Machine Learning based Cooling Time Prediction in Plastic Injection Molding Process

by

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Machine Learning based Cooling Time Prediction in Plastic Injection Molding Process

Koç University

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This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
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ABSTRACT

Machine Learning based Cooling Time Prediction in Plastic Injection Molding Process
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This thesis presents a new approach to develop a machine-learning model for the cooling profile prediction of a planar part produced through the plastic injection molding. Design parameters related to the cooling stage of injection molding, such as distance between the cooling channel and plastic part surface, the distance between cooling channels, the cooling channel diameter, the thickness of the part, as well as plastic material properties including density, mass, thermal conductivity, and specific heat are considered. A wide range of scenarios are created considering the design parameters, ensuring the creation of a comprehensive dataset. To manage this extensive collection of cases, scripts are used to automate designs and simulations. The scripts first generate the required cooling channels for each scenario, then simulate the cooling stage of the injection molding process and collect the relevant results. Then, the physics of the cooling is discussed to estimate the time-dependent temperature of the part in the plastic injection process. An LSTM machine-learning model is used to forecast the simulation results and a regression model is used to predict the cooling profile of the parts. The validation of the developed machine-learning model is done by estimating the cooling time of two industrial parts, produced by plastic injection. One of the parts is cooled with the conformal cooling channels and the estimated cooling time is found with a 2.67% error. On the other hand, the second part is cooled with conventional cooling channels and the estimated cooling time is found with an 11.44% error. In addition, the impact of each design parameter on the cooling time was examined. After the examination, it was noticed that the plastic part should be designed as thin as possible during the design to reduce the cooling time. Also, designing cooling channels as close to the surface of the plastic material as possible was very important to reduce the cooling time.

ÖZETÇE

Makine Öğrenmesi ile Plastik Enjeksiyon Prosesinde Soğuma Süresi Tahminleme

Yiğit Konuşkan
Makine Mühendisliği, Yüksek Lisans
11 Ocak 2024

Bu tez, plastik enjeksiyon ile üretilen düzlemsel bir parçanın soğutma profili tahmini için bir makine öğrenimi modeli geliştirmeye yönelik yeni bir yaklaşımı sunmaktadır. Soğutma kanalı ile plastik parça yüzeyi arasındaki mesafe, soğutma kanalları arasındaki mesafe, soğutma kanalı çapı, parça kalınlığı gibi plastik enjeksiyonda soğutma aşamasıyla ilgili tasarım parametrelerinin yanı sıra yoğunluk, kütle, termal iletkenlik ve özgül ısı gibi plastik malzeme özellikleri de dikkate alındı. Tasarım parametreleri dikkate alınarak çok çeşitli senaryolar oluşturulmakta ve kapsamlı bir veri setinin oluşturulması sağlanmaktadır. Bu kapsamlı vaka koleksiyonunu yönetmek için, tasarımları ve simülasyonları otomatikleştirmek için yazılım geliştirildi. Komut dosyaları önce her senaryo için gerekli soğutma kanallarını oluşturur, ardından plastik enjeksiyon işleminin soğutma aşamasını simülasyonunu yapar ve ilgili sonuçları toplar. Daha sonra, plastik enjeksiyon işleminde parçaların zamana bağlı sıcaklıklarını tahmin etmek için soğutmanın fiziği ele alınmıştır. Simülasyon sonuçlarını tahmin etmek için bir LSTM makine öğrenmesi modeli kullanılmış ve parçaların soğuma profilini tahmin etmek için bir regresyon modeli geliştirilmiştir. Geliştirilen ML modelinin doğrulaması, plastik enjeksiyon ile üretilen iki endüstriyel parçanın soğuma süresi tahmin edilerek yapılmıştır. Parçalardan biri konformal soğutma kanalları ile soğutulmaktadır ve soğuma süresi %2.67 hata ile tahmin edilmiştir. İkinci kısım ise konvansiyonel soğutma kanalları ile soğutulmaktadır ve soğutma süresi %11.44 hatalık bir hata payı ile tahmin edilmiştir. Ayrıca, her bir tasarım parametresinin soğutma süresi üzerindeki etkisi incelenmiştir. Yapılan inceleme sonrasında soğuma süresini azaltmak için tasarım sırasında plastik parçanın mümkün olduğunca ince tasarlanması gerektiği fark edilmiştir. Ayrıca soğutma kanallarının plastik malzemenin yüzeyine mümkün olduğunca yakın tasarlanması soğuma süresini azaltmak için çok önemlidir.

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I want to express my heartfelt gratitude to my family- my mother, Buket; my father, Yalçın; and my brother, Mert -for their unwavering support and encouragement throughout this academic journey.

Last but not least, I am deeply thankful to my wife, Betül, for providing relentless support and understanding during the challenging process of completing this thesis. Her encouragement, patience and unwavering belief in my abilities were instrumental in reaching the finish line. In moments of self-doubt, her reassuring presence was a constant source of strength, turning obstacles into stepping stones.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

PI	Plastic Injection
CCC	Conformal Cooling Channel
CC	Cooling Channel
ML	Machine Learning
LSTM	Long Short Term Memory
FEM	Finite Element Method
CFD	Computational Fluid Dynamics
D	Diameter of the Cooling Channel
P	Distance Between Two Cooling Channels
L	Distance Between Cooling Channel and Plastic Part
s	Thickness of the Plastic Part
τ	Time Constant

Chapter 1

INTRODUCTION

1.1 Overview

Plastic injection (PI) is a versatile manufacturing process and due to its ability to produce products with complex shapes and different sizes, is widely used to produce plastic parts[Mohamed, 2013]. The PI process is known to be the most efficient technique for the manufacturing of plastic goods, making it the main reason for its significance. In 2022, the worldwide market for injection molded plastics reached a value of USD 303.78 billion, and it is projected to experience a compound growth rate of 3.6% from 2023 to 2030 [Grand View Research, 2023]. In response to the increasing global demand for plastic parts, increasing the efficiency of the process and product quality has become a necessity [Arman S., 2023]. Increasing the efficiency of the PI process is aimed by different research teams; however, most of the studies are not very effective because the consistency of the process is heavily dependent on the long-term experienced skilled operators instead of the systematic engineering approach. Factors such as batch-to-batch material characteristic changes, machine parameter fluctuations, and environmental variations significantly impact both the process and the resulting product [Wen et al., 2014]. Possible defects that may occur in the process include warpage, sink marks, flash, short shots, voids, and dimensional instability [Mourya et al., 2023].

1.2 Plastic Injection Machine

The plastic injection machine consists of two main parts: the clamping unit and the injection unit (Figure 1.1). The clamping unit ensures the mold closure before the PI process and keeps the mold closed throughout the process. The mold consists of a stationary and a movable side, and at the end of the process, the clamping unit retracts the movable side to eject the plastic part.

The injection unit comprises several key components, including a hopper, a reciprocating screw, heaters, and valves. The plastic material is loaded into the plastic injection machine in granule form through the hopper. The heaters melt these granules, while the reciprocating screw contributes to the homogenization of the plastic. Once the plastic has melted and become homogeneous, it is injected into the mold through valves.

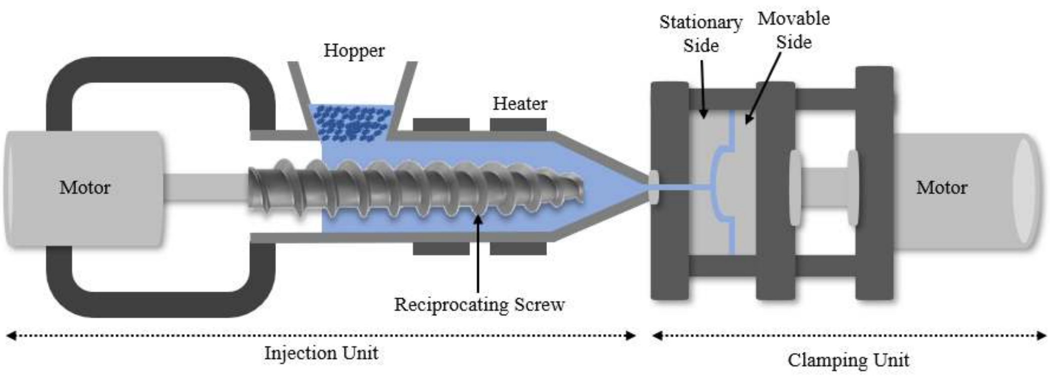

Figure 1.1: Schematic of plastic injection machine.

1.3 Plastic Injection Process

The plastic injection process consists of four main stages: clamping, injection, cooling, and ejection (Figure 1.2). Before the injection process, the movable and fixed mold parts are closed and remain closed throughout the process due to the force applied by the clamping unit. The injection phase can be divided into two stages: filling and packing. During the filling stage, the molten plastic in the machine is injected into the mold through valve gates by the movement of the reciprocating screw. In the packing stage, pressure is applied to ensure that the injected plastic reaches a uniform density. In the cooling stage, the injected plastic material in the mold is allowed to cool until it reaches to the desired temperature for the part to separate from the mold. Heat transfer occurs between the mold, plastic material, and the flowing coolant in the cooling channels (CC) present in both molds. In the final stage, ejection, after the part has reached the desired temperature, the movable mold portion is opened and the part is separated from the mold with the help of ejectors present in the molds.

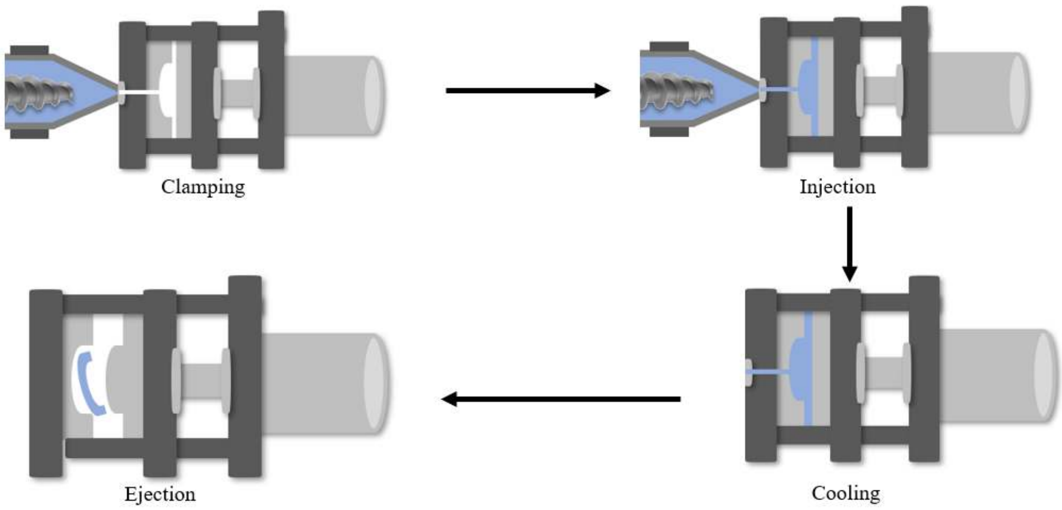

Figure 1.2: Plastic injection process

The process parameters must be correctly adjusted for the part to be successfully manufactured and the process to be controlled. During the clamping stage, the force applied to the mold should be set properly. In the injection stage, the melting temperature should be adjusted according to the material to ensure a homogeneous filling of the part in the mold, and the injection time and packing pressure should be set to ensure a complete filling of the mold. For the part to be released from the mold, it needs to fully solidify, so it is important to design the CCs in the mold appropriate for the part, and adjust the cooling temperature and cooling time parameters.[Kitayama et al., 2017]

1.4 Cooling Channel Design

In PI, the cooling stage involves cooling and solidification of the plastic part until it reaches a specific temperature[Kumar et al., 2020]. Cooling is typically achieved through conduction and convection heat transfer between the coolant flowing through the CCs, mold, and plastic part. The cooling channels are often designed as straight channels as seen in Figure 1.3 due to the limitations of the conventional drilling method used to manufacture them[Dimla et al., 2005]. This limits the ability to design CCs evenly distributed across the entire plastic part, resulting in slow and non-uniform cooling. In addition, uneven cooling of the plastic part leads to defects such as warpage and sink marks. As a result, the cooling stage accounts for approximately 60% of the total cycle time in the plastic injection process[Silva et al., 2022]. Furthermore, as the complexity of the plastic part geometry and the number of components like ejector units inside the mold increase, designing efficient cooling channels becomes challenging[Kirchheim et al., 2021].

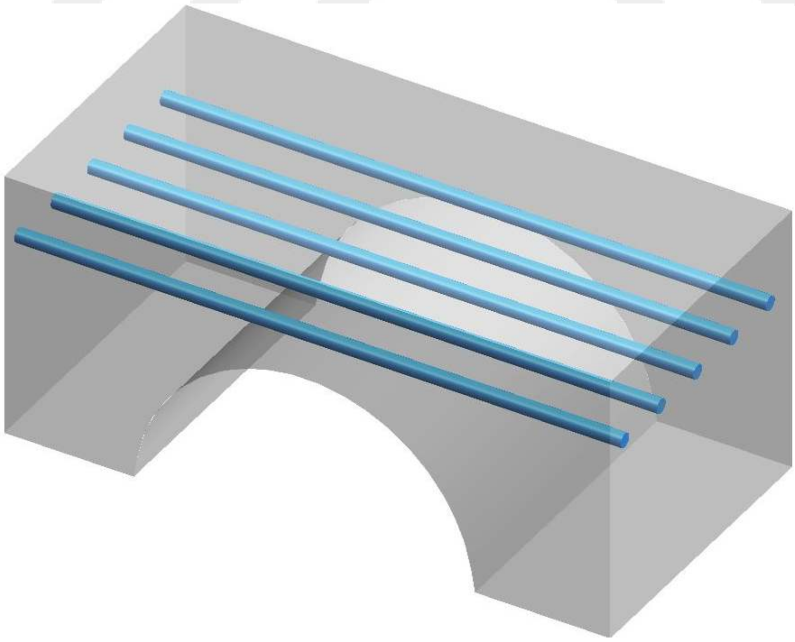

Figure 1.3: Conventional cooling channel design

Conformal cooling channels (CCC) have emerged as a solution to address these issues. The term "conformal" in this design method refers to the ability of the cooling channels to follow the geometry of the part[Sachs et al., 2000], which can be seen in Figure 1.4. Advances in additive manufacturing (AM) have enabled the design of more complex CC configurations, allowing channels to pass at approximately equal distances from the plastic part, resulting in more uniform and rapid cooling[Feng et al., 2021]. Additionally, AM allows for the creation of CCs with different cross-sections and sizes[Běhálek and Dobránsky, 2013].

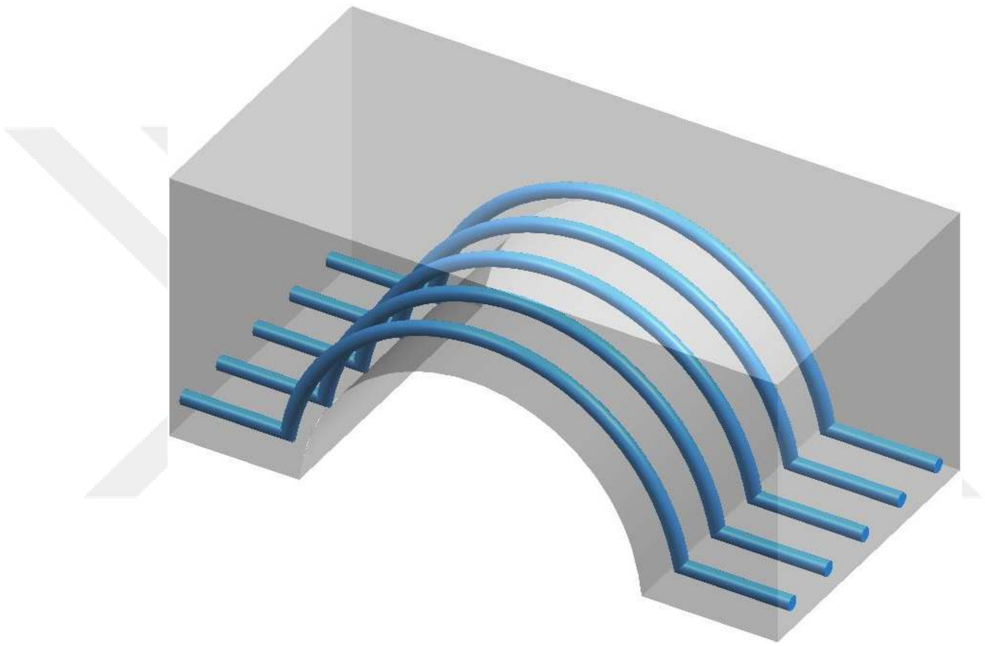

Figure 1.4: Conformal cooling channel design

1.5 Objective of Research

The cooling process is the longest and a crucial stage in PI. Conformal cooling, through channel design, can reduce cooling-related defects and significantly decrease the cooling time. However, in the design of CCC, the channel geometry parameters and the material properties of the plastic part are important. This study aims to observe the impact of design parameters and plastic part properties on cooling.

Additionally, to determine the optimal channel parameters, the process involves designing the channels and then conducting simulations iteratively. After this iteration process, the cooling time of the part in the PI process can be estimated.

The aim of this thesis is to estimate the cooling behavior of plastic materials produced by the PI process with different materials and thicknesses. The estimation is made taking into account the constraints imposed by the cooling channel diameter, the distance between the cooling channel and the plastic part, and the distance between the cooling channels. A dataset is created on the design parameters of the plastic part and the cooling channel, the material properties of the plastic part with their simulation results. The created dataset is used to develop an ML model and industrial parts with known cooling time are used to validate the developed ML model.

Figure 1.5: Workflow of this thesis

1.6 *Thesis Outline*

This thesis provides a method to estimate the cooling stage cycle time in the PI process by developing an ML model. Chapter 1 introduces an overview of PI. It explains in detail the PI machine and the PI process. Also, the importance of CC design is explained briefly.

Chapter 2 presents a literature review on the subject. It begins by discussing studies comparing CCC with conventional CC with Finite Element Method (FEM) and Computational Fluid Dynamics (CFD) analysis and experimental setup. Then it covers important design parameters and considerations during the design process. The chapter contains the optimization of CCC design and procedure of automated CC design. Lastly, it mentions the mathematical methods used to calculate the cooling time in the PI process.

Chapter 3 discusses the methodology of this thesis for predicting cooling time. It includes the creation of the dataset and the development of an ML model. For the creation of the dataset, this chapter explains the determination of the parameter set affecting cooling time, automated design and simulation studies using this parameter set, and the results obtained. With the created dataset, this chapter also focuses on the development of the ML model using the physics of cooling a material.

Chapter 4 describes the validation procedure of the developed ML model with the selected industrial parts by estimating their cooling time.

Chapter 5 explains the effect of each design parameter on the cooling at the PI process. The chapter includes a comparison of each design parameter as well as a discussion about choosing the optimum design parameters while designing CC.

Finally, Chapter 6 provides a summary of the research and suggests future work for further development.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The design of the CCC plays a crucial role in reducing the cooling time, which is the most important bottleneck to optimize the cycle time in PI and increase the quality of the finished plastic part. The literature review focuses on the advantages of CCCs, optimization studies to obtain optimum design parameters of CCC, calculating the cooling time of PI, and automation of CC design.

2.2 Conformal Cooling Channels

Several studies in the literature have focused on comparing CCC with conventional CC in plastic injection processes. These studies have demonstrated that CCC can effectively address defects such as warpage, sink marks, and volumetric shrinkage that arise from the cooling stage. Engineering software tools such as Moldex, Moldflow, and ANSYS, which use FEM and CFD, are commonly used for these comparisons[Jauregui-Becker et al., 2009]. [Venkatesh et al., 2017] conducted a study in which the CCC design was implemented in a specific part, resulting in a significant reduction in warpage and volumetric shrinkage defects. Similarly, [Zink et al., 2017] compared CCC and conventional CC designs and found that even in simple parts, CCC design had a positive impact on defect reduction and cycle time. [Dobránsky et al., 2016] examined the effect of CCC on mold temperatures and observed that CCC provided a more uniform temperature distribution compared to conventional cooling channels. [Hsu et al., 2013] employed CFD analysis to evaluate the cooling performance of CCCs and found that CCCs exhibited higher heat absorption compared to the conventional CC design. [Marques et al., 2015], made a comparison between conventional CC, parallel and series CCC design. They observed that parallel and series CCC designs are more efficient than conventional CC in terms of Reynold's number of the flow in the channels, cooling efficiency, pressure drop, and mold temperature. However, in parallel CCC, there were decreases in Reynolds number, which resulted in lower cooling efficiency compared to series CCC. In a similar study [Chinchkhede and Ashtankar, 2016], compare series, parallel, and robust conventional CC designs with CCC design on a selected part. After conducting simulations, it is observed that conventional CC design yields similar results, while CCC provides a uniform part temperature and reduces cooling time.

Experimental comparisons can also be carried out by producing separate molds with CCC and conventional CC designs to further support the findings obtained from engineering software tools. In a study by [Evens et al., 2019], the mold with CCC demonstrated a significant reduction in warpage in the plastic part. [Park and Dang, 2017], proposed a comparison between CCC and conventional CC conducted on an automotive part. After performing FEM analysis on the conventional CC, the regions of the part that slowly cool due to wall thickness are identified, and CCC design is implemented in those areas. Following the comparison of the results obtained from FEM analysis, a mold with CCC is produced using AM. Experimental trials reveal a 23% reduction in the cooling time of the part.

2.3 Cooling Channels Design Parameters

The design of the cooling channels plays a crucial role in the production of parts with minimal errors and an optimal production time. In addition, proper design helps prevent defects in the mold and extends its lifespan.

In the book, [Kazmer, 2016] underscores the importance of choosing appropriate parameters during the design phase, with particular emphasis on the influence of cooling channel diameter on flow characteristics. The book emphasizes the importance of achieving turbulent coolant flow, which requires a Reynolds number (Re) greater than 4000.

$$Re = \frac{4.\rho_{coolant}\dot{V}_{coolant}}{\pi\mu_{coolant}D} > 4000 \tag{2.1}$$

By using the flow rate ($\dot{V}_{coolant}$), the coolant viscosity ($\mu_{coolant}$), and the CC diameter

(D), the maximum feasible CC diameter (D_{max}) can be accurately calculated.

$$D_{max} = \frac{\rho_{coolant}\dot{V}_{coolant}}{1000\pi\mu_{coolant}} \tag{2.2}$$

Additionally, the proximity of cooling channels to the mold surface plays a critical role. Stress analysis resulting from various cooling channel designs, under the influence of injection pressure, helps determine the optimal distance of the CC from the mold surface (L). The book establishes that this distance should fall within the range of $2D$ to $5D$.

The pitch distance (P), representing the spacing between cooling channels, is another vital parameter discussed. Although the narrow pitch distance design provides faster and uniform cooling, it may cause the cooling channels to conflict with the mold components and hinder the channel design. To prevent regional temperature differences, the books recommendation for design range of P is $L < P < 2L$.

Numerous studies have been conducted in the literature to examine the impact of cooling channel design parameters on cooling performance. In a study [Kuo et al., 2021], a design parameter set with different D, L, and P was created while adhering to the constraints of CC design using a water cup geometry. Cooling simulations were performed using Moldex3D software to compare the cooling times and temperature differences in the parts. The analysis revealed that the proximity of CCs to the plastic part was an influential parameter in the cooling time. In another study [Jahan et al., 2016], simulations were conducted using ANSYS software on a cylindrical part, considering both circular and rectangular CCs by establishing a design parameter set. The temperature distribution, cooling time, and warpage in the part were compared, leading to the determination of optimal design parameters for rectangular and circular CC designs. Similarly, in a comprehensive study [Jahan and El-Mounayri, 2018], the full-factorial DOE method was employed to establish correlations between design parameters, such as channel diameter, pitch distance and the distance between the plastic part and the cooling channel. They examined the effects of the parameters on the cooling performance by comparing the cooling time and the maximum von-Mises stress of the parts. The investigation involved parts with different geometric structures and thicknesses to develop a design guideline for optimal cooling performance.

2.4 Optimization of CCC Design

There are also several studies in the literature that focus on the optimization of CCC design using different methods rather than comparing simulation results for each case by creating a design parameter set to find the optimal CC design based on the part geometry.

In a study [Torres-Alba et al., 2020], filling stage simulation is performed for the plastic part, without considering cooling channels. After the filling analysis, clusters are formed based on the temperature distribution in the part. An optimization study is carried out for each cluster by incorporating parameters such as mold cavity temperature, coolant temperature, and coolant pressure in addition to the D, L, and P parameters. The optimization algorithm is tested with different plastic materials for the same geometry to find the optimal cooling channel designs for each material. The developed algorithm is validated by comparing the simulation results with the optimization study. In a similar study [Park and Pham, 2009], developed an algorithm to calculate the optimal cooling channel design parameters based on the clusters generated using heat transfer equations for the optimization of temperature distribution in the part after the filling analysis. The comparison of the found design parameters with the existing conventional CCs in the part through simulation shows improvements in productivity and part quality.

In another study by [Wu et al., 2017], a FEM-based thermomechanical optimization study is conducted for a mold. In this study, the Nelder-mead simplex, constrained optimization by linear approximation (COBYLA), and Genetic algorithm (GA) methods are used to optimize the helix CCC design. These methods are employed to minimize displacement, Von Mises stress, and temperature distribution in the mold, leading to the identification of the optimal cooling channel design. [Agazzi et al., 2013], proposed a procedure to determine the optimal distribution of coolant temperature across a cooling surface. Furthermore, a heat transfer analysis of the mold is conducted to determine the appropriate shape and location of cooling channels. The final design is then adjusted to meet the constraints imposed by fluid dynamics and mechanical rigidity of the mold. [Hopmann et al., 2021], introduced a methodology to design the cooling channels to reduce the warpage with the optimization of temperature distribution. A quality function is defined and compared across three different quality areas, 2D, 3D, and midplane. Thermal optimization is done in Comsol software to define the iso-flux surfaces which indicates the locations of the cooling channels. A comparison between the cooling channel designs of different quality areas is done and it is stated that selecting the quality area based on the part thickness is crucial for obtaining the most accurate result. Another optimization algorithm applied by [Wang et al., 2015], used Boundary distance mapping (BDM), to create uniformly spaced and smooth spiral channels on freeform surfaces. They achieve this by maintaining a constant pitch distance. Additionally, their algorithms can handle complex surfaces by decomposing them into simpler components before further processing. Furthermore, [Kanbur et al., 2022], conducted a multi-objective optimization algorithm to obtain the design that optimizes CC temperature and pressure drop by determining the lower and upper boundaries of parameters such as arc radius of the CC and mold height, in addition to D, L, and P.

2.5 Automated Cooling Channel Design

Studies have been conducted in the literature on automating the design phase of both conventional cooling channels (CC) and conformal cooling channels (CCC). [Mercado-Colmenero et al., 2018] discusses an algorithm to automatically design conventional cooling channels based on the part geometry. This algorithm determines the boundary box based on the size of the part and through depth analysis, identifies areas in the part that require cooling with baffles. It also considers components such as the ejector unit in the mold that constrain the channel design, completing the optimal CC design that can be achieved. In another study, [Li et al., 2005] proposed a graph-traversal algorithm to generate all possible CC configurations from the preliminary design. Then, using the tree search method based on this algorithm, it automatically designs channel layouts according to the part geometry.

In a similar study, [Li et al., 2012] explored the use of configuration space and GA to generate feasible designs and optimize cooling channel layouts while considering constraints such as channel distance and manufacturability.

Regarding the automation of CCC design, [Wang et al., 2011] developed a software that automatically designs cooling channels on the part using the centroidal Voronoi diagram (CVD) by creating offsets from the part surface. This software also allows the user to input parameters such as D and L to generate a design that suits their needs. Machine learning can also be employed for CCC design. In their study, [Gao et al., 2021] introduced a machine learning-aided design approach for three distinct conformal cooling designs: zigzag, spiral, and porous. The methodology utilizes an artificial neural network machine learning model to comprehensively explore the design space, enabling the determination of optimal design parameters and the automated creation of cooling channels that result in a globally optimal cooling channel distribution.

2.6 Cooling Time Calculation

Simulation studies using FEM and CFD-based software or experimental setups are conducted to determine whether the most optimal design can be achieved in CC design. After these studies, if the desired result is not achieved, it is necessary to return to the design phase. To shorten this process, theoretical calculations of cooling time can be used to assess the gains of the designed CC.

One of the most commonly used methods to calculate cooling time is the one-dimensional cooling analysis of a plastic slab. By employing the conductive heat transfer formula, the heat transfer between plastic and mold can be accurately determined.

$$\frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial z^2} \tag{2.3}$$

Here, α represents thermal diffusivity and can be defined as follows:

$$\alpha = \frac{k}{\rho c_p} \tag{2.4}$$

In these formulas, T represents temperature of the plastic part, t represents time, z represents the thickness dimension of the plastic part, k represents plastic thermal conductivity, ρ represents density, and c_p represents specific heat of plastic.

Through the solution of the second-order partial differential equation in Equation 2.3, theoretical minimum cooling time can be calculated [Rashid et al., 2020]. This calculation accounts for the part thickness (s), plastic ejection temperature (T_{eject}), plastic melting temperature (T_{melt}), and the coolant temperature ($T_{coolant}$). Significantly, the cooling time determination considers the thickest and the most challenging cooling area of the part.

$$t_c = \frac{s^2}{\pi^2 \alpha} ln(\frac{4}{\pi} \frac{T_{melt} - T_{coolant}}{T_{eject} - T_{coolant}}) \tag{2.5}$$

The 1D analytic solution algorithm is introduced by [Xu et al., 2001] to calculate cooling time in CCC design. According to the algorithm, thickness averaged part temperature at the end of the cooling stage can be obtained using the Fourier Series.

$$T_p = \overline{T_m} + \sum_{n=0}^{\infty} \frac{2}{(2n+1)^2 \pi^2} (T_{melt} - \overline{T_m}) e^{-\frac{\alpha (2n+1)^2 \pi^2 t_{cycle}}{4s^2}} \tag{2.6}$$

In this equation $\overline{T_m}$ is cycle averaged mold temperature at steady state. Since higher order terms at Fourier series are negligible, only considering the first term, T_{eject} can be obtained as follows:

$$T_{eject} = \overline{T_m} + \frac{2}{\pi^2} (T_{melt} - \overline{T_m}) e^{-\frac{\alpha \pi^2 t_{cycle}}{4s^2}} \tag{2.7}$$

From Equation 2.7, t_{cycle} can be calculated as:

$$t_{cycle} = -\frac{4s^2}{\alpha \pi} ln(\frac{\pi^2}{2} \frac{T_{eject} - \overline{T_m}}{T_{melt} - \overline{T_m}}) \tag{2.8}$$

To calculate $\overline{T_m}$, energy conservation among plastic part, mold, and coolant is formulated. From the calculations $\overline{T_m}$ is formulated as:

$$\overline{T_m} = T_{coolant} + \frac{\rho c_p s (2KP + h\pi DL)(T_{melt} - Teject)}{h \pi D K t_{cycle}} \tag{2.9}$$

Here K is the thermal conductivity of the mold and h is the heat transfer coefficient.

Since both $\overline{T_m}$ and t_{cycle} are unknown they introduced an iterative algorithm. At the beginning of the iteration procedure plastic and mold material properties, and parameters of CC design are inserted. Then an assumption for $\overline{T_m}$ is done to calculate t_{cycle} through Equation 2.8, with the calculated cooling time $\overline{T_m}$ is calculated through Equation 2.9. The iteration continues until the calculated $\overline{T_m}$ reaches the predetermined error margin of the estimated value. At the end of the iteration, the cooling time is calculated using the last calculated $\overline{T_m}$.

Chapter 3

DATASET CREATION AND MACHINE LEARNING MODEL DEVELOPMENT FOR COOLING TIME PREDICTION

3.1 Creation of the Dataset

3.1.1 Overview

It is crucial to create a data set for ML-based estimation of the cooling profile in the PI process. The procedure of constructing the dataset involves creating a parameter set related to the CC design and the plastic material properties and performing design and Moldflow simulations using this parameter set. This section primarily examines the selection of design parameters, the design and the simulation process, and the dataset obtained from these activities.

3.1.2 Design Parameters for the Dataset

While creating the dataset, design parameters, that affect the cooling performance, such as the cooling channel diameter (D), the pitch distance (P), distance between the cooling channel and the plastic part (L), and the thickness of the plastic part (s), which can be seen in Figure 3.1, is taken into consideration.

The parameter set used for the cooling channel design is given in Table 3.1. While creating the parameter set, first the ranges of the part thickness and the CC diameter are determined. L and P parameters are set dependent on the D parameter to ensure that the designed cooling channels remains at a certain distance from the part and do not contact with each other.

In addition, four different plastic materials are selected to include the density (ρ), specific heat (c) and thermal conductivity (k) to the dataset with a fixed 4 mm

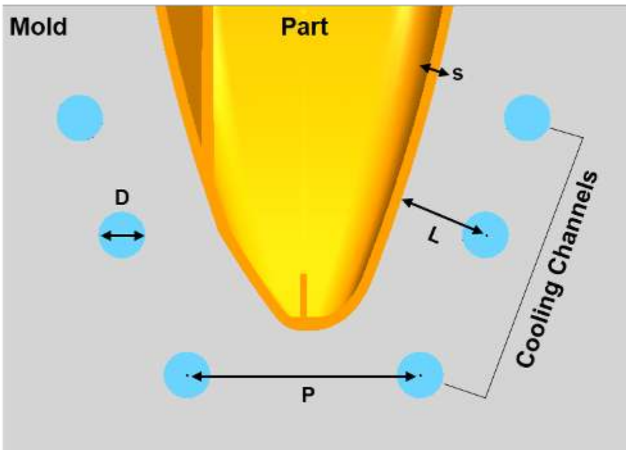

Figure 3.1: Parameters of CC

Table 3.1: Design parameters of the model

Design Parameters	**Parameter Set**
D (mm)	5 - 6 - 7 - 8 - 9 - 10 - 11 - 12
L (mm)	1.5D - 1.75D - 2D - 2.25D
P (mm)	1.5D - 1.75D - 2D - 2.25D
s (mm)	2 - 2.5 - 3 - 3.5 - 4

thickness in order to shorten the simulation time. The selected plastic materials and their properties are presented in Table 3.2.

Table 3.2: Chosen plastic materials and properties

Material	ρ ($\frac{g}{mm^3}$)	k ($\frac{W}{mmC}$)	c ($\frac{J}{gC}$)
Polypropylene (PP)	$9.05\text{x}10^{-4}$	$2.8\text{x}10^{-4}$	1.92
Polystyrene (PS)	$9.6\text{x}10^{-4}$	$1.2\text{x}10^{-4}$	1.1
Acrylonitrile butadiene styrene (ABS)	$1.05\text{x}10^{-3}$	$1.8\text{x}10^{-4}$	2.1
Polyoxymethylene (POM)	$1.41\text{x}10^{-3}$	$3.1\text{x}10^{-4}$	1.47

After the determination of the parameter set for the cooling channel and the part design, it is necessary to develop scripts to automate the design and simulation process. First, a script is developed to design cooling channels and parts according to the specified parameter set, and then a script is written to simulate the cooling analysis of the parts with these designs.

3.1.3 Automation of Generating CC According to the Parameter Set

CC design according to the parameter set, consists of four main stages. In the first stage, part design is made according to the part thickness. Then, an offset is applied to the part according to the L parameter to determine the distance between CC and the part. After that, places where the CC will pass are determined on the offset according to the P parameter, and finally, the centerlines of the CC is drawn. The workflow of the written script is given in Figure 3.2.

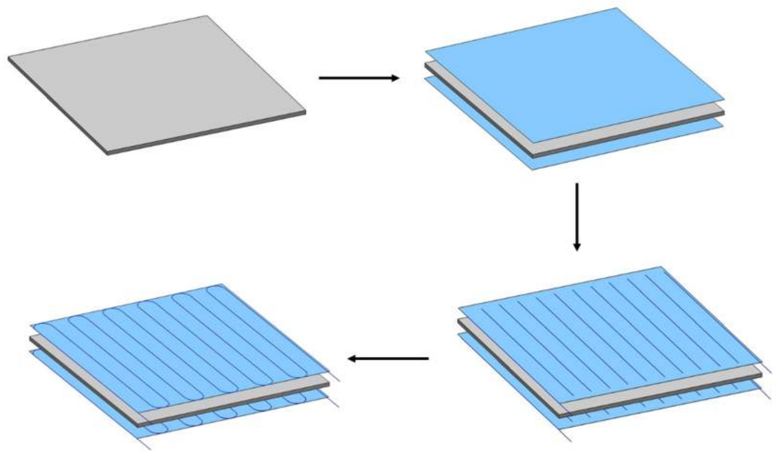

Figure 3.2: Script of designing cooling channels

3.1.4 Automation of Cooling Simulation and Data Extraction Process

To automate the simulation process, first a simulation is prepared that the script can use as a base. In this base simulation, the part and the CC design are uploaded to Moldflow. After the mold is automatically determined according to the part geometry, mesh is applied to the part, mold and the cooling channel. In order to ensure consistency in the simulations, the location of the injection point on the part is fixed. Boundary conditions, selected to be used in all simulations, are presented in Table 3.3.

Table 3.3: Boundary conditions of simulations

Mold Material	Tool Steel P-20
Initial Mold Temperature	50^{o}C
Ambient Temperature	25^{o}C
Coolant Type	Water
Coolant Inlet Temperature	20^{o}C
Coolant Inlet Pressure	5 bars
Cooling Time	10 seconds

The developed script first, uploads the part to be simulated and the centerlines of the CC to Moldflow. Then, the diameter of the CC is determined according to the case to be simulated, and the simulation is completed by taking the mesh structure and boundary conditions from the prepared base simulation. The working procedure of the script can be seen in Figure 3.3.

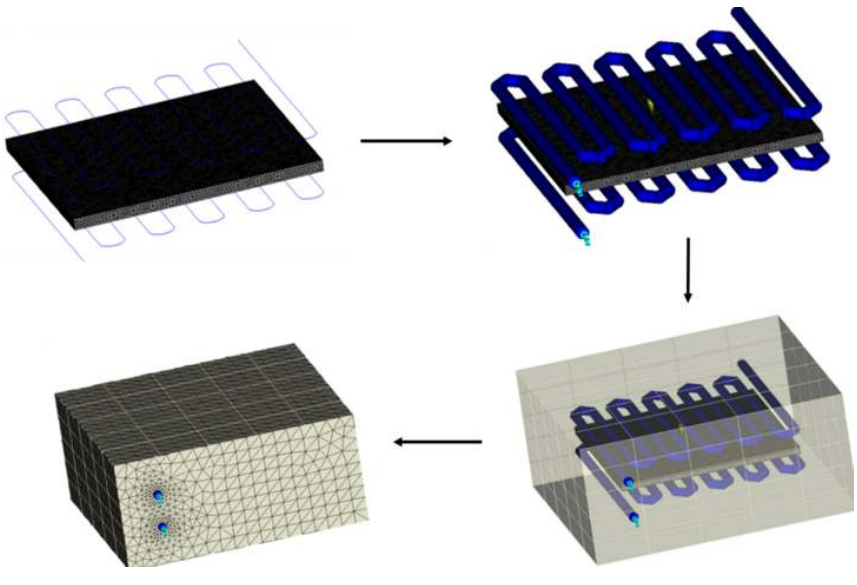

Figure 3.3: Procedure of automation of simulations

After completing all analyses, another script is written to get the analysis results from Moldflow. From 10-second cooling simulations, Moldflow can export the temperatures of each node for each time step with the .nod extension. After these files are prepared for all analyses, the average temperature of the part at each time interval are calculated with a Python code and a table is created. This table contains average temperatures of each case for each time step during the 10-second simulation period.

3.2 Developing ML Model

3.2.1 Overview

After generating the dataset from Moldflow simulations, it is required to create an ML model that predict the cooling profile and cooling time of the part. In this section, first, the physics of cooling of materials will be examined. Afterwards, the methodology of preparation of the dataset for the ML model and the ML model developed with this dataset will be explained.

3.2.2 Physics of Material's Cooling

Newton's law of cooling can be applied for cooling of a body at given temperature to ambient temperature[da Silva, 2021]. The following first-order differential equation (ODE) can be used for the time-dependent cooling of a part to ambient temperature.

$$\frac{dT(t)}{dt} = -\tau(T(t) - T_a) \tag{3.1}$$

In this equation, T_a is the ambient temperature and τ is the time constant. To solve this ODE, the required initial condition is taken as $T(0) = T_0$, and the following equation can be found.

$$T(t) = T_a + (T_0 - T_a)e^{-\tau t} \tag{3.2}$$

T_0 is the melting temperature of the plastic material and T_a is the ambient temperature, which is a default input in Moldflow as 25^oC. To find the time-dependent temperature of the part in the PI process, the only unknown parameter,

τ, must be found. The calculation procedure of τ, which varies depending on the CC and the part design, and plastic material properties, is explained in the next section.

3.2.3 Estimation of Time Constant

To determine the τ, Equation 3.2, needs to be fitted to each simulation result. The description of the fitting process is explained through a selected case with the parameters in Table 3.4

Table 3.4: Parameters of the selected case in which procedure of the τ calculation is explained

D (mm)	11
L (mm)	22
P (mm)	19.25
s (mm)	4
$\rho(\frac{g}{mm^3})$	1.05 x 10^{-3}
$k(\frac{W}{mmC})$	1.8 x 10^{-4}
$c(\frac{J}{gC})$	2.1
Mass (g)	39.55

The value of T_a in Equation 3.2 is 25^oC and as can be seen in Figure 3.4, the average temperature of the part at the end of the simulation is over 100^oC. An accurate τ can be found by estimating when each case reaches 25^oC.

The long short-term memory (LSTM) model is used to forecast the cooling profile. The LSTM model is a time-recurrent neural network which uses forget, input and output gates, to filter the relevant information. The model learns the weights of these gates over time to effectively capture the long-term relationships in its cell states [Biswas et al., 2023].

With the developed LSTM model, it is forecasted when the selected case will reach 25^oC and the resulting cooling profile can be seen in Figure 3.5.

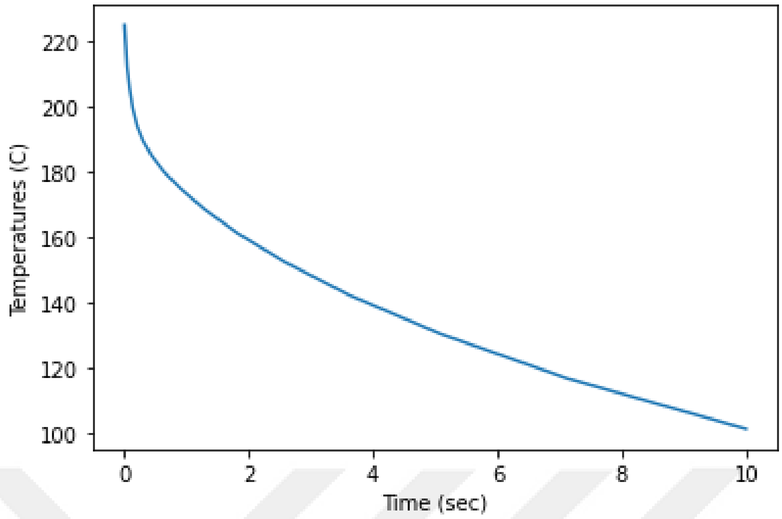

Figure 3.4: Cooling Profile of Selected Case

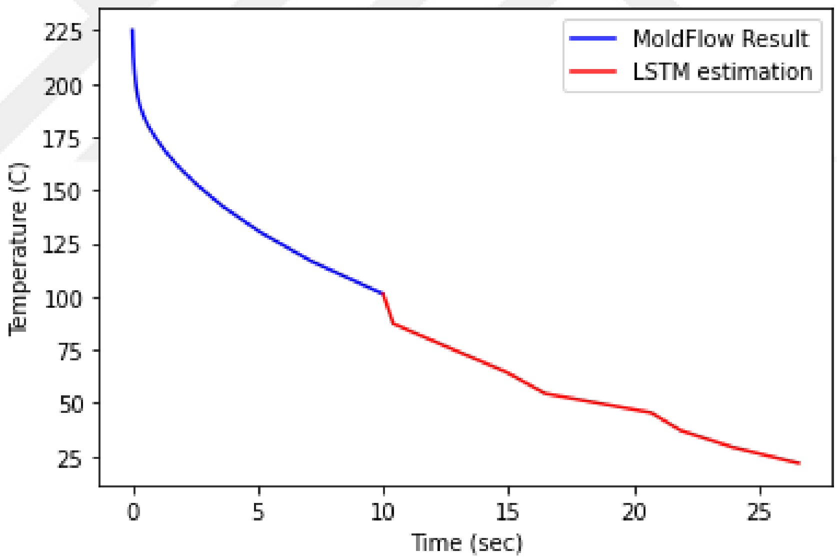

Figure 3.5: Cooling Profile After Forecasting

To find the τ value, the closest curve is found by fitting Equation 3.2 with the cooling profile in Figure 3.5. The τ value of the selected case is calculated as 0.13 and to compare with the LSTM approach time-dependent temperature profile is plotted in Figure 3.6.

The proximity of these two curves is calculated using R-squared error by using

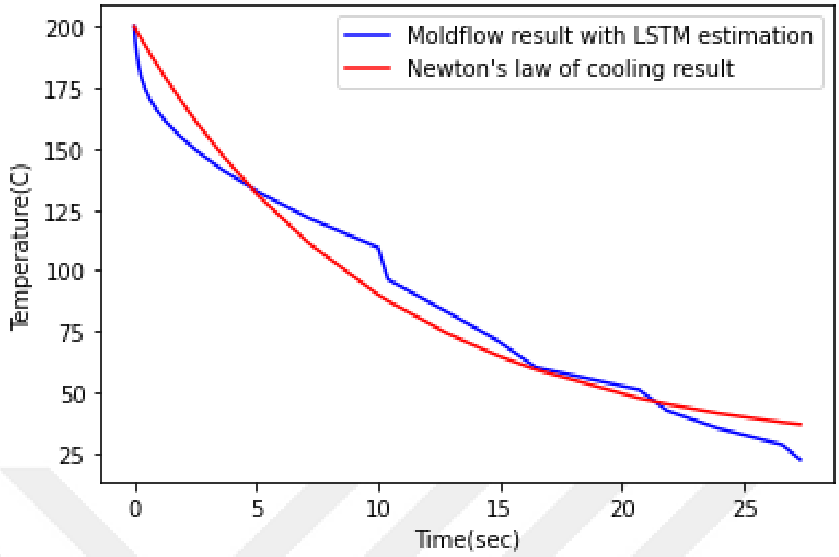

Figure 3.6: Comparison between LSTM estimation and τ estimation

the following equation:

$$R^2 = \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \overline{y}_i)^2} \tag{3.3}$$

where y_i is the actual value, $\hat{y}_i$ is value from the fitted function and $\overline{y}_i$ is the average of actual values and R^2 of the fitted function is found as 0.93.

3.2.4 Predicting Cooling Profile

As explained in the previous section, after calculating τ for the selected case, by using same LSTM model, τ value of all cases are estimated. Afterward, a dataset was prepared to develop the ML model. The first five rows of this dataset, as shown in Table 3.5, includes the columns D, L, P, s, ρ, k, c, Mass, which serve as features for the ML model, and the τ column, which represents the label for the ML model.

A gradient-boosting regression model is used to estimate τ. The dataset is divided into 80% training set and 20% test set. In order to increase the performance of the ML model, the grid search method is used to find the most suitable hyperparameters. The performance of the ML model is measured by calculating R^2 on the test dataset as in Equation 3.3. The R^2 value between the τ values in Table 3.5 and

Table 3.5: First five row of the finalized dataset

D (mm)	L (mm)	P (mm)	s (mm)	$\rho(\frac{g}{mm^3})$	$k(\frac{W}{mmC})$	$c(\frac{J}{gC})$	Mass (g)	$\tau(\frac{1}{s})$
5	7.5	7.5	2	8.95x10^{-4}	1.1x10^{-4}	1.92	17.9	0.281
5	7.5	8.8	2	8.95x10^{-4}	1.1x10^{-4}	1.92	17.9	0.280
5	7.5	10	2	8.95x10^{-4}	1.1x10^{-4}	1.92	17.9	0.282
5	7.5	11	2	8.95x10^{-4}	1.1x10^{-4}	1.92	17.9	0.279
5	8.8	7.5	2	8.95x10^{-4}	1.1x10^{-4}	1.92	17.9	0.278

the τ values predicted by the ML model is calculated as 0.98. A comparison of the test dataset and the predictions can be seen in Figure 3.7.

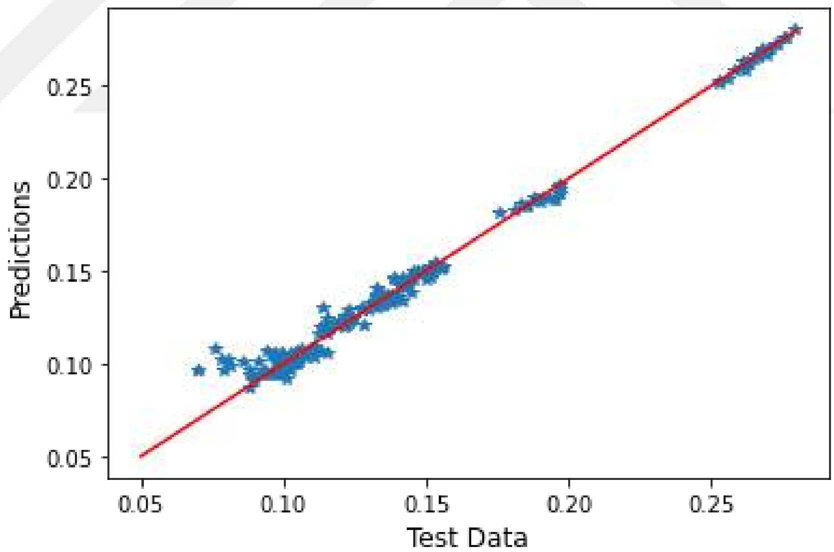

Figure 3.7: τ values for the test data and predictions

Chapter 4

VALIDATION OF THE MACHINE LEARNING MODEL

4.1 Overview

The estimation procedure of τ by using Equation 3.2, which provides the time-dependant temperature of the part at the cooling stage of the PI process, was explained in Chapter 3. To validate the developed model, real industrial parts can be used. The material properties, CC design parameters, and cooling times of these parts are known. During the PI process, a thermal camera is placed on the PI machine to measure the temperature at which the part is ejected from the mold. The cooling time can be calculated using the inverse of Equation 3.2. Therefore, the cooling time can be determined as follows.

$$t = \frac{1}{\tau} ln \frac{T_0 - T_a}{T - T_a} \tag{4.1}$$

The effect of τ on the cooling time can be examined by selecting two cases with the same plastic material, PP, from the dataset which have the maximum and the minimum calculated τ. The design parameters and τ values for the selected cases can be seen in Table 4.1

Table 4.1: Cases with minimum and maximum τ for PP

	D (mm)	**L (mm)**	**P (mm)**	**s (mm)**	**Material**	$\tau(\frac{1}{s})$
Case 1	5	10	11.25	4	PP	0.075
Case 2	5	7.5	10	2	PP	0.282

Differences in the cooling profile for these two selected cases can be seen in Figure 4.1. To calculate the cooling time of these two cases from Equation 4.1, the initial temperature, T_0, is taken as 225^oC. The ambient temperature, T_a, is 25^oC and the ejection temperature of the plastic part, T, is chosen as 50^oC. The cooling time of the plastic part with 4 mm thickness is found as 27 seconds, whereas the cooling time of the part with 2 mm thickness can be calculated as 7 seconds.

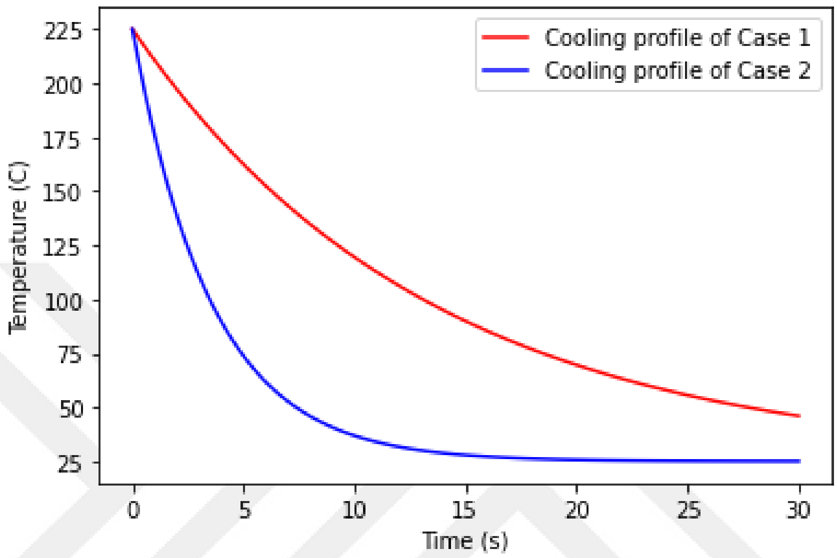

Figure 4.1: Cooling comparison of the selected cases

In the following sections, the developed ML model will be tested on two selected parts. The first part to be used for validation is the drum wing component of the dryer machine, while the other part is the vapor chamber component of the refrigerator.

4.2 Drum Wing of Dryer Machine

The first part selected to validate the ML model is a component of a dryer machine which is manufactured by the PI process with CCC designed mold. The selected component is the drum wing of a dryer machine. Drum refers to the place where laundries are put to be dried into the dryer machine. The drum wing is a component inside the drum, and it creates an additional mechanical effect by colliding with the laundries as the drum rotates, which helps to mix the rotation and allows the laundries to dry faster. The photograph of a dryer machine and the inside of the drum can be observed in Figure 4.2.

Figure 4.2: Picture of dryer machine and drum

The computer-aided design (CAD) of the drum wing is illustrated in Figure 4.3

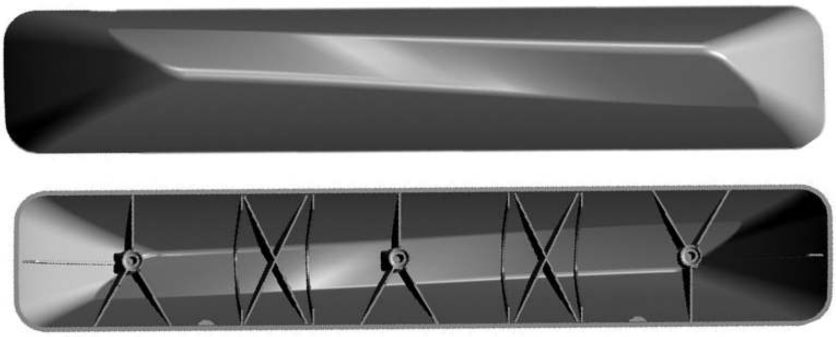

Figure 4.3: CAD of drum wing

Since effective cooling cannot be achieved with conventional CC design due to the design of the drum wing, the part is cooled with CCCs, as can be seen in Figure 4.4.

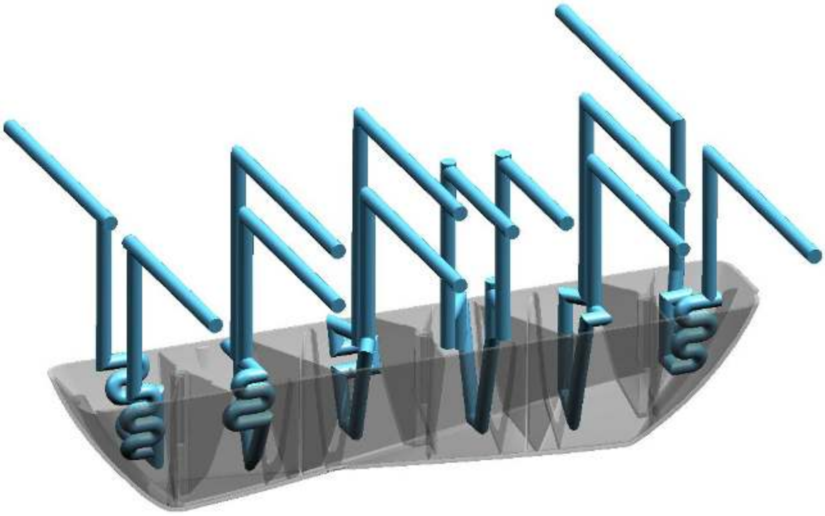

Figure 4.4: CCC design of drum wing

The developed ML model requires cooling channel parameters, part thickness, and material properties of plastic material to estimate the τ. Required inputs for the ML model for the drum wing can be seen in Table 4.2.

Table 4.2: Design parameters and material properties of the drum wing

$D(mm)$	8
$L(mm)$	10
$P(mm)$	10
$s(mm)$	4
$\rho(\frac{g}{mm^3})$	1.13x10^{-3}
$k(\frac{W}{mmC})$	2.16x10^{-4}
$c(\frac{J}{gC})$	2.1
Mass (g)	238
Melting Temperature (C)	240

τ value of the drum wing is predicted as 0.098 by the developed ML model. The time-dependent temperature of the drum wing in the PI process can be calculated by the following equation.

$$T(t) = 25^oC + (240^oC - 25^oC)e^{-0.098t(s)} \tag{4.2}$$

From the equation time-dependent temperature of the drum wing is plotted in Figure 4.5, for the first 25 seconds.

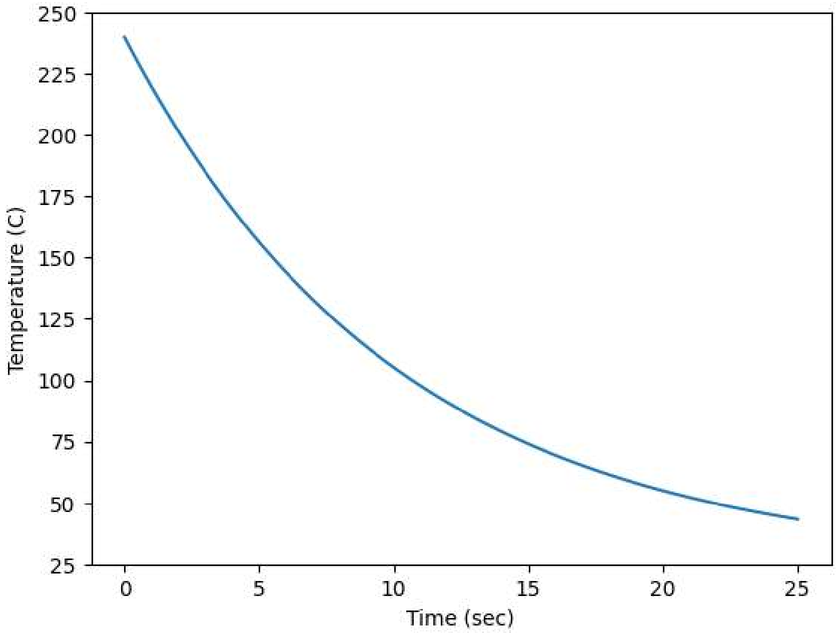

Figure 4.5: Cooling profile of the drum wing

To calculate the cooling time using Equation 4.1, the ejection temperature of the part, T is required. To measure T, a thermal camera is placed on the plastic injection machine. In the thermal camera measurement shown in Figure 4.6, the cooling time of the part is 15 seconds and the average ejection temperature is measured as 72.5^oC.

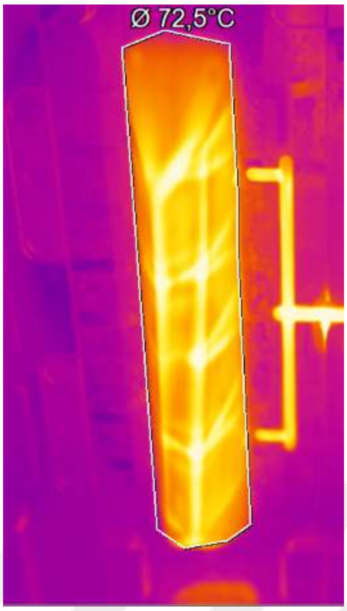

Figure 4.6: Average temperature of the part at the end of the process

The cooling time can be calculated using Equation 4.1, where $\tau = 0.098$, $T_0 = 240^oC$, $T_a = 25^oC$ and $T = 72.5^oC$. Cooling time is found as 15.40 seconds with an error of 2.67%.

4.3 Vapor Chamber of Refrigerator

The validation of the developed ML model was performed not only with CCC design but also with a part cooled by conventional CC. A component of a refrigerator, vapor chamber, which is connected to the compressor and aims to retain the water vapor, was selected for validation. The CAD data of the component can be seen in Figure 4.7.

Figure 4.7: CAD of vapor chamber

Despite the presence of depths in the part where conventional manufacturing methods cannot create channels, cooling of the part is achieved using conventional CCs instead of CCCs, along with baffles placed in areas inaccessible to these channels. The cooling channels, shown in blue in Figure 4.8, are the ones responsible for cooling, while the yellow components shown are the baffles.

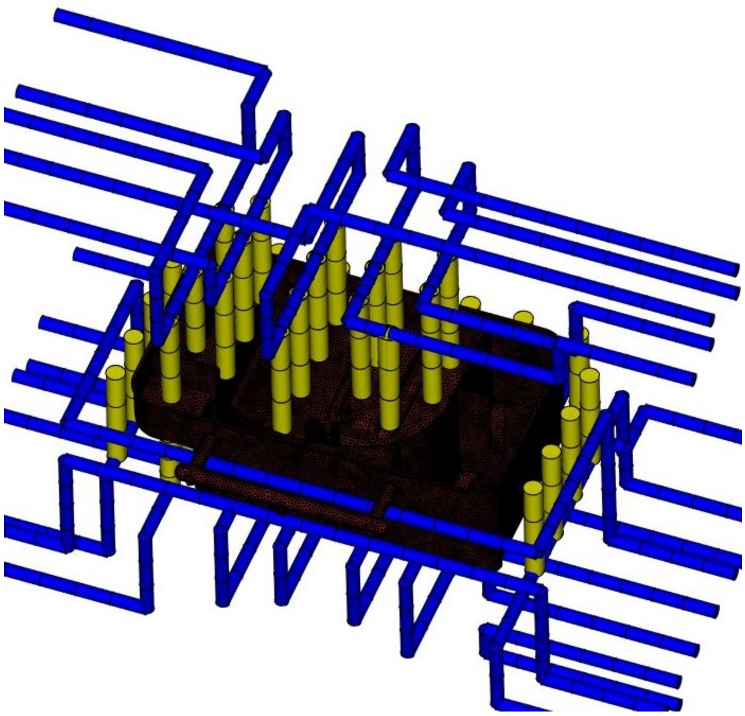

Figure 4.8: Cooling channels of vapor chamber

To estimate the τ, cooling channel parameters, part thickness, and plastic material properties are required for the developed ML model. Required parameters for the ML model for the vapor chamber can be found in Table 4.3.

Table 4.3: Design parameters and material properties of the vapor chamber

$D(mm)$	10
$L(mm)$	31
$P(mm)$	36
$s(mm)$	3.2
$\rho(\frac{g}{mm^3})$	8.95x10^{-4}
$k(\frac{W}{mmC})$	1.1x10^{-4}
$c(\frac{J}{gC})$	1.92
Mass (g)	228
Melting Temperature (C)	220.15

τ value of the vapor chamber is predicted as 0.079 by the developed ML model. The time-dependent temperature of the vapor chamber in the PI process can be found as:

$$T(t) = 25^oC + (220.15^oC - 25^oC)e^{-0.079t(s)} \tag{4.3}$$

From the equation, the time-dependent temperature of the drum wing is plotted in Figure 4.9, for the first 50 seconds.

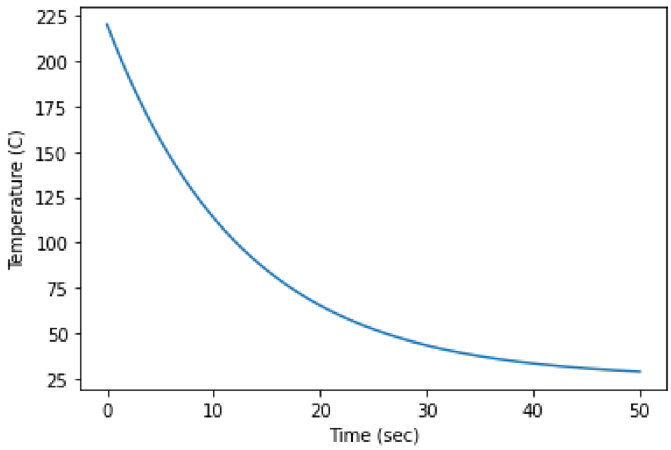

Figure 4.9: Cooling profile of the vapor chamber

The ejection temperature of the part from PI is found by attaching a thermal camera to the plastic injection machine and measuring the average temperature of the part when the mold is opened. The cooling time of the part is defined as 45 seconds in the PI process. As shown in Figure 4.10, the average temperature of the part is 33.6^oC when the mold is opened after 45 seconds.

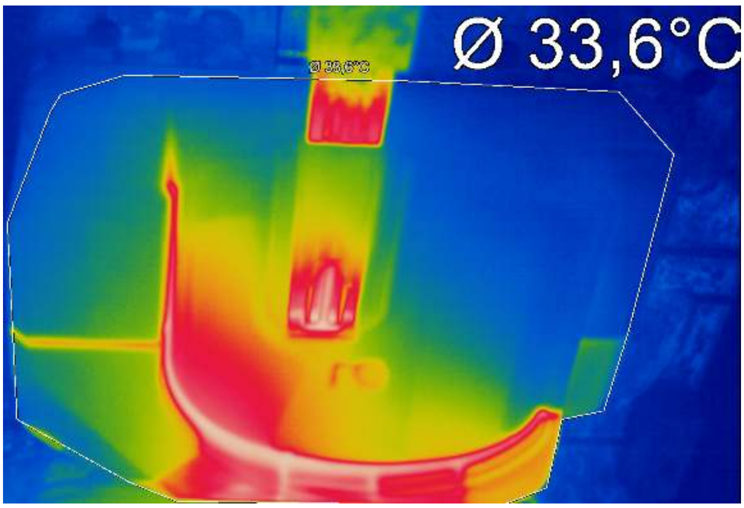

Figure 4.10: Measured ejection temperature of the vapor chamber

Cooling time of the vapor chamber can be calculated using Equation 4.1, where $\tau = 0.0079$, $T_0 = 220.15^oC$, $T_a = 25^oC$ and $T = 33.6^oC$. Cooling time is found as 39.85 seconds with an error of 11.44%.

Chapter 5

EFFECTS OF DESIGN PARAMETERS ON TIME CONSTANT

5.1 Overview

In this chapter, the influence of design parameters such as channel diameter (D), distance between the CC and the plastic part (L), the pitch distance (P), and the plastic part thickness (s) on τ is examined. For all cases, calculated τ values by using Equation 3.2 can be analyzed separately based on the plastic material and part thickness, as shown in Figure 5.1. Particularly, the significant impact of s on τ can be observed in this figure.

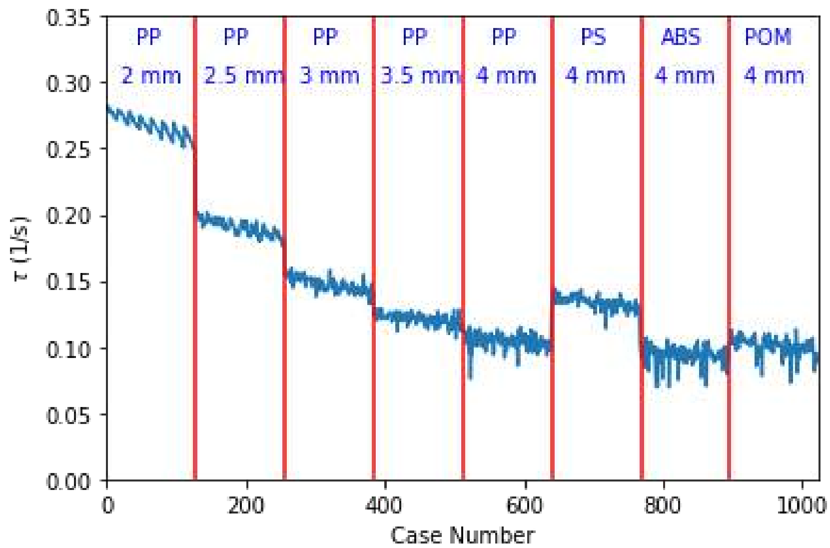

Figure 5.1: Estimated τ values for each case

The effect of the τ on the cooling performance of the part can be investigated by selecting the cases with maximum and minimum τ values from the created dataset. Table 5.1 shows the design parameters of the selected cases.

Table 5.1: Cases with minimum and maximum τ

	D(mm)	**L(mm)**	**P(mm)**	**s(mm)**	**Material**
Case with maximum τ	5	7.5	10	2	PP
Case with minimum τ	7	14	12.25	4	ABS

The time-dependent cooling profile of these two selected cases is compared in Figure 5.2 for 25 seconds, with the initial temperature selected as 225^oC. According to this figure, it is observed that as τ increase, the part cools faster.

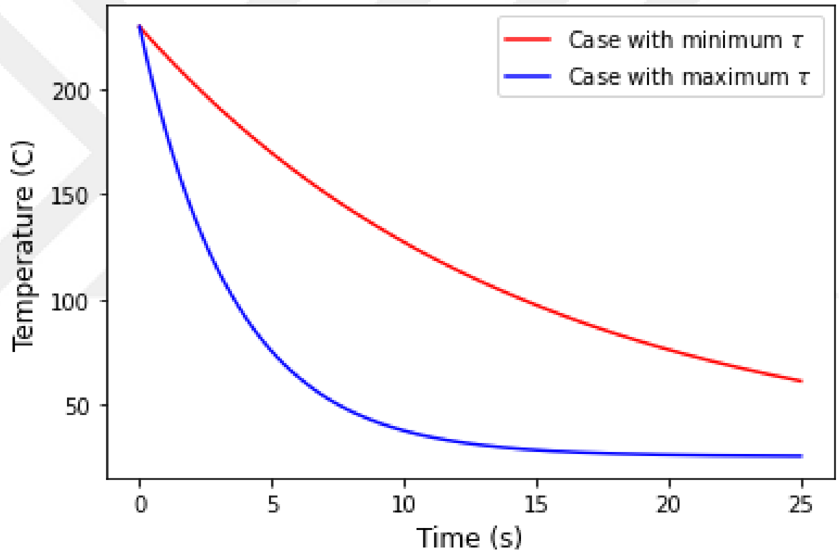

Figure 5.2: Cooling profile comparison for cases with minimum and maximum τ

It is aimed to examine the effect of each design parameter on τ as percentage. For this reason, τ values are normalized using Equation 5.1.

$$\tau' = \frac{\tau - \tau_{min}}{\tau_{max} - \tau_{min}} \tag{5.1}$$

When calculating the effect of each design parameter, cases are selected where the parameter examined is varied and other parameters are constant. Afterward, the linear line that best fits the τ values corresponding to the design parameter is found, and the slope of this line gives the percentage change of τ when the design parameter changes by 1 mm.

5.2 Channel Diameter

First, effect of the cooling channel diameter on τ is examined. As explained in the previous section, cases where all parameters are the same except the cooling channel diameter have been selected as in Table 5.2

Table 5.2: Cases with same parameters except D

D (mm)	**L (mm)**	**P (mm)**	**s (mm)**	**Material**	$\tau(\frac{1}{s})$
8	18	18	2	PP	0.904
9	18	18	2	PP	0.912
10	18	18	2	PP	0.917
11	18	18	2	PP	0.918
12	18	18	2	PP	0.929

A plot is created with the τ values in Table 5.2 and the corresponding D values, and the best fitted linear line and equation of the line are given in Figure 5.3.

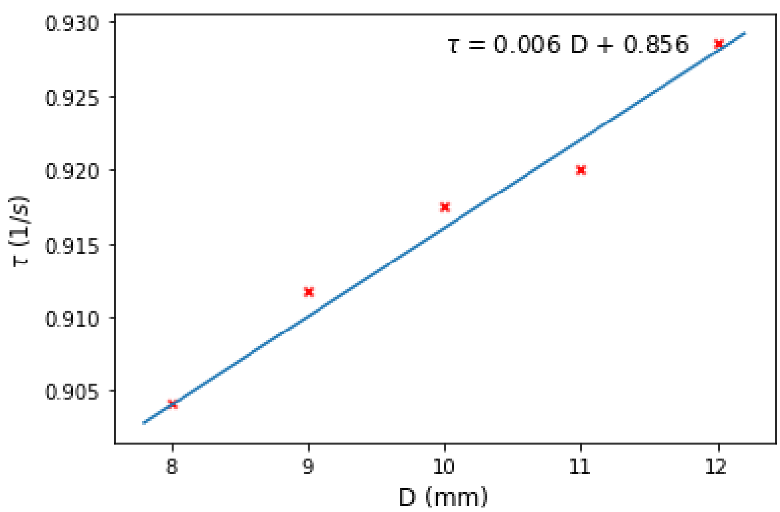

Figure 5.3: Best linear fitted line for D vs τ

Based on this equation, the slope of the linear line is 0.006, which shows that every 1 mm increase in the cooling channel diameter, will increase the τ value by 0.6%.

5.3 Distance Between Channel and Part Surface

The next parameter to be examined for its effect on cooling performance is the distance between the cooling channel and the plastic part surface. For this reason, cases where all parameters except L are the same were selected, as can be examined in Table 5.3.

Table 5.3: Cases with same parameters except L

D (mm)	**L (mm)**	**P (mm)**	**s (mm)**	**Material**	$\tau(\frac{1}{s})$
5	7.5	7.5	2	PP	0.999
5	8.75	7.5	2	PP	0.981
5	10	7.5	2	PP	0.972
5	11.25	7.5	2	PP	0.956

A plot is created with the τ values and the corresponding L values and the best fitted linear line with these values can be observed in Figure 5.4

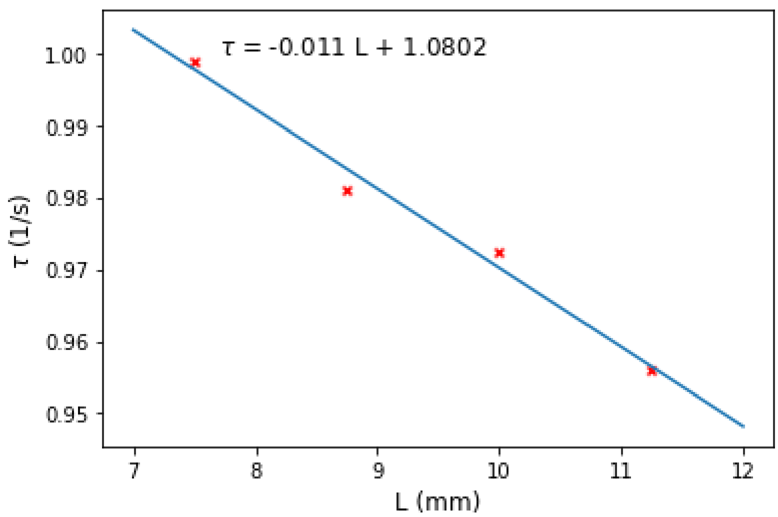

Figure 5.4: Best linear fitted line for L vs τ

According to the equation, L and τ are inversely proportional, and when the cooling channel moves 1 mm away from the part surface, τ decreases by 1.1%.

5.4 *Pitch Distance*

Finally, as a cooling channel design parameter, the effect of pitch distance on the cooling performance is examined. Selected cases and τ values can be observed in Table 5.4.

Table 5.4: Cases with same parameters except P

D (mm)	**L (mm)**	**P (mm)**	**s (mm)**	**Material**	$\tau(\frac{1}{s})$
5	7.5	7.5	2	PP	0.996
5	7.5	8.75	2	PP	0.992
5	7.5	10	2	PP	0.990
5	7.5	11.25	2	PP	0.989

The P and τ values were plotted as shown in Figure 5.5, and a linear line that best fits these values was found.

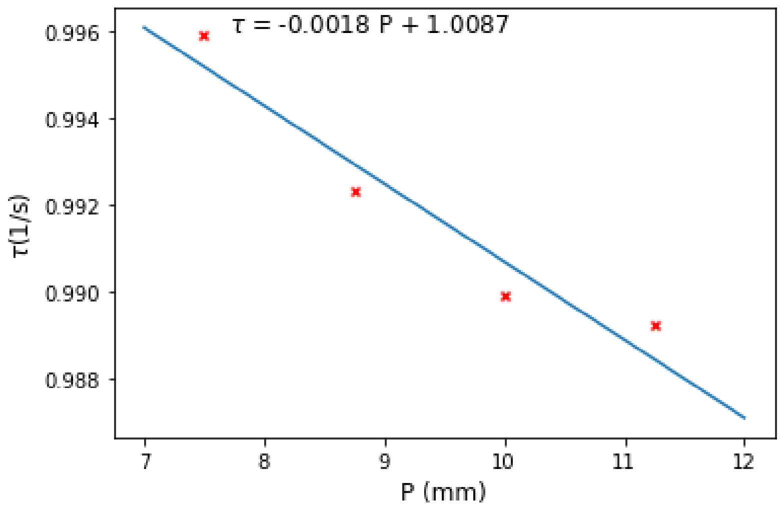

Figure 5.5: Best linear fitted line for P vs τ

According to the equation of the trendline, when the distance between cooling channels increases by 1 mm, τ decreases by 0.18%.

5.5 Thickness of Plastic Part

After examining CC design parameters, the thickness of the plastic part is selected to investigate its impact on the cooling performance of PI process. Cases where parts with different thicknesses cooled with the same CC design and their corresponding τ values can be seen in Table 5.5

Table 5.5: Cases with same parameters except s

D (mm)	L (mm)	P (mm)	s (mm)	Material	$\tau(\frac{1}{s})$
5	7.5	7.5	2	PP	0.999
5	7.5	7.5	2.5	PP	0.611
5	7.5	7.5	3	PP	0.398
5	7.5	7.5	3.5	PP	0.255
5	7.5	7.5	4	PP	0.218

The plot of s and τ values, the linear line that fits these values and the equation of the line can be seen in Figure 5.6.

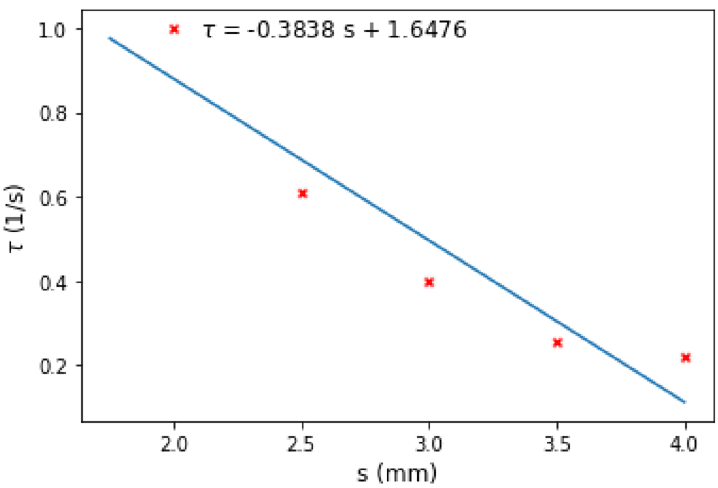

Figure 5.6: Best linear fitted line for s vs τ

Based on the equation, the thickening of the plastic part part makes the cooling difficult, and when the plastic part is thickened by 1 mm, τ decreases by 38%.

5.6 Discussion

When the effect of CC parameters and the thickness of the plastic part on the cooling in the PI process is compared, it is seen that the thickness of the part has the highest impact on the cooling performance. Therefore, in order to increase the performance of the PI process, first of all it is necessary to focus on the part design and design the part as thin as possible. The parameter that most affects cooling after the part thickness is, the distance between the cooling channel and the plastic part surface, and the closer the CCs are to the surface, the faster the part can cool. CC diameter is also an important parameter to ensure that the CCs are close to the surface. The smaller the CC diameter, the closer the CC can get to the part. However, reducing the CC diameter not only causes slower cooling but also increases the risk of blockage of the CC due to calcification.

Chapter 6

SUMMARY AND CONCLUSION

6.1 Summary

PI is the most widely used manufacturing method in the world for plastic parts in complex shapes. Due to the increased market share of PI every year, increasing the efficiency of the process to control plastic consumption is very crucial. For this purpose, studies such as reducing the amount of scrap in the produced plastic, increasing the efficiency of the machine, or reducing the cycle time of the process are carried out.

The PI machine consists of 2 main parts, clamping and injection unit. The clamping unit keeps the mold closed during the cycle and takes part in the ejection of the produced part from the machine by opening it at the end of the cycle, while the injection unit plays a role in melting the plastic granules loaded into the machine and injecting them into the mold. Based on what these 2 main components do, the PI process is divided into 4 main stages: clamping, injection, cooling, and ejection. In the first stage, the clamping stage, it is ensured that the mold remains closed with the force applied by the clamping unit. The injection stage can be divided into two sub-stages, namely filling and packing. In the filling phase, melted plastic raw material is injected into the mold with a reciprocating screw. In the packing phase, pressure is applied to the plastic material in the mold to achieve uniform density. For the plastic material injected into the mold in molten state to freeze and ejected from the mold, cooling is provided by the coolant fluid flowing from the CCs at the cooling stage. In the last stage, ejection, the plastic part that reaches the desired temperature is separated from the mold with the help of the ejectors.

Reducing the cooling time is very significant in increasing the efficiency of the PI process. Since CCs produced by conventional manufacturing methods such as drilling, mostly consisted of straight channels, they could not reach all sections of the plastic part equally and it took a long time for each section of the plastic part to cool to the desired temperature. To overcome this problem, CCC designs were made with the developments in additive manufacturing (AM) technology. The cycle time of the plastic injection process is improved by designing channels that can pass at equal distances to all sections of the plastic part with CCC. However, since CCC design is carried out with an iterative study over design and simulation, it takes time to find the optimum CC design.

In order to shorten this iterative process, this thesis aims to develop an ML model that calculates the cooling according to the part geometry with the design parameters before CC design. In Chapter 1, information about the general PI process and CC is given, and in Chapter 2, studies in the literature on the advantages, design criteria, and optimization of CCCs are included. First, the literature studies comparing the CCC design with conventional CCs are included and then the design parameters that should be considered in the CCC design and the research aiming to find the optimum design parameters are included. Optimization studies applied to find the optimum channel design during the design process also occupy a lot of space in the literature. In addition, many studies have been carried out on the automated design of CCs that will shorten the cooling time according to the geometry of the part. Finally, in the literature review section, studies on the calculation of theoretical cooling time have been included instead of the ML-based cooling time calculation in this thesis.

The methodology required to develop the ML model is included in Chapter 3. In this chapter, the methodology of creating a design parameter set according to the design criteria, making these channel designs automatically with a script, and performing cooling analyses with FEM-based software, Moldflow, automatically with the help of a script for each design are included. It is also explained how the results after the simulation are extracted from Moldflow and how the dataset is created for the ML model. Then, using Newton's Law of Cooling equation, which mathematically models the cooling of a part, the development procedure of the ML model is explained. In Chapter 4, the validation of the developed ML model on two separate plastic components used in the white goods industry was explained. To validate cooling times in the PI process were compared with the cooling time estimated by the developed ML model.

The effect of each design parameter on the cooling of the plastic part was examined through the dataset created in Chapter 5, and the points that should be considered while designing are included. According to this examination, it has been observed that keeping the thickness of the plastic part to be produced as low as possible and ensuring that the CCs pass to the surface of the plastic part as close as possible is effective in reducing the cooling time.

6.2 Conclusion

In this thesis, an ML-based model was developed with the geometrical properties and material properties of the plastic part, and the design parameters of the CCs to estimate the cooling time in the PI process. For this purpose, a comprehensive dataset was created with the important parameters of CC design. The procedure of automated design in Siemens NX and automated simulation in Moldflow through script is explained. In addition, the result files exported from Moldflow have been turned into a meaningful dataset with a script prepared in Python.

With the created dataset, an ML model was developed to obtain the time-dependent temperature of the part by using an equation that mathematically models the cooling of a material. Afterwards, the equation to be used to calculate the cooling time was determined and the developed ML mode was verified on industrial parts.

As a result, the most effective parameter on the cooling time in the PI process was found to be the thickness of the plastic part. For the CC design, the most important parameter is the distance of the CC to the plastic part surface, while the distance of the CCs to each other is the least effective parameter. In addition, after the validation study, the cooling time could be estimated with an error margin of 2.76% for the part cooled with CCC, while the cooling time could be estimated with an error margin of 11.44% for the part cooled with conventional CC and baffles.

In the next section, studies that can be done so that the ML model can give more accurate results and work with wider parameter sets are mentioned.

6.3 Future Work

To further improve the study conducted in this thesis, the number of features used in the dataset can be increased. Total CC length and CC surface area, which have an impact on the cooling of the part, can be added to the dataset. Additionally, the surface area of the plastic part is an important parameter. In the dataset, the masses of plastic parts are from 10 to 40 grams. This variation in the part weight can pose challenges in predicting the cooling time of heavier parts, so increasing the size of the part would be beneficial. Another significant parameter that has not been explored in this thesis is the mold material. Since cooling occurs through heat transfer between, CC, mold, and the plastic part, the thermal conductivity of the mold is also crucial for cooling. Particularly, by simulating with mold materials, that are commonly used for mold production, the dataset can be expanded, and the ML model can be enhanced.

In addition to these considerations, as seen in Chapter 4, the developed ML model cannot precisely predict the cooling time of the part, cooled with conventional CC. To overcome this issue, designs with conventional CC and baffles can be implemented to enhance the dataset.

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