neural networks.

Discussion

This paper presented an innovative machine learning method for predicting the thermal performance of conformal cooling systems. Combining a non-linear regression model and a neural network enables the precise prediction of thermal performance behavior of conformal cooling molding systems. It empowers designers to identify optimal conformal cooling design parameters for injection molds without relying on manual and laborious thermal fluid simulation processes.

The research explored and compared the fitting accuracy of three non-linear regression algorithms (polynomial, logarithmic, and exponential) across different functional degrees. Logarithmic regression with a degree of 4 emerges as the best fitting for the collected sample data. Additionally, three neural network architectures (single ANN, multiple NNs, and branch NN) were developed and evaluated to predict the thermal performance of conformal cooling systems. The branch NN demonstrated superior performance without requiring further optimization. The validation results obtained from the collected sample datasets and a real case study revealed that the presented machine learning method can accurately predict the thermal performance of diverse conformal cooling systems.

Significantly, the presented method is not limited to the exclusive application in conformal cooling systems; it can be directly employed in conventional cooling mold systems as well. Furthermore, this methodology holds broad applicability across various fields, including but not limited to dynamic computational simulations, design optimizations, and multi-object optimizations.

The following suggestions are recommended to advance the presented methods in future research:

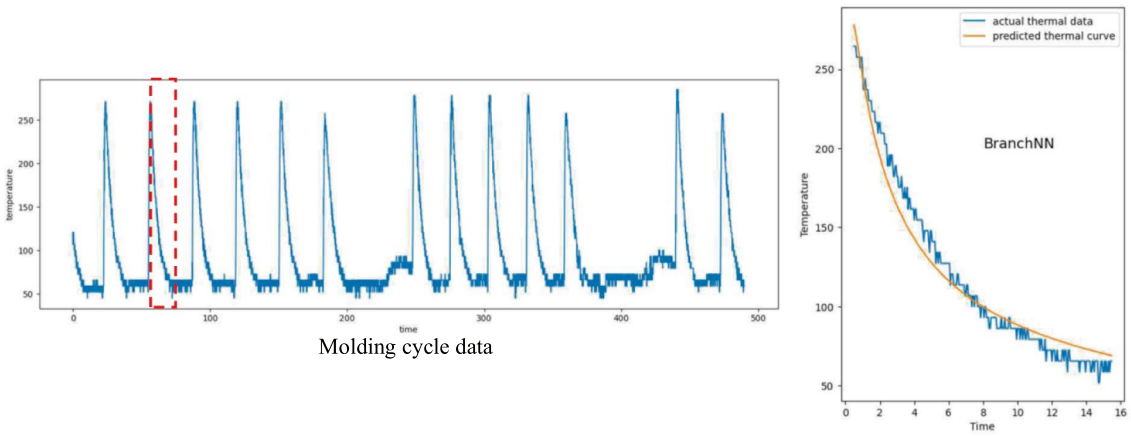


Figure 8. Model evaluation with real molding cycle data.

- Collection of more sample data from diverse case studies: Enhancing the robustness and performance of the machine learning methods for training and validation can be achieved by gathering more extensive range of sample data from diverse mold case studies.
- Optimization of neural networks: Strengthening the capability and effectiveness of the three neural networks (single ANN, multiple NNs, and branch NN) can be achieved through the optimization of their architectures. This involves tailoring their layers, neurons, activation functions and regularizations, considering their unique characteristics and advantages.
- Validation with more real molding systems: While it can be a resource-intensive task, validating the presented methods with a more extensive set of real molding systems is crucial. These validations serve to confirm the applicability of the method in real-world scenarios and provide additional real-world data for refining the methods and associated algorithms too.
- Automated determination of optimal conformal cooling design parameters: In this paper, the automated identification of optimal conformal cooling parameters is not addressed. Leveraging the predicted thermal performance graph from the presented method, optimal conformal cooling parameters could be automatically identified using other intelligent approaches such as fuzzy logic, expert systems, neural networks, or grid search. Additional considerations should be taken regarding design guidelines and constraints for conformal cooling design and additive manufacturing fabrication processes.

Data availability

Data and Steps to replicate the results are provided within the two supplementary information files, Supplementary.zip and Supplementary.pdf.

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Author contributions

Dr Zhiqiang Zhao is the only author and contributes to the entire research work and writting manuscript.

Competing interests

The author declares no competing interests.

Additional information

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