ML-Driven Cognition for Advanced Plastic Injection Molding and Industrial Implementation

by

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ML-Driven Cognition for Advanced Plastic Injection Molding and Industrial Implementation

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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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Dedicated to my family, who have supported me unconditionally throughout this journey and shown me endless love.

ABSTRACT

ML-Driven Cognition for Advanced Plastic Injection Molding and Industrial Implementation

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For a long time, plastic injection molding has been an important part of mass production in many fields. But in today's competitive market, traditional molding methods don't always work well when you need high efficiency and quality that stays the same. We need better and smarter ways to make things because of the need for more sustainable practices, the use of more recycled materials, shorter production times, and rising labor costs.

This thesis describes a cognition-based method that is meant to work without depending on the shape of the parts, the type of material, or the specific production equipment used in the injection molding process. To do this, cavity pressure sensors were carefully put in key parts of the mold to collect data that was unique to each cycle. This information helped us find a stable operational range, or "reliable zone," that guarantees that high-quality parts are always made. One important thing this work does is show that changes in the cavity pressure curve are related to both the quality of the parts and the settings of the machine. Using this connection, a convolutional neural network (CNN) was trained to create a basic knowledge system that helps operators by suggesting ways to fix problems when they notice that something is wrong. The model that was made was able to correctly classify 98% of the time.

After the baseline was made, the proposed method was used on two real-world case studies that involved parts with different shapes, materials, and quality standards. For each application, a method for adapting knowledge to specific tasks was used, and when the system was put into real-world production environments, it had an average accuracy rate of 95%.

ÖZETÇE

Gelişmiş Plastik Enjeksiyon Kalıplama ve Endüstriyel Uygulama için ML Odaklı Biliş

Ecesu Arslan

Makine Mühendisliği, Yüksek Lisans

23 Eylül 2025

Plastik enjeksiyon kalıplama, uzun yıllardır birçok endüstride seri üretimin temel unsurlarından biri olmuştur. Ancak, günümüzün artan rekabet koşullarında bu geleneksel yöntem, istenilen verimlilik ve kaliteyi sağlamakta yetersiz kalmaktadır. Sürdürülebilirliğe verilen önemin artması, geri dönüştürülmüş hammaddelerin daha fazla kullanılması, üretim hızındaki yükselme ve iş gücü maliyetlerindeki artış gibi etkenler, üretim süreçlerinin daha gelişmiş ve akıllı sistemlerle desteklenmesini zorunlu hale getirmiştir.

Bu tez çalışması, plastik enjeksiyon kalıplamada parça geometrisi, hammadde ve üretim ekipmanından bağımsız çalışabilen bilişsel bir sistem geliştirmeyi amaçlamaktadır. Bu kapsamda, kalıbın kritik bölgelerine yerleştirilen kalıp içi basınç sensörleri aracılığıyla her üretim çevriminde elde edilen veriler analiz edilerek, yüksek kaliteli ürünlerin üretimini garanti altına alan güvenli bir bölge tanımlanmıştır. Çalışmanın yenilikçi yönlerinden biri, kalıp içi basınç eğrisindeki dalgalanmalar ile hem ürün kalitesi hem de makine parametreleri arasındaki ilişkinin ortaya konmasıdır. Bu ilişkiye dayanarak, güvenli bölgeden sapma durumlarında operatöre yönlendirici öneriler sunan makine öğrenmesi temelli bir biliş oluşturulmuştur. Geliştirilen yaklaşım, %98 doğruluk oranıyla uygulanmıştır

Temel biliş katmanının oluşturulmasının ardından, önerilen yöntem iki farklı endüstriyel uygulamada test edilmiştir. Farklı geometrilere, hammaddelere ve kalite kriterlerine sahip bu parçalar üzerinde görev odaklı biliş uyarlaması gerçekleştirilmiş ve üretim ortamına entegrasyonu ortalama %95 doğrulukla sağlanmıştır.

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ABBREVIATIONS

ML	Machine Learning
CNN	Convolutional Neural Network
CAGR	Compound Annual Growth Rate
DoE	Design of Experiment
AI	Artificial Intelligence
MBSO	Model-Based Self-Optimization
ILC	Iterative Learning Control
PP	Polypropylene
PS	Polystyrene
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
ANN	Artificial Neural Network
MLR	Multiple Linear Regression
MVS	Multivariate Sensor
SVR	Support Vector Regression
ABS	Acrylonitrile Butadiene Styrene
OEE	Overall Equipment Effectiveness
CAE	Computer-Aided Engineering
GS-GBoost	Grid Search Gradient Boosting
FEA	Finite Element Analysis
MLP	Multi-Layer Perceptron
ReLu	Rectified Linear Unit
GF	Glass Fiber
HIPS	High Impact Polystyrene
PPM	Parts Per Million

Chapter 1:
INTRODUCTION

1.1 Overview

Plastic injection molding is a vital manufacturing technique commonly used in numerous branches of industry to manufacture parts of complex shapes with high dimensional precision and large production throughput. It operates by melting thermoplastic and injecting it into a precision-made mold cavity, where it is forced to cool down and hardens to the end product. This process allows for the mass production of identical parts, which may have complex shapes, without costly tooling, and it allows for the manufacture of very tight tolerance parts.

Its applicability to a wide spectrum of polymers and automation potential make it a core technology in industries including automotive, aerospace, medical devices, consumer electronics and packaging. From lightweight structural elements in automobiles to sterile components in medical, injection molding ensures both the scale and material range necessary for large industrial needs.

In functional terms, plastic injection molding apparatus usually comprises a raw material feeding hopper, a heated barrel containing a reciprocable screw for plasticizing and injecting the material, and a mold clamping section. Progress in sensor integration, data-driven machine learning, and real-time analysis and control have enabled the traditional molding machine to turn into a system with intelligence able to adapt itself to perform a constant quality.

Due to its strategic nature for both high-volume and high-precision manufacturing applications, the global plastic injection molding market size is expected to be at around $285 billion in 2024, with a CAGR of 5.1% from an estimated value of $280 billion in 2019 in 2023 [1]. As cost effectiveness, product personalization, and sustainability become of greater and greater importance to industrial users, injection molding technology has evolved into an incredibly competitive and indispensable production process.

1.2 Process Cycle of Plastic Injection Molding

In the plastic injection molding process, each cycle consists of five basic phases [2]. The first phase begins with the closing of the mold, initiating the formation of the plastic product. During this phase, granular raw material from the hopper begins to melt due to the heaters surrounding the barrel. A specially designed screw inside the barrel homogeneously mixes the molten material and injects it into the mold under controlled pressure. This initial stage, where the material starts to fill the mold, is called the filling phase. At this point, approximately 98% of the mold cavity is targeted to be filled.

In the subsequent holding and packing phases, the mold cavity is filled, and the molten material takes its final shape. A significant proportion of product defects arise from incorrect process settings during these second and third phases. Therefore, precise control of pressure, temperature, and timing is critical.

Once the cavity is filled, the cooling phase begins, accounting for approximately 50% of the cycle time. During this phase, the part is uniformly cooled to the mold ejection temperature using cooling channels that surround it. For plastic materials, thermal distribution plays a crucial role in determining part quality. If parts are ejected at temperatures above the required threshold, they continue to cool in the external environment, potentially leading to dimensional inconsistencies. Additionally, non-uniform temperature distribution upon ejection can result in warpage defects. Thus, designing cooling channels in accordance with the part geometry is of great importance [3].

Upon completion of the cooling phase, the mold opens, and the part is ejected.

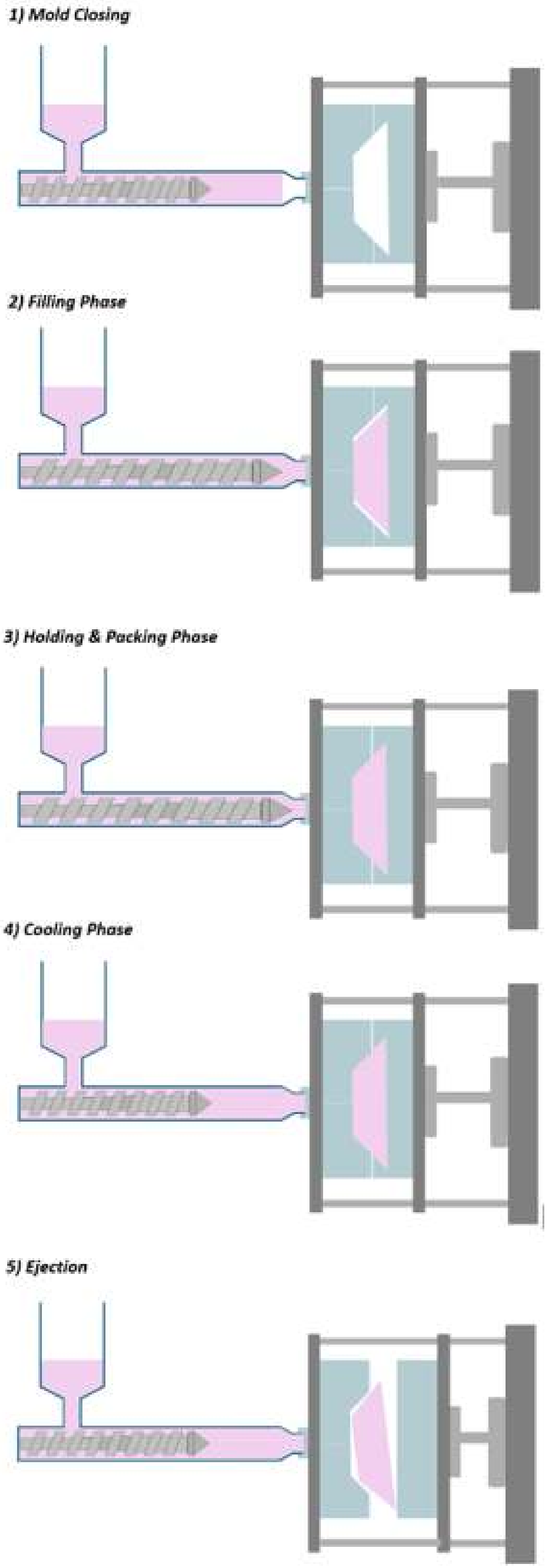


Figure 1.1: Phases of plastic injection molding cycle

1.3 *Understanding and Managing the Challenges of Plastic Injection Molding*

The injection molding process functions nonlinearly and is time-dependent, which is typical of batch processes. The intrinsic complexity substantially influences the quality of the final outcome. Six principal types of independent factors exacerbate the situation: time, pressure, temperature, material qualities, environmental conditions, machine configurations, and operator activities. These factors collectively hinder the attainment of a stable production process, as illustrated in **Error! Reference source not found.**.

A detailed examination of the time variable as cycle time encompasses the optimization of several parameters, including injection, holding & packing, and cooling durations. For instance, if the injection phase ends too soon, the part gets a short shot, which makes it defective. In the same way, not giving enough time for cooling can cause internal stresses that make the finished part shrink and change shape.

Pressure is a critical variable in a process. The molten material must be meticulously inspected to ensure proper flow and uniform distribution within the mold. Excessive pressure can induce turbulence, resulting in surface imperfections, particularly in visually sensitive regions. Also, this condition makes materials more expensive and causes operations that don't add any value because of flash defects. Conversely, insufficient pressure during injection results in loose packing, leading to sink marks on the surface. Maintaining pressure profiles within appropriate ranges throughout the cycle is essential for achieving consistent filling and superior product quality.

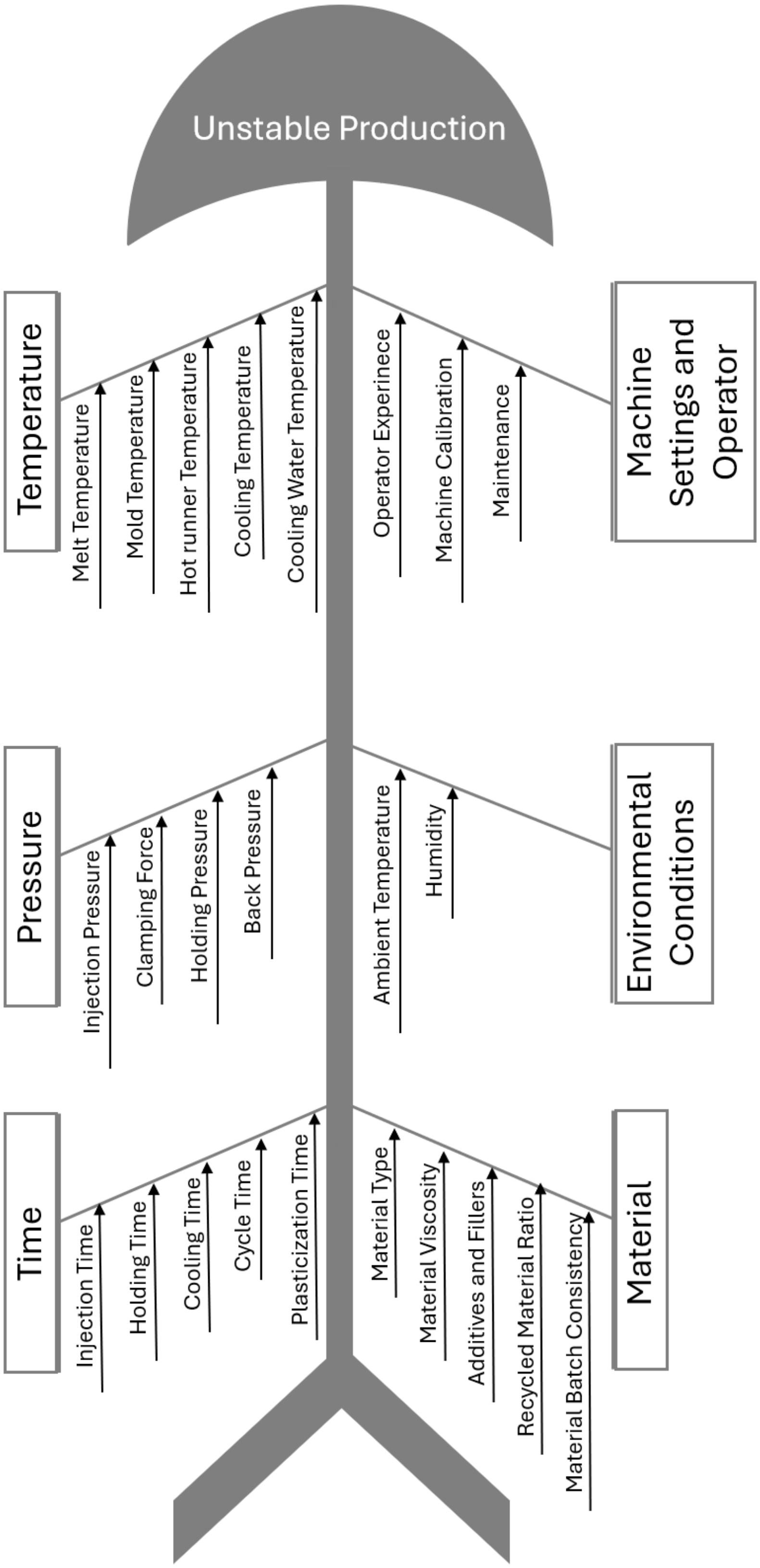


Figure 1.2: Fishbone diagram of plastic injection molding parameters

Temperature is a critical determinant influencing both machine setups and material characteristics. Accurate calibration of parameters, including melt temperature, injection temperature, mold temperature, and cooling water temperature is crucial for optimizing cycle durations by regulating material viscosity to the desired level. Starting the process with excessively high melt temperatures can cause thermal degradation, while insufficient temperatures can impede flow within the mold and increase scrap rates. Uniformity of temperature distribution is equally important; variations in mold temperature or cooling rates cause uneven shrinkage in different areas of the part. This results in dimensional imperfections, manufacturing irregularities, and alignment and assembly complications. Consequently, accurate temperature regulation during the transformation of the raw material from granular to molten is crucial for maintaining process stability and ensuring uniform product quality.

The principal problem concerning materials is the incorporation of recycled plastics to foster a cleaner and more sustainable environment. Increasing the percentage of recycled content in raw materials results in heterogeneity in the properties of each batch. This unpredictability requires regular parameter changes and, if inadequately controlled, can reduce the life of both the mold and the machine. With the increasing emphasis on sustainability and the improvement of industrial standards, there is an increasing demand for control systems that can address quality issues resulting from changes in material composition [4].

Environmental conditions represent the greatest challenge to maintaining consistent quality in plastic injection molding. Although manufacturers often establish seasonal parameter sets for each product, these are insufficient to guarantee consistent quality. Fluctuations in ambient temperature and humidity prevent uniform results from being achieved with a fixed set of parameters, even when using the same materials, machines, and molds. For example, increased humidity can cause surface defects and bubble formation, especially in hygroscopic materials. The need for constant monitoring of these elements and immediate intervention by skilled operators complicates the process and increases the dependence on human control.

When all independent variables interact, stable production using fixed machine settings becomes unsustainable. Considering the difficulties associated with hiring highly skilled operators, the long training periods required for new personnel, and the increasing turnover rates, achieving operator-independent production processes has become a key goal. An extensive analysis of these aspects underscores the necessity for a stringent control system in the plastic injection molding process. The intricacy of executing frequent and accurate modifications across all variables has generated a distinct need for creative solutions. This study presents a machine learning-based decision support algorithm by using cavity pressure sensors to monitor the uniform distribution and cooling of molten material in the mold.

1.4 *Objective of Research*

This thesis presents methodologies and industrial applications developed to maintain stable production within an efficient range during the plastic injection molding process. The proposed methodologies utilize cavity pressure sensors placed inside the mold. By leveraging a base cognitive model developed for advanced plastic injection molding, optimal part production is achieved regardless of the machine, raw material, or part geometry used in the process. This machine learning-based cognitive model provides real-time decision support to operators during production, enabling the adjustment of optimal machine parameters independent of the operator's experience.

Furthermore, the study demonstrated that once the base cognition is established, it can be scaled to parts with varying requirements using a relatively smaller dataset. These parts, selected from industrial applications, were representative of two distinct categories: mechanically critical parts and visually critical parts.

Additionally, the study examined the occurrence of short shot and flash defects and concluded that no manual readjustment of machine parameters was required to address these issues. To manage such deviations, an adaptive valve-gate control system was developed. This system autonomously adjusts the opening and closing times of valve gates in a closed-loop manner based on the cavity pressure curve, thereby eliminating operator dependency for resolving these two types of defects.

1.5 *Thesis Outline*

This thesis presents a methodology developed to maintain high-quality stability in production processes within plastic injection molding. The proposed method, which eliminates the need for highly skilled operators during production, comprises reliable zone identification for the process, a decision support algorithm (ML-driven cognition) for predicting the required process parameters, and an adaptive valve gate control system.

Chapter 2 includes a comprehensive review of studies conducted in the literature to improve the final product quality using cavity pressure sensors. The reviewed studies are divided into experimental, analytical and data-driven artificial intelligence according to the technical differences of the application method.

Chapter 3 serves as an introduction to the methodology proposed in this thesis. It defines the relationship between cavity pressure sensors and the process, and describes in detail the stages of reliable zone identification.

Chapter 4 discusses the creation of the dataset for the base cognition model designed for the plastic injection molding process and presents the technical details of the machine learning-based model structure.

Chapters 5 and 6 present the industrial applications of the proposed methodology. At this stage, final products with different requirements were selected, and it was demonstrated that the proposed methodology can operate independently of mold, part, and material.

Chapter 7 describes the adaptive valve gate control system, which operates in closed-loop mode to eliminate dependencies during the application phase of the developed methodology and prevent short shot and flash defects.

Finally, Chapter 8 discusses the results of the studies conducted within the scope of this thesis. It also summarizes the advantages and disadvantages of the method and provides recommendations for future research.

Chapter 2:
LITERATURE REVIEW

2.1 *Overview*

In this chapter, studies from the literature focusing on zero-defect production in the plastic injection molding process are imposed. The literature review is structured around the use of cavity pressure sensors as a central theme. Accordingly, the reviewed studies are categorized into three main groups based on the methodological approach adopted.

The Experimental Methods section covers studies that involve systematic, repeated experimentation based on a defined experimental setup, along with the results derived from these investigations.

The Analytical Methods section includes studies that contribute to the injection molding process through mathematical modeling and/or simulation, utilizing information extracted from cavity pressure data within the developed applications.

The Data-Driven Artificial Intelligence section presents studies in which data-driven algorithmic frameworks, developed using cavity pressure sensor data, are employed to propose solution methodologies for process optimization and defect prevention.

2.2 *Experimental Methods*

Experimental studies consist of repeating the procedures defined for each case study. In this way, the effects of independent variables on dependent variables were tested and revealed. However, material behavior is one of the most critical parameters at this stage. Verifying part behavior with different material types increases the reliability of the results. In this context, Hassan [5], who worked with polystyrene and low-density polystyrene materials, investigated the correlation between machine parameters, such as injection pressure, speed and time, packing pressure and time, and cooling time, using a cavity pressure sensor. He then examined the effect of these changes on part weight. As a result, it was observed that injection pressure, packing pressure, injection temperature, and packing time correlated with cavity pressure, while an inverse correlation was found with injection time.

The plastic injection molding process's dependence on external factors has prompted researchers to develop adaptive control systems to maintain consistent part quality in mass production. Historically, studies have experimentally demonstrated the relationship between part quality and parameters such as clamping force and the V/P switchover point [6] [7].In a study conducted by Chen et al., it is demonstrated that the profiles of tie-bar elongation were effectively applied to realize a V/P switchover control for better molding quality, energy-saving, and parts with less defects [7]. Similarly, adaptive control was also reported in the studies of Su et al., based on the variation in the viscosity index (integration of pressure curve), peak pressure, and clamping force peaks, measured by nozzle pressure sensors and tie-bar sensors [6].

Another article about the feasibility and efficiency of using in-cavity data for failure diagnosis in the injection molding process is Araújo et al. [8]. The interpretation of cavity-pressure data was used to monitor and analyze process variables that affect cavity pressure and part quality. The method provides valuable information related to flow behavior of the polymer during injection (in particular, filling) stage. In addition, the study related the observed results to a standard cavity pressure profile and was able to support the determination of defect origins in in-molded parts. The study not only looked at the velocity-to-pressure switch over, but also the first part of the pressure curve, as it is essential in understanding the filling phase and its effect on end part quality. A major accomplishment of the current work is the emulation of the experimental Read parameters, which gives clues about the relationship between real and 'simulated' cases. Comparing these results with simulation data, the need for simulation to predict behavior of polymer melts and to back up mold tool design has been demonstrated. Coupled experimental- and simulation-based analysis results presented useful guidelines for process improvement and fault detection during the injection molding process.

Conclusions about part quality drawn from mold cavity pressure measurements are not limited to part weight. One common defect in parts produced by plastic injection molding is warpage. This defect typically arises from non-uniform cooling of the molten material injected into the mold cavity. However, because of the characteristics of plastic materials, warpage can appear soon after manufacture or sometimes even hours after production. In order to overcome this limitation, Zamani et al. [9] investigated the early warpage risk prediction by monitoring cavity pressure on the production cycle. In their investigation, the researchers applied two cavity pressure sensors at varied distances from the central point of a centrally gated disk-shaped part. Such that the pressure differentials over the radial flow path region were closely correlated with the magnitude of the part deformation based on analysis of experimental data using the Taguchi method. Major components responsible for substantial warpage were the conflicting tendencies within the part, i.e. the viscoelastic recovery of the binder in the core and the thermal shrinkage of the edges. It was determined that the injection speed was the predominant factor influencing the deformation of the parts.

One of the earliest works for zero defect manufacturing was done by Nian et al. [10] when manufacturing a multi-lane IC tray portion. The article paid attention to obtain a better approach for detecting shrinkage, warpage, flash, sink marks and using communication network cavity pressure sensors at different distance from the gates. The results indicated that cognitive rules could be established by observing the flow state of molten resin with cavity pressure sensors, and then adjust the molding to process based on these rules such as V/P switching time, choke-off time, and 2-stage lot-packs. Meanwhile, the three-stage packing strategy verified on the IC-tray molded parts successfully controlled warpage (below 0.42 mm) and free-from surface defects. With a strong die preparation (molding conditions), the residual warpage of the molded piece was 0.20 mm or less. In addition, a repeatable molding window (peak pressure and injection time) was found for on-line quality warpage monitoring.

Its results imply that the proposed approach could help injection molding engineers upgrade methodically and scientifically the process parameters without using lengthy trial and error or personal experiences. This method is believed to be advantageous in that it allows for enhancing the production output of the injection molding and the overall efficiency of production.

Recent researches have not only concentrated on the improvement of the quality of part but also on the reduction of energy used in the processes of production. Párizs et al. [11] carried out experiments with in-mold pressure sensors to maximize the clamping force, switchover time and hold phase in a multicavity mold configuration. The research tested four major algorithms. It suggested: (i) for Switchover Time Control to apply in-channel sensors for pressure-controlled switchover and cavity sensors for end of filling detection in volume-controlled hybrid processes. Secondly the phenomenon of Mold Filling Imbalance was addressed, and it was shown that imbalance grows with injection rate, but can be reduced by increasing melt temperature, as inferred from the in-mold sensor data. Thirdly, the study also investigated the Gate Freeze-Off Time and predicted that in-mold pressure can be utilized to predict the holding stage accurately. Lastly, for Cuff Force Optimization, pressure curves and pressure integrals were identified as good indicators for the optimal clamping force and enough to achieve good time and end results. By this means the research achieved not only a reproducible geometry of the component to be produced on a par with mass production but also a contribution to sustainability.

Many experimental works showed the key dependence of the injection molding process parameters on the part quality. Of these, Yeh and Wu that also consider energy efficiency. They systematically evaluated how important machine parameters (melt temperature, screw speed, injection velocity, holding pressure, holding time and cooling time) influence the total energy consumption. They showed using Design of Experiments (DoE) methods that energy use can be decreased by 29–33% with the optimum setting of parameters without degrading part quality [12]. This in turn underscored the dual advantage of process optimization to simultaneously improve product performance and sustainability.

These findings accentuate the development of experimental protocols from classic DoE-based parameter optimization to data-rich, smart systems, laying down a framework for future incorporation of AI in process control.

2.3 Analytical Methods

The experimental results indicate that the proposed approach has promising potential for injection molding engineers to optimize process parameters and avoid time-consuming trial-and-error approaches as well as costly experience systematically and scientifically. This method has been recognized to be effective in increasing the throughput of injection molding and enhancing the overall production efficiency.

The most innovative works made thanks to cavity pressure sensors are probably the iterative learning technique developed by Hopmann and co-workers [13]. In this work, a closed-loop quality monitoring platform was also accomplished, ensuring the immediate quality control of 30 HACCP due to primary refrigerated production, during real process operation. The control systems delivered were installed to make up for process variations by monitoring vital process functions, i.e., cavity pressure and cavity temperature, in the mold cavity and providing real-time control of them in order to ensure optimum part quality. The pressure set point during hold was determined as a function of time from a Joule heating (pvT-)model to optimize cavity pressure as a function of the particular melt temperature and the melt mass specific volume. The research results showed that the pvT-optimization method applied to the cavity pressure control of the injection molding can reduce the standard deviation of part weight from 0.297 g to 0.014 g with conventional control methods, especially under the influence of varying melt temperature. As a result, this optimization method showed a great potential to enhance the reproducibility of the important quality characters (i.e., part weight and warpage) in the injection molding process.

The contribution of this paper is the introduction and the application of a model-based self-optimization (MBSO) concept [14] to injection molding machines concerning cavity pressure control. This idea allows for on-the-fly adjustment of process parameters to correct for variations and to improve quality metrics (real-time adjustment). Through the incorporation of adaptive and self-optimizing control loops, the project aimed at enhancing process and product quality and stability of the injection molding process while at the same time having more direct control of desired quality characteristics by means of standard multivariate quality prediction models that have been integrated into the process control architecture.

The iterative learning control (ILC) technique used in this study further enhanced cavity pressure regulation by leveraging data from previous cycles to generate optimal controller outputs for subsequent cycles. This improved both reference tracking and compensation for repetitive disturbances. The screw's feed speed was controlled iteratively via the ILC system, allowing the process to converge toward the reference pressure curve associated with high-quality parts. The application of ILC enabled substantial improvements in control precision after only a few cycles, significantly reducing the need for manual parameter tuning and making cavity pressure control more feasible for industrial applications.

Another noteworthy approach focuses on deriving part quality indicators using only a single pressure sensor, particularly for components with variable wall thickness. The key innovation in this method is the use of a single pressure sensor positioned outside the mold, at the front of the screw, to monitor melt pressure during the injection molding process. By mapping a simulated filling process onto the real process, this method identifies and correlates characteristic event points between virtual and physical scenarios. This correlation enables the accurate determination of the flow front position and velocity, supporting effective process control strategies. Furthermore, it facilitates the extraction of machine-independent parameters such as melt front velocity, wall stress, shear rate, and melt viscosity, parameters that are critical for optimizing injection molding and ensuring consistent part quality. The potential for integrating this method into automated control frameworks marks a significant step toward autonomous injection molding processes, enhancing both operational efficiency and process reliability [15].

While numerous studies have examined the impact of cavity pressure sensors on part quality in plastic injection molding, a recent innovative perspective expands this approach by incorporating pressure sensors not only in the cavity but also in the barrel and nozzle. In a comprehensive study by Liew and his team [16], quality-related indices such as melt pressure measurements, part weight, and dimensional consistency were evaluated through variations in critical process parameters—including screw speed, back pressure, melt temperature, injection speed, and V/P switchover position. The study validated its findings across two distinct materials: polypropylene (PP) and polystyrene (PS).

The results revealed that variations in melt pressure, back pressure, and melt temperature play a crucial role in determining molding characteristics and final part quality. Elevated melt pressures were found to influence the viscosity index, thereby affecting the melt's flowability and molding behavior. Monitoring these fluctuations proved essential for ensuring optimal part quality. Adjustments to back pressure had a significant impact, enhancing material density and peak melt pressure, though excessive back pressure was shown to damage molecular chains and reduce the part’s resistance to shrinkage during cooling. Changes in melt temperature similarly affected viscosity and flowability, with higher temperatures leading to reduced viscosity and lower pressure peaks. These effects were more pronounced in polystyrene than in polypropylene.

Farahani et al. have published a seminal work on process monitoring of injection molding with cavity pressure and temperature sensors. They captured max and min characteristics from time-series sensor information gathered in each cycle and related these to quality indicators such as part weight and diameter. Their results showed that the instantaneous measurement of part quality is feasible with cavity sensors [17].

Similar to that, Chen et al. noted that associating sensor data to both part quality and machine parameters is essential for the implementation of closed-loop control of processes. They determined the V/P switchover point and optimized multiple holding pressures for proper part quality [18].

Meanwhile, in order to overcome the time and cost constraints of experimental data collection, Wang et al. introduced a simulation driven method, which calibrated a model to actual process conditions using the cavity sensor data. This approach substantially diminished simulational and actual production inhomogeneity, resulting in better quality [19].

Combined, these works indicate increasing infusion of sensor data, machine settings and simulation methods to further improve process monitoring and control in the context of injection molding, enabling more efficient and accurate quality control methodology.

2.4 *Data-Driven Artificial Intelligence*

Studies conducted to optimize the injection molding process using multiple in-mold sensor data typically involve a system comprising sensors, a data acquisition card, and an intelligent control mechanism capable of executing procedures in real time [20]. Although collectively categorized under quality control, these studies span a wide range of scopes and technical details that are meticulously examined.

A study by Chen et al. introduced an economic monitoring and controlling of the injection molding process using an artificial intelligence-based edge computing system [21]. This equipment combines temperature and pressure sensors with the Arduino Mega and the ESP32D, real-time to monitor the process and detect variations. An AI model developed on TensorFlow Lite analyzes these sensor data to detect the amount of molded parts in real time precisely. Results showed that the in-batch edge computing system improved the process performance with accurate monitoring, control, and prediction. The AI model has obtained a mean absolute error (MAE) of 0.0048 and root mean squared error (RMSE) of 0.0062, illustrating its prediction accuracy specific volume values using pressure–temperature data. Moreover, validation with simulated pvT curves has verified the model accuracy in predicting specific volumes.

Another relevant contribution in a related field dealt with an artificial neural network (ANN)-oriented online defect detection for high precision injection molding, using real time data recorded by in-mold temperature and pressure sensors [22]. The approach was based on a DoE paradigm that explored machine settings alongside sensor data to establish a large set of data through the eDART system. Nine input parameters were identified using regression analysis, and MLR-ANN models were developed and cross-validated. Comparative analysis revealed that the error between model-predicted and experimentally measured GC-FID response values was significantly lower (98.34%) and a higher R^2 value of (91.37%) for the ANN model as compared to the MLR model. Moreover, ANN model obtained a defect detection rate of 94.4% which validates the proposed model's capability in recognizing dimensional defects in the molded parts. These results illustrate that ANN-based systems are excellent for real-time dimensional monitoring and quality control, which is a notable breakthrough of smart injection molding applications.

A novel nontraditional sensor-based method was adopted by using a self-designed Multivariate Sensor (MVS) directly installed inside the mold cavity (in a parallel study) [23]. With a Support Vector Regression (SVR) model, the MVS realized real-time prediction of the part dimension at the time of injection molding and performed better than conventional sensor systems. The prediction accuracies were very high over 93.9% in thickness and over 91.9% in width. The integrated platform showcases the importance of online measurement for quality control and productivity along with advanced sensor technologies for sustainability in the context of the injection molding.

The method proposed in Guo et al. incorporates an ANN model that is constructed by a set of process parameters such as packing pressure, packing time, melt temperature, and mold temperature. When used for optical lens manufacturing, the algorithm shows a good satisfaction with the machine parameters and quality factors, with the R^2 values of 0.998. The results indicate the effectiveness of the proposed online scheduling algorithm in achieving the desired quality index as compared to those by the classical static approaches [24].

In another study toward zero-defect manufacturing for plastic injection molding, another ANN model was developed that uses machine parameters as the input. This model was validated on the factory floor with three injection molding machines and three raw materials, including PP, ABS, and Tritan. This resulted in measurable and significant improvements in mass production, such as an 11% increase in Overall Equipment Efficiency (OEE), and 6.2% increase in First Pass Yield, and a 7% reduction in downtime [25]. A comprehensive review of the literature on this subject attests to the necessity of dynamic control systems for processes of plastic injection molding [26] [27] [28].

One of the main weaknesses of the supervised learning methods is the cost of quality data. Addressing this, Jung et al. input data based on Moldflow simulation process parameters. They first employed a multi-objective Bayesian Optimization strategy using Gaussian Process regression. They also suggested a restricted generative IIDN framework. Such approaches utilize active learning techniques that iteratively improve the data suggestions and model update and can be used to converge quickly to the optimal configurations with a modest amount of data. It is reported that considerable decrease in the cycle time can be achieved by proper optimization of the process [29].

Another work also used mold features and computer-aided engineering (CAE) simulations to optimize process parameters. A set of experiments using Taguchi approach in five parameters: melt temperature, mold temperature, injection speed, packing time, and packing pressure were conducted. Using a GS-XGBoost model structure, the work was able to predict optimal process parameters with 99% accuracy. This method allows for the creation of a digital twin of the process and thus enables intelligent and dependent parameter estimation without the need for physical mold trials, resulting in significant cost and cycle time savings [30].

Additional process optimization was focused on minimizing blush on molded articles. Through an investigation of the most significant parameters involved in this defect, an ANN model was established and validated in comparison to finite element analysis (FEA) with a 99.99% convergence rate. The damaged part area was then reduced by 81.7% [31].

In addition to previous methods, the trend has been the development of artificial intelligence (AI) algorithms since the big data and accelerated computation has become ubiquitous. At this point, Gao et al. designed a mold with an in-built multivariate sensor which can measure the pressure, temperature, velocity and the viscosity of flowing melt simultaneously. They were able to predict critical part quality attributes (such as part thickness and width) with a prediction accuracy of 92.9% by means of SVR, reaching quality control at line levels, and showing that the proposed online monitoring system has a great potential for productivity and quality enhancements and reduction of material wastes [32]. Concurrently, new and forward-thinking research has accordingly solidified the direct relationship between in-mold cavity pressure measurements and final part quality, evident in plastic injection molding applications. For instance, Ke et al. where essential process quality indicators were directly extracted from cavity pressure data and then an MLP of which gave satisfying prediction of the parts dimensional uniformity [33]. Based on this knowledge, Gim and Rhee studied the correlation between changes in the pressure profile in the cavity and part quality by modeling the effect of 10 parameters of the pressure signal on part weight, also by using an MLP approach [34]. Another contribution is Kim and Lee, which focused on the use of machine vibration information, cavity pressure, and temperature readings—which were taken using accelerometers—into a neural network to predict part quality. The system output was the predicted quality class of the part taken from images acquired by a visual camera, and the results suggested that the integrated system has the potential to accomplish stable, high-quality production in industrial environments [35]. In total, these few examples can be attributed on a higher level into a general trend in injection molding towards advanced process control [36], better prediction of quality [37] and sustainability also promoted by approach of artificial intelligence technologies.

Chapter 3:
OPTIMIZATION METHODOLOGY OF PRODUCTION WITH CAVITY PRESSURE

3.1 Identifying the Reliable Zone

A cavity monitoring system was developed to track the entire process of plastic material melting, injection into the mold, solidification, and ejection. The system utilized piezoelectric cavity pressure sensors (Kistler 6157C) to capture pressure data. Signals from these sensors were transmitted to a data acquisition unit (Ascenix ADCR1.0), which supports simultaneous data collection from four pressure sensors at a sampling frequency of 5 kHz. The acquired data was then forwarded to a kiosk for real-time visualization and analysis. This kiosk incorporates an edge PC for on-site data processing, a cloud-based storage solution, a router, and a Siemens S7-1200 PLC responsible for controlling valve-gate timing. Each measurement cycle was assigned a unique identifier, allowing for effective production tracking through the recorded data.

Studies conducted across different molds, part geometries, and injection molding machines used in production processes have demonstrated a direct correlation between pressure fluctuations within the mold and the machine parameters. Within this context, the proposed novel method defines a dependable zone along the pressure curve for the entire cycle. This reliable zone represents the pressure interval in which manufacturing can proceed without producing defects in the part. The procedure to establish this range follows the steps illustrated in Figure 3.1.

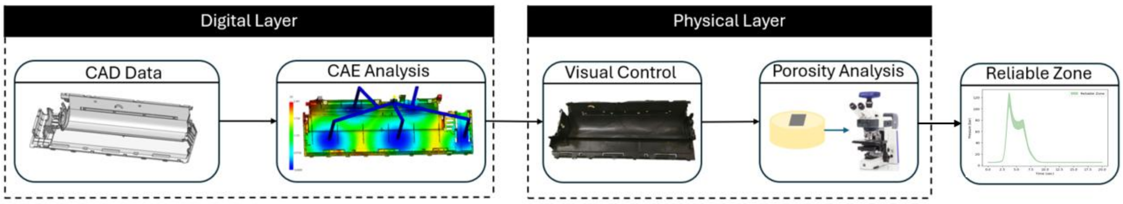


Figure 3.1: Procedure for identifying reliable zone

The methodology is executed in two distinct phases: the digital layer and the physical layer. During the initial phase, the digital layer, CAE analyses focusing on filling, packing, and cooling are performed utilizing the part's CAD data. Based on the results of these analyses, process parameters are estimated, and critical regions on the part are identified. These regions are designated as cut-off points where cavity pressure sensors are subsequently installed.

At the physical layer of the methodology, production was conducted using the prescribed process parameters. This stage was based on the assumption that the parts exhibited no visible defects such as short shots, flash, or weld lines. However, visual inspection alone is insufficient for components where mechanical strength is prioritized over appearance. To ensure consistent density, it was verified that critical areas of the parts were free from porosity. Consequently, for parts that passed the visual inspection, production was performed at the boundary process parameters, and samples were collected to further refine the reliable zone. Macro-level porosity assessment was conducted using an optical microscope to confirm adequate filling in the critical regions identified from these samples. This approach effectively excluded issues like balance problems in components such as fans or propellers—which are not detectable through visual inspection—from the reliable zone.

3.2 Analysis of the Correlation Between Cavity Pressure and Process Parameters

The most effective approach to preserving the actual pressure curve within the established reliable zone is to correlate the curve with the respective production phases [38]. In the plastic injection molding process, these stages are categorized as mold closing, filling, holding & packing, cooling, and ejection phases. Each stage of the injection molding cycle exerts a distinct influence on the pressure profile, as illustrated in Figure 3.2. During the filling phase, molten material is injected into the mold cavity. As the initial layer of plastic contacts the cavity wall and begins to solidify near the pressure sensor, the pressure curve starts to rise. The point at which maximum pressure is observed typically indicates the near completion of volumetric filling. Subsequently, in the holding phase, additional material is packed into the cavity to compensate for shrinkage and to ensure the part fully conforms to the mold geometry. This results in a secondary local peak on the pressure curve, which then begins to decline. Following the completion of injection and packing, the pressure continues to drop toward zero, signaling the onset of the cooling phase. Once uniform cooling is achieved, the cycle concludes with the ejection phase, during which the solidified part is released from the mold.

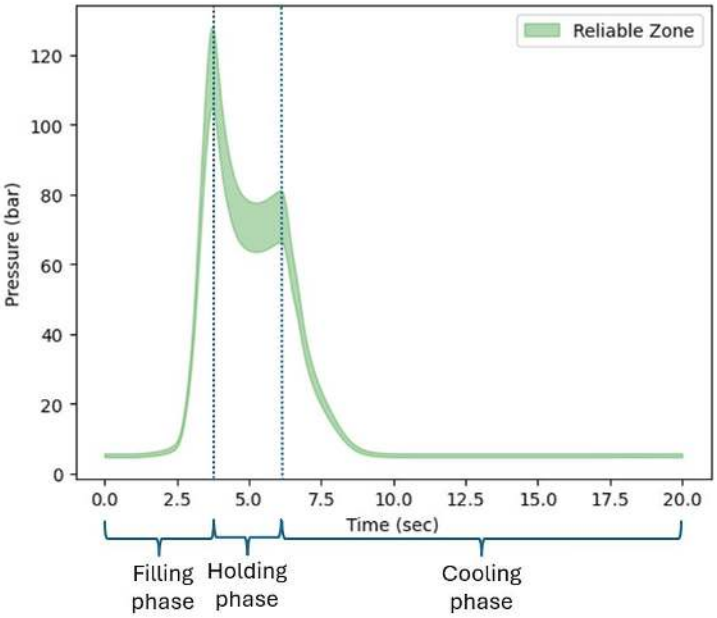


Figure 3.2:Cavity pressure-based segmentation of injection molding phases

Under mass production conditions, deviations from the expected pressure curve may occur due to various unforeseen factors, resulting in increased scrap rates. To mitigate this issue, adjustments to machine parameters are necessary. Accordingly, the primary objective of this study is to investigate the relationship between machine parameters and the resulting pressure curve. A review of the existing literature indicates that this correlation is predominantly influenced by key parameters such as injection pressure, holding pressure, and holding time. In line with this, a DoE was developed to evaluate the effects of six distinct machine parameters, along with their interactions, as outlined in Table 3.1: Independent process parameters for DoETable 3.1.

Table 3.1: Independent process parameters for DoE

Process Parameter	Unit	Level	Total Changing Rate (± %)
Injection Pressure	bar	5	35
Injection Time	second	5	25
Injection Speed	mm/s	4	20
Holding Pressure	bar	5	37,5
Holding Time	second	5	50
Material Shot Volume	cm^3	4	12

Analysis of cavity pressure sensor data from individual cycles reveals several key features. The first notable point is where the pressure curve begins to rise (Figure 3.3a). Experimental findings indicate that the timing of this initial rise is directly influenced by the injection speed. The second characteristic point corresponds to the peak of the pressure curve (Figure 3.3b). While the horizontal shift of this peak along the time axis reflects changes in injection time, variations along the pressure axis are indicative of the applied injection pressure. Following the filling phase, the pressure decreases and then forms a local maximum due to the holding phase (Figure 3.3c). At this stage, the timing of the local peak correlates with the holding time, whereas the magnitude of the peak reflects the holding pressure.

Another significant feature observed is the time interval between the onset of the pressure rise and the return to baseline pressure (approximately zero), as shown in Figure 3.3d-a. This duration represents the valve-gate open time, which encompasses both the filling and holding phases. Unlike the previously mentioned parameters, the relationship between the shot volume and cavity pressure is represented by the area under the pressure curve, offering a cumulative measure of the pressure applied throughout the cycle.

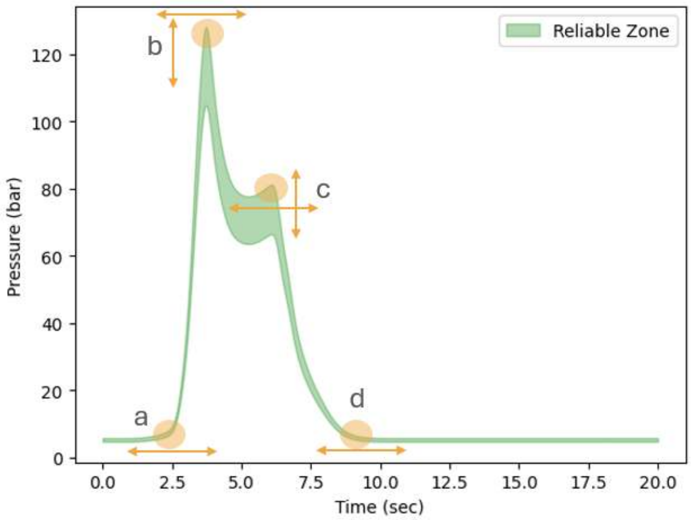
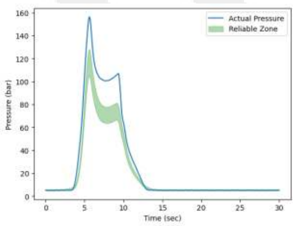
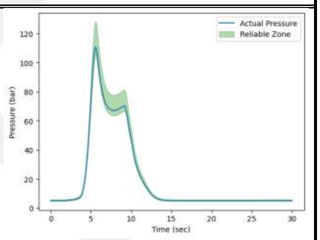


Figure 3.3: Characteristic Features extracted from cavity pressure data

Based on the findings obtained from controlled experiments, targeted interventions are planned to restore the production process to the reliable zone in the event of anomalies or defect occurrences during plastic injection molding.

DoE studies, as illustrated in Table 3.1Table 3.2, yield highly effective results within controlled and limited scenarios. However, such approaches are insufficient to achieve comprehensive control over the plastic injection molding process. Given the inherent complexity and the near impossibility of modeling every potential fluctuation, traditional methods fall short in ensuring robustness. In contrast, the development of machine learning models presents a promising solution for uncovering intricate, non-linear relationships within the process and enabling the implementation of real-time control mechanisms.

Table 3.2: Sample of scrap cases and solutions

<table>
<tr><th>Scrap Case</th><th>Suggested Solution</th><th>Result</th></tr>
<tr><td>
</td><td>▪ Material shot volume should be decreased.</td><td>
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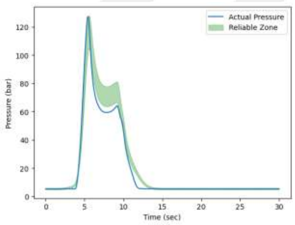
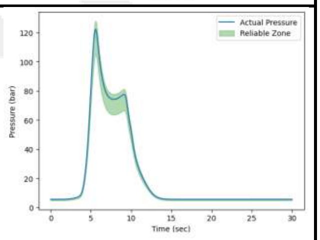
<tr><td>
</td><td>▪ Holding pressure should be increased.
▪ Holding time should be increased.</td><td>
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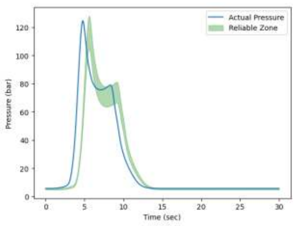
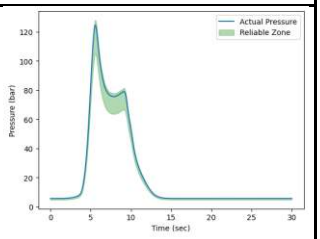
<tr><td>
</td><td>▪ Injection speed should be decreased.</td><td>
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Chapter 4:
CREATION OF BASE COGNITION FOR ADVANCED PLASTIC INJECTION MOLDING

4.1 Structure of Machine Learning-based Decision Support

The machine learning-based decision support algorithm is designed to operate with high accuracy, independent of part geometry, mold design, or the specific injection molding machine used. It is well established that machine learning models require large datasets to accurately capture underlying patterns. Taking these considerations into account, the proposed algorithm is structured around its association with the reliable zone, without relying on data specific to the produced part, mold, or machine dynamics. To accelerate deployment and facilitate system adaptability, a baseline model was initially developed. The transferability of this model to different parts—while significantly reducing the need for additional data—was then evaluated. The architecture of the baseline knowledge learner and the task-specific knowledge adaptation algorithms is illustrated in Figure 4.1.

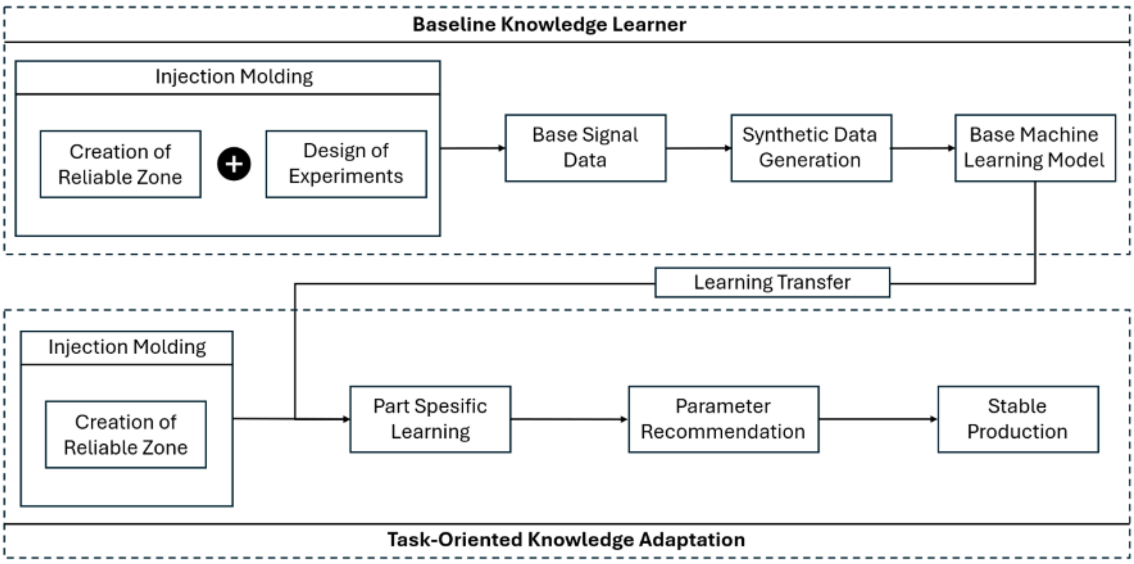

Figure 4.1: Structure of machine learning-based decision support

4.2 Creation of Dataset

During the dataset generation phase, reproducing every possible scenario that may arise under mass production conditions proves to be highly inefficient in terms of both time and cost. To improve dataset diversity and ensure broader coverage of potential process variations, this study incorporates synthetic data alongside the base signals obtained during the DoE phase, thereby creating a more extensive and representative dataset.

In total, 200 base signal samples were utilized in the study. Of these, 50 samples were classified within the previously defined reliable zone, while the remaining 150 were associated with defect scenarios, either partially or completely falling outside this zone. To generate synthetic signals that accurately mimic real-world data, the methodology outlined in Section 4.1 was applied. Based on their defining characteristics (Figure 4.2), each cycle's pressure data was segmented into six distinct regions.

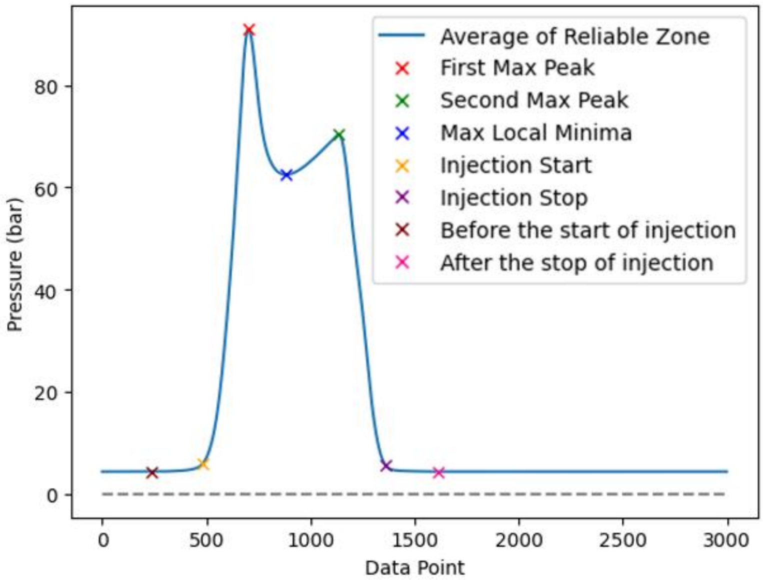

Figure 4.2: Feature extraction from injection molding pressure curve

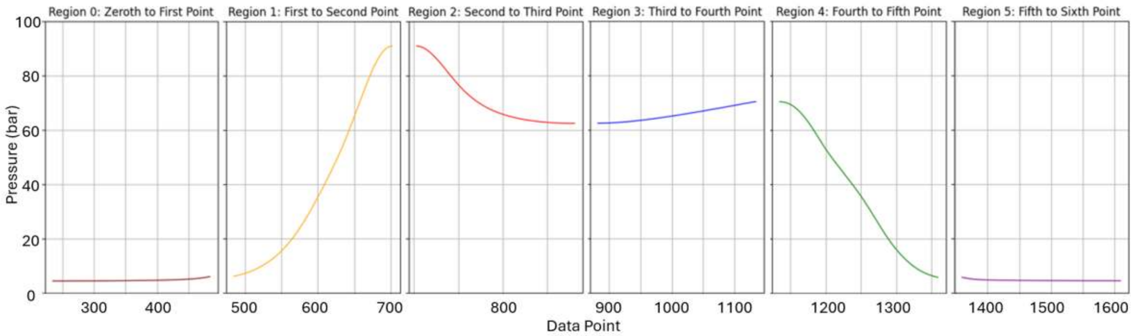

Figure 4.3: Pressure curve segmented into six distinct regions from feature extraction

The synthetic data generation process was conducted following the segmentation of the cavity pressure curve into six distinct regions, as illustrated in Figure 4.3. For each of these regions, the original pressure profile was used as a baseline, and new curves were generated by applying random scaling factors ranging from 0.1 to 1.8. Additionally, to mimic temporal variations, five key points on the curve—namely injection start, injection stop, first maximum peak, second maximum peak, and the local minimum—were randomly shifted along the time axis within a ±1.5 second window. The overall methodology for synthetic data generation is visualized in Figure 4.4, where the blue line represents the original pressure curve and the gray lines correspond to synthetically generated curves derived from the original signal.

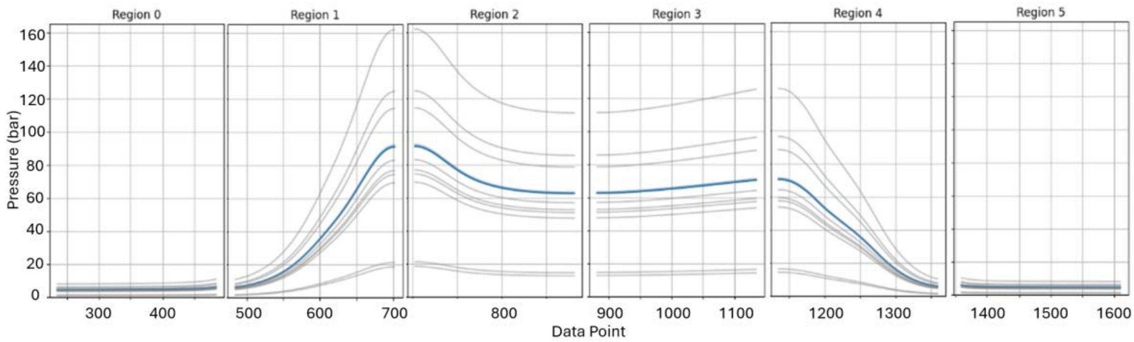

Figure 4.4:Synthetic data creation based on original pressure curve

As a result, a total of 5000 cavity pressure cycle graphs were generated. Of these, 1000 belonged to the previously defined reliable zone, while the remaining 4000 represented cases entirely or partially outside this zone.

A notable aspect of this study is that the time-series pressure data captured during each cycle was not directly employed as input for the machine learning-based model. Instead, to better reflect the physical characteristics of the plastic injection molding process, a 6×6 feature matrix was extracted from each pressure curve. This transformation significantly reduced data dimensionality, thereby accelerating the model training process. Particularly in the context of model explainability [39] and computational efficiency, this method proves advantageous for handling complex time-series data [40] [41].

Each column in the constructed input matrix corresponds to one of the six distinct regions identified on the cavity pressure curve. In contrast, each row represents a specific quality indicator used to evaluate the alignment with the defined reliable zone. For instance, the P_{up} value in the first row quantifies the proportion of pressure data points that exceed the upper boundary of the reliable zone within the actual pressure curve (as described in Equation 4.1). This enables the detection of excessive pressure in each segmented region. Here, N denotes the total number of recorded data points, while U stands for the upper threshold of the reliable range.

$$P_{up} = \frac{1}{N}\sum_{i=1}^{N} \Pi(x_i > U) \tag{4.1}$$

The second row of the matrix is defined by the P_{in} value represents the proportion of pressure data points that fall within the reliable zone. The primary objective of the algorithm is to maintain this ratio consistently at 1.0. At this point, the variable L is introduced into the equation to denote the lower boundary of the reliable zone.

$$P_{in} = \frac{1}{N}\sum_{i=1}^{N} \Pi(L \le x_i \le U) \tag{4.2}$$

The P_{down} value, corresponding to the third row of the matrix, reflects the proportion of data points that fall below the defined reliable zone. The algorithm aims to reduce this value to zero, thereby minimizing the risk of defects such as short shots, which are typically associated with insufficient pressure levels.

$$P_{down} = \frac{1}{N}\sum_{i=1}^{N} \Pi(x_i < L) \tag{4.3}$$

The fourth feature, denoted as Δt_{Pmax}, represents the normalized time difference between the peak pressure point of the reliable zone within a given region and the corresponding peak point on the actual pressure curve.

$$\Delta t_{Pmax} = \frac{|\,argmax(P_{reliable}(t),\ t \in [t_0, t_1]) - argmax(P_{actual}(t),\ t \in [t_0, t_1]\,|}{t_0 - t_1} \tag{4.4}$$

The fifth row of the input matrix contains the Δt_{Pmin} value, which is used to monitor the end times of the filling and holding phases. This feature helps identify cases of inadequate filling speed or prolonged holding durations by capturing timing deviations in the pressure curve.

$$\Delta t_{Pmin} = \frac{|\,argmin(P_{reliable}(t),\ t \in [t_0, t_1]) - argmin(P_{actual}(t),\ t \in [t_0, t_1]\,|}{t_0 - t_1} \tag{4.5}$$

The final row of the matrix corresponds to the D_{Pmax} value. This is calculated by first identifying the maximum pressure value of the actual curve within the relevant region. Next, the average of the lower and upper bounds of the reliable zone for that region is determined. The difference between these two values is then normalized. This feature provides insight into how far the actual peak deviates from the target range, particularly in scenarios where scrap may occur.

$$D_{Pmax} = round\left(\frac{argmax(P_{actual}) * 0.5}{argmax\left(\frac{U-L}{2}\right)}\ , 2\right) \tag{4.6}$$

The dataset, composed of input matrices derived from individual pressure curves, was annotated for use in supervised learning. During the labeling process, the six parameters detailed in Table 3.1 of Section 3.2 were taken into account. Variations in these parameters—whether increases, decreases, or stability—were independently evaluated to assign appropriate labels.

4.3 *Baseline Model Design for Data-Driven Prediction*

The baseline model receives as input a matrix that captures the relationship between the actual cavity pressure curve and the corresponding reliable zone. Its output indicates the corrective actions necessary to restore the process to within acceptable operational boundaries. A sequential neural network architecture was employed in the development of this method. The feedforward model begins with a 2D convolutional layer, structured as a 6×6×1 input, and includes a total of 13 hidden layers—an architectural choice influenced by the small size of the input matrix and the specific requirements of the application (Figure 4.5). Rectified Linear Unit (ReLU) was selected as the activation function across the hidden layers. Given the multi-label nature of the classification task, a sigmoid activation function was applied at the output layer.

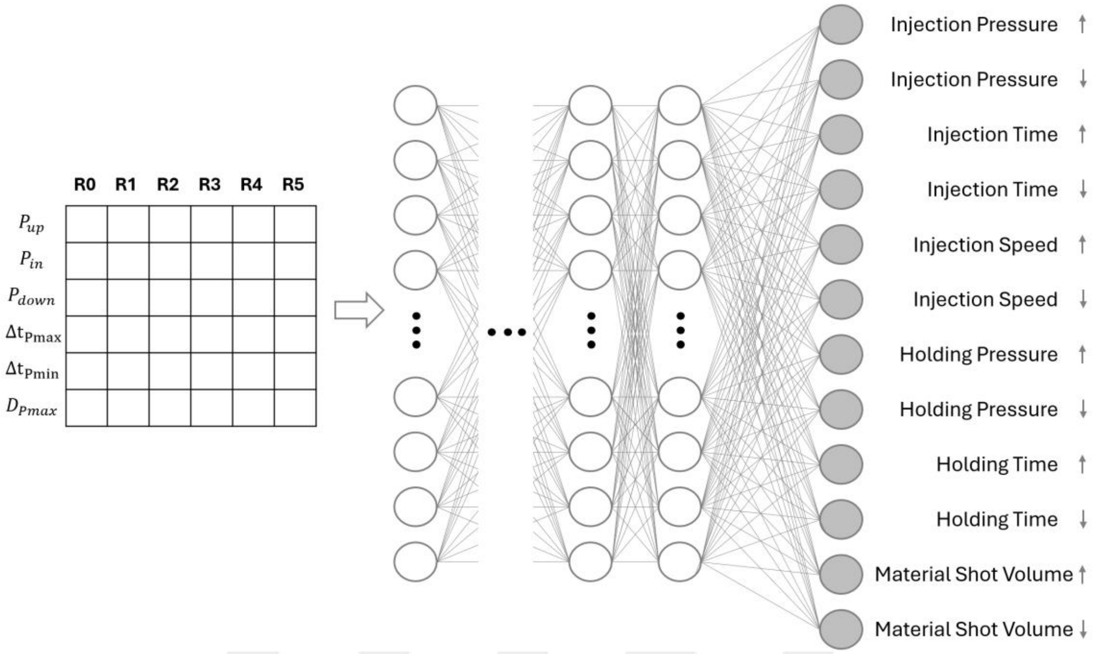

Figure 4.5: Representation of the baseline predictive model for plastic injection molding

The performance of the developed sequential neural network model was assessed based on the loss values recorded during both the training and validation phases. In this work, binary cross-entropy served as the loss function, as defined in Equation 4.7.

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N} y_i \log\left(p(y_i)\right) + (1 - y_i)\log\left(1 - p(y_i)\right) \qquad (4.7)$$

Bayesian Optimization was employed to fine-tune the hyperparameters within the model architecture, effectively reducing the number of experiments needed to assess performance. This approach uses a probabilistic model to predict the effectiveness of different hyperparameter configurations, allowing the selection of the most promising candidates for evaluation [42]. Following this optimization process, the hyperparameter values presented in Table 3.1 were chosen.

Table 4.1: Hyperparameters for baseline predictive model

Hyperparameters	Search Space	Selected Value
Activation Function	-	ReLu
Output Layer Activation Function	-	Sigmoid
Learning Rate	[0.01-0.0001]	0.0002
Batch Size	[16-64]	62
Number of Epochs	[30-100]	66
Drop Out Rate -1	[0.2-0.5]	0.38
Drop Out Rate -2	[0.2-0.5]	0.27

After completing the training and validation stages using the chosen hyperparameters, a confusion matrix was constructed (Figure 4.6). As expected, classes supported by larger amounts of data exhibited higher accuracy levels.

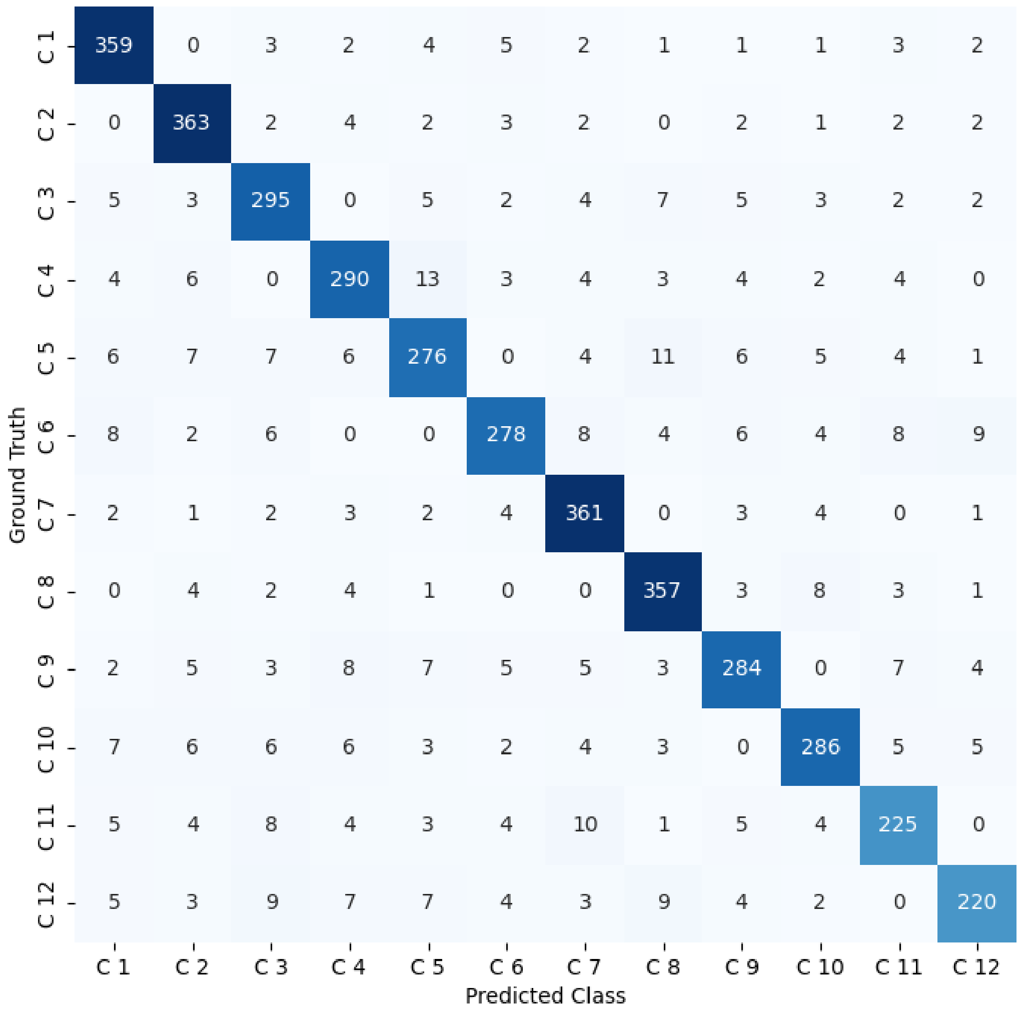

Figure 4.6: Confusion matrix of baseline predictive model

C1: Increase Injection Pressure
C2: Decrease Injection Pressure
C3: Increase Injection Time
C4: Decrease Injection Time
C5: Increase Injection Speed
C6: Decrease Injection Speed
C7: Increase Holding Pressure
C8: Decrease Holding Pressure
C9: Increase Holding Time
C10: Decrease Holding Time
C11: Increase Material Shot Volume
C12: Decrease Material Shot Volume

The proposed sequential neural network model attained a total accuracy of 98%.

Chapter 5:
IMPLEMENTATION OF MECHANICAL PRODUCT

The dishwasher bottom cover is a component that is mounted to the bottom of the chassis (as shown in Figure 5.1, the chassis is black and the bottom cover is gray). A float is attached to the center of this cover using snap-fit connections. The float plays an important role in controlling the dishwasher water level by absorbing excess water and helping to prevent leaks. However, if the manufacturing settings are not properly calibrated, the snap-fit connections that hold the float in place can break. The same problem can affect the snap-fit connections that hold the bottom cover to the chassis. When these small parts fail, they can cause delays on the assembly line, reduce the overall durability of the product, and increase the likelihood of failure when the dishwasher is first put into service.

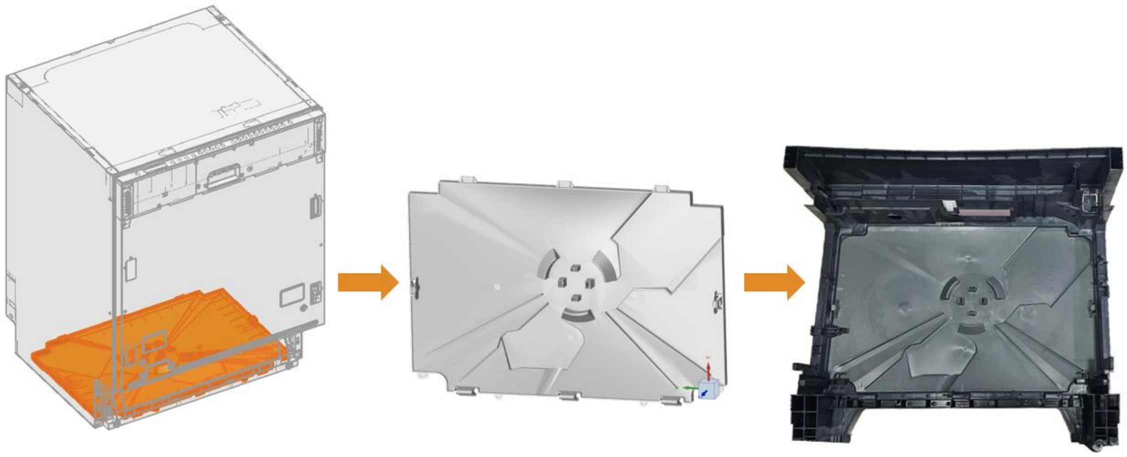

Figure 5.1: The bottom cover of dishwasher

The part was produced using a 600-ton injection molding machine and is made entirely from recycled materials. Its composition is 70% polypropylene and 30% glass fiber (GF), offering a balance between strength and sustainability.

The part is filled through four hot runner ports that provide efficient material distribution during the molding process. Given the intended function of the component, maintaining uniformity throughout the filling, holding, packing, and cooling stages is particularly important. Reinforcement of the interlocking areas is particularly critical, as these features are important to the structural performance of the part. As a result, the most commonly observed defects include short throws, flashes, and shrink marks.

To identify the optimum production parameters and establish a reliable processing window, CAE analyses were performed as a first step. As shown in Figure 5.2, the analysis results (displayed from right to left) include the V/P transition point, filling time, and filling pressure.

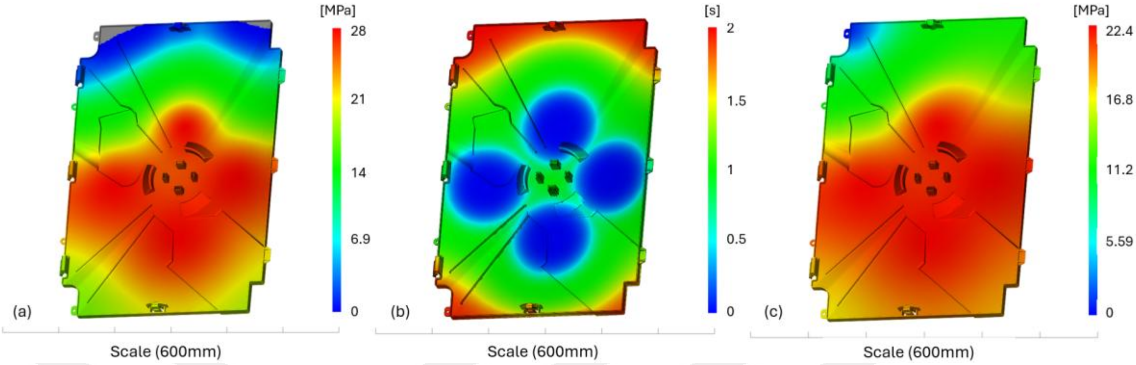

Figure 5.2: Simulation results of the bottom part, (a) switch-over point, (b) filling time, (c) pressure end of the filling

Based on the analysis results, key locations for monitoring pressure during the filling phase were determined. To capture accurate data, four cavity pressure sensors were placed on the core-side surface of the mold, as shown in Figure 5.3.

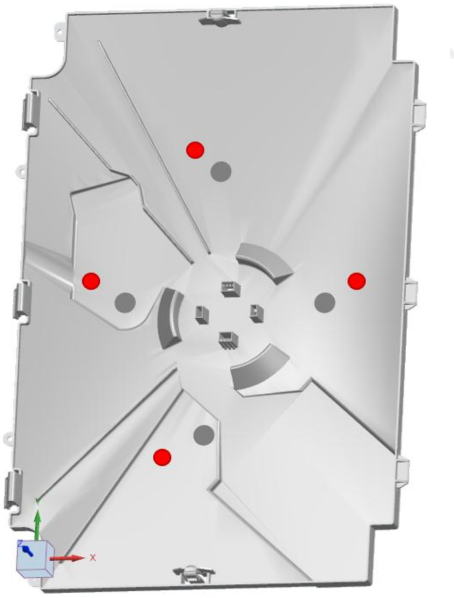

Figure 5.3: Placement of cavity pressure sensors on the dishwasher bottom cover part with sensor locations marked in red and valve-gate positions highlighted in gray.

To define the reliable zone, the process parameters summarized in Table 5.1 were used and data were collected through a DoE study conducted at the specified settings. A total of 500 production cycles were recorded. At this stage, short bursts, flashes, and shrinkage defects were excluded to clearly define the boundaries of the reliable region.

Table 5.1: Dishwasher bottom part's process parameters

Process Parameter	Unit	Value	Level	Total Changing Rate (± %)
Injection Pressure	bar	120	5	35
Injection Time	second	2.8	5	25
Injection Speed	mm/s	66	4	20
Holding Pressure	bar	90	5	37,5
Holding Time	second	2	5	50
Material Shot Volume	cm^3	523	4	12
Barrel Temperature	C0	220	-	constant
Back Pressure	Bar	5	-	constant

In addition to visual inspection of scrap parts, special attention should be paid to the interlocking areas where mechanical strength is critical. Due to their location relative to the valve gates and the geometry of the part, these areas may experience changes in density. These differences are mainly due to porosity that may develop during the filling, holding and packaging stages. Therefore, porosity has been studied as an important factor in optimizing process parameters.

Samples were collected from parts produced under various process settings and were classified as defect-free by visual inspection. In these samples, the areas of the snap-fits where final filling had occurred and the pressure was relatively low were examined closely, as shown in Figure 5.4. These critical points were then compared with areas near the valve gate assembly where filling was completed earlier under higher pressure. Finally, the samples were examined using an optical microscope to evaluate any subtle differences.

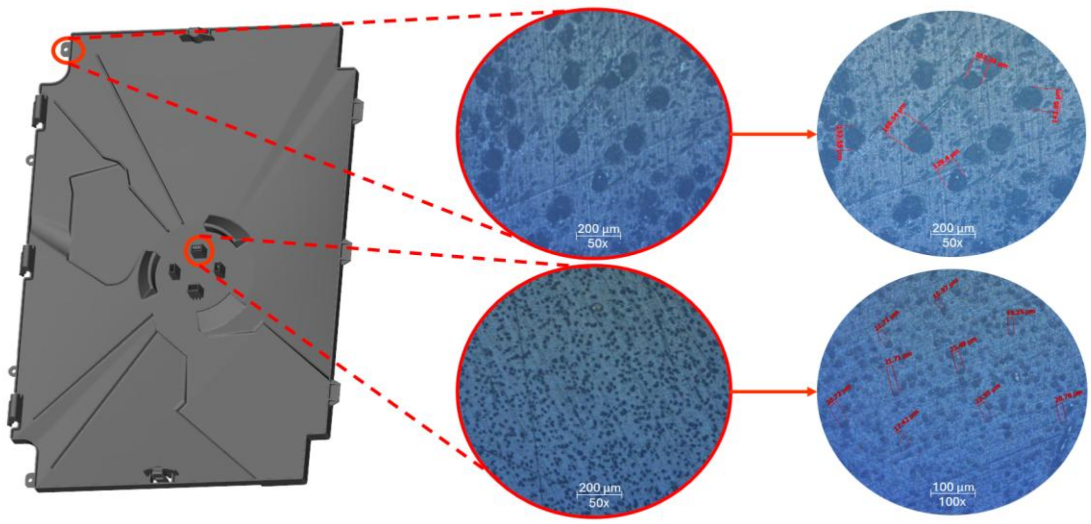

Figure 5.4: Optical microscope results for porosity analyses of snap-fits

During the optical microscope analysis, the structure of the glass fiber reinforced polypropylene material was carefully examined. Regular circular shapes measuring up to 35 µm correspond to glass fibers embedded in the material, while irregular circular formations larger than 100 µm were defined as porosity. The outer parts of the part, which solidified faster due to its flow properties, showed a relatively porous structure. In contrast, when the cross-section of the sample was examined, higher levels of porosity were found near the center. Tests conducted under varying processing conditions revealed that porosity in the center of the part could reach up to 17% in an area of 3 mm² seen in Figure 5.5. These local differences in density contribute to the increased brittleness in these areas.

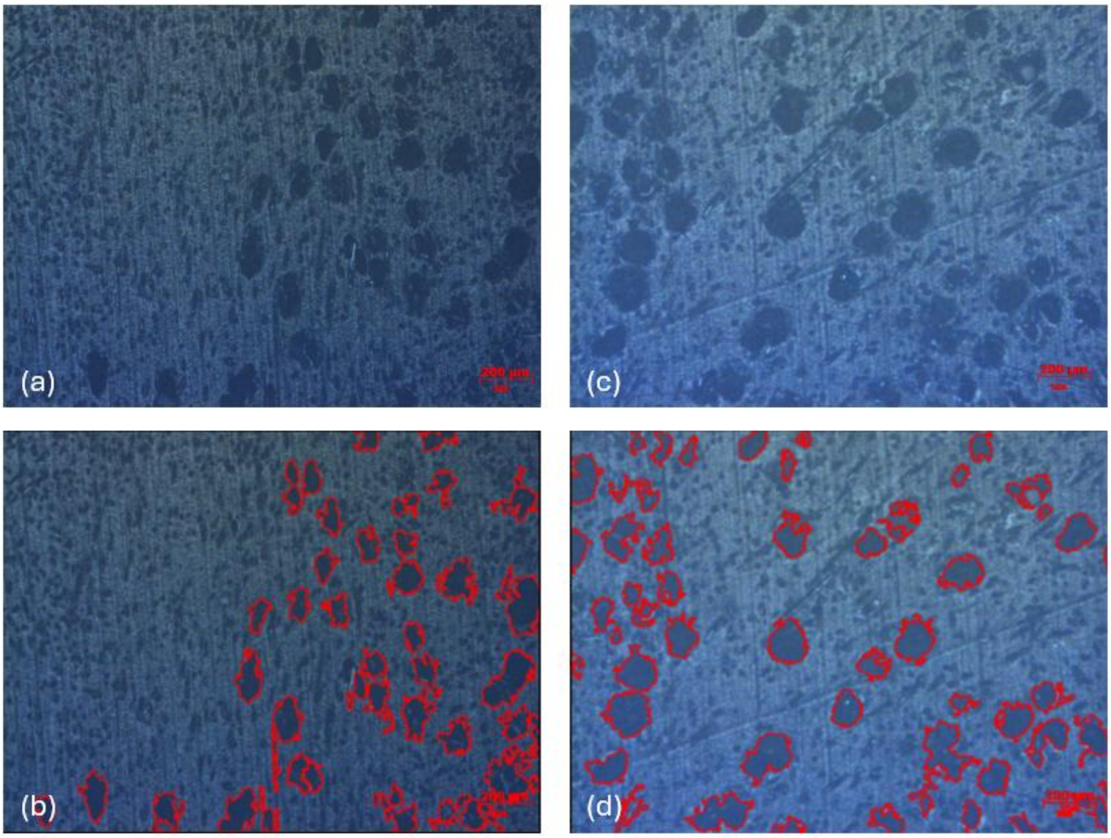

Figure 5.5: Porosity levels, (a) and (b) are optical microscope results, (c) and (d) highlight the detected porosity zones marked in red.

By combining visual and mechanical inspections, a reliable processing window was established for the part, as shown in Figure 5.6. Manufacturing within this pressure range ensures an optimum end product. However, when the actual pressure curve falls partially or completely outside this range, production deviates from ideal conditions and results in scrap parts.

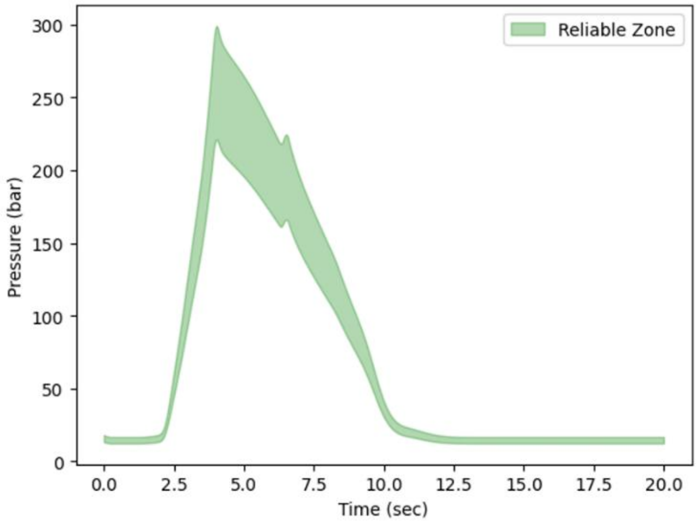

Figure 5.6: Reliable zone from dishwasher's bottom cover part

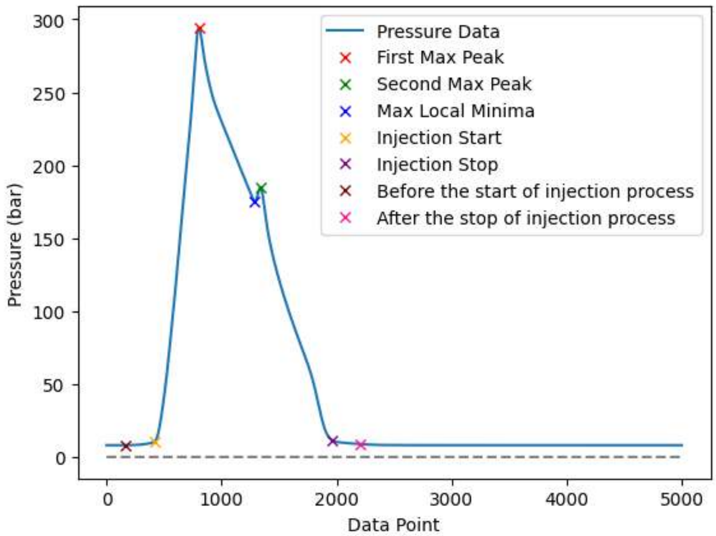

Figure 5.7: Significant features from the bottom cover part

As detailed in Section 4.2, the significant features of the reliable zone were identified and shown in Figure 5.7. Based on these features, the zone was then divided into six separate regions as shown in Figure 19. To increase the sensitivity of the analysis, the time axis was evaluated using separate data points.

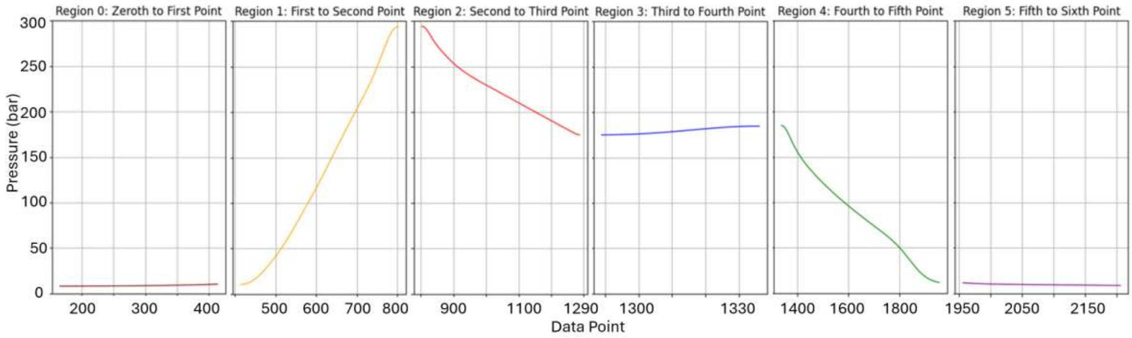

Figure 5.8: Divided regions of the bottom cover part

As mentioned in Section 4.2, the pressure data from 500 production cycles collected during the DoE studies were multiplicatively augmented, yielding a total of 2000 datasets. Following the generation of these synthetic pressure curves, the corresponding input matrices were calculated using the method described in the same section.

The learning transfer process was built on a basic knowledge learning model that served as the basis for training. Due to the relatively compact architecture of the model, the frozen layers technique was not applied. Instead, additional hidden layers were integrated into the basic structure to extract task-specific information. Five hidden layers and two dropout layers were added to improve the model and reduce the risk of overfitting. The Adam optimizer (Adaptive Moment Estimation) was chosen due to its efficiency and stability. The dataset was split into two, 80% for training and 20% for testing, and the model was trained for 14 epochs using a batch size of 32. During the training phase, binary cross-entropy was used as the loss function, as defined in Equation 7.

Analysis of the test results showed that the model achieved an average accuracy of 97% across all 12 classes. The change in prediction performance for each class is shown in the confusion matrix presented in Figure 5.9.

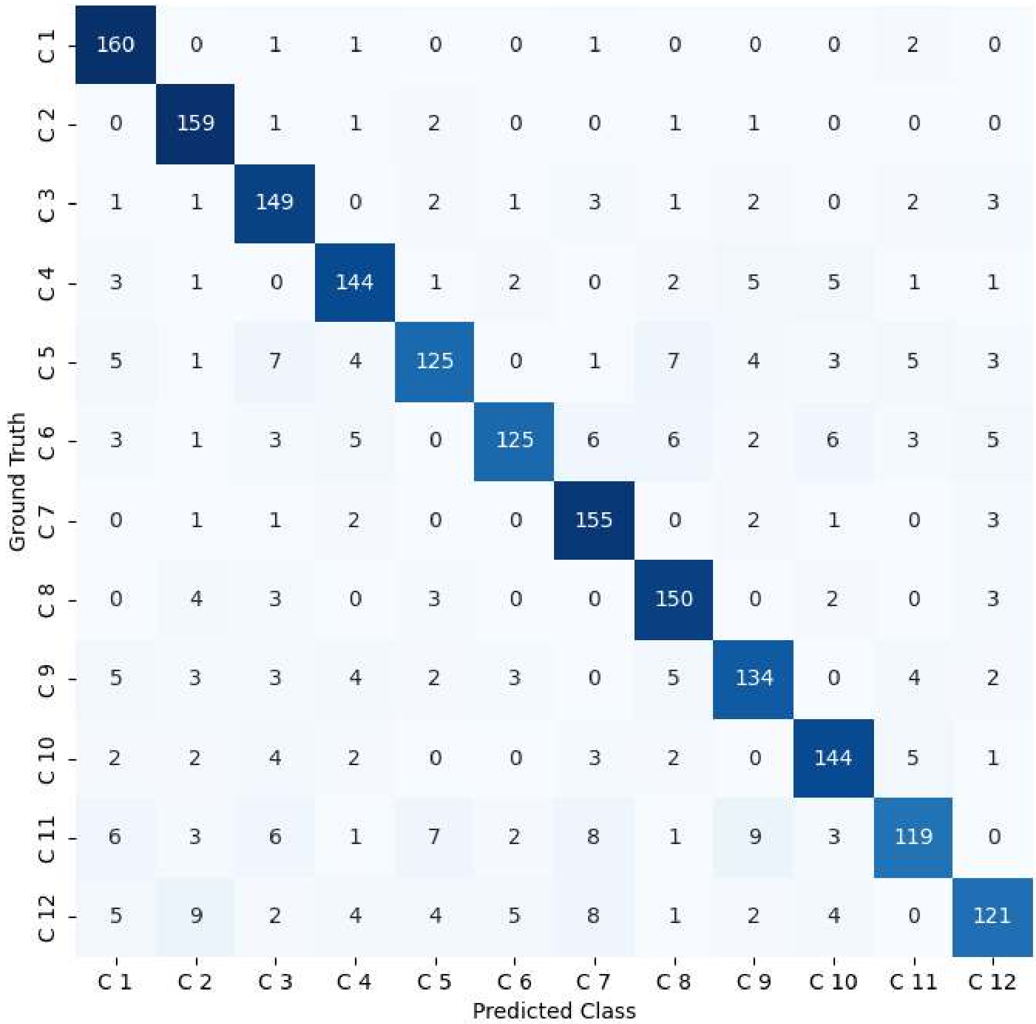

Figure 5.9: Results of the ML-based cognition for dishwasher's bottom cover part

Chapter 6:
IMPLEMENTATION OF VISUAL PART

The inner beyond cover, which acts as the back panel for the refrigerator shelf placement, requires a high level of visual quality. Because it is in direct contact with the end user and covers a large surface area, the part is manufactured using a 1000-ton plastic injection molding machine. The raw material is High Impact Polystyrene (HIPS) combined with 3.5% white masterbatch. The core side of the mold is polished to a mirror-like finish to enhance its glossy surface. On the cavity side, nine consecutive hot runner ports are used to ensure uniform filling, as shown in Figure 6.1(a). Given these design and material considerations, the most common defects in this part include sink marks, weld lines, short throws, flashing, and door browning.

In order to better understand the error formation and define the reliable processing area, CAE analyses were performed as seen in Figure 6.1.

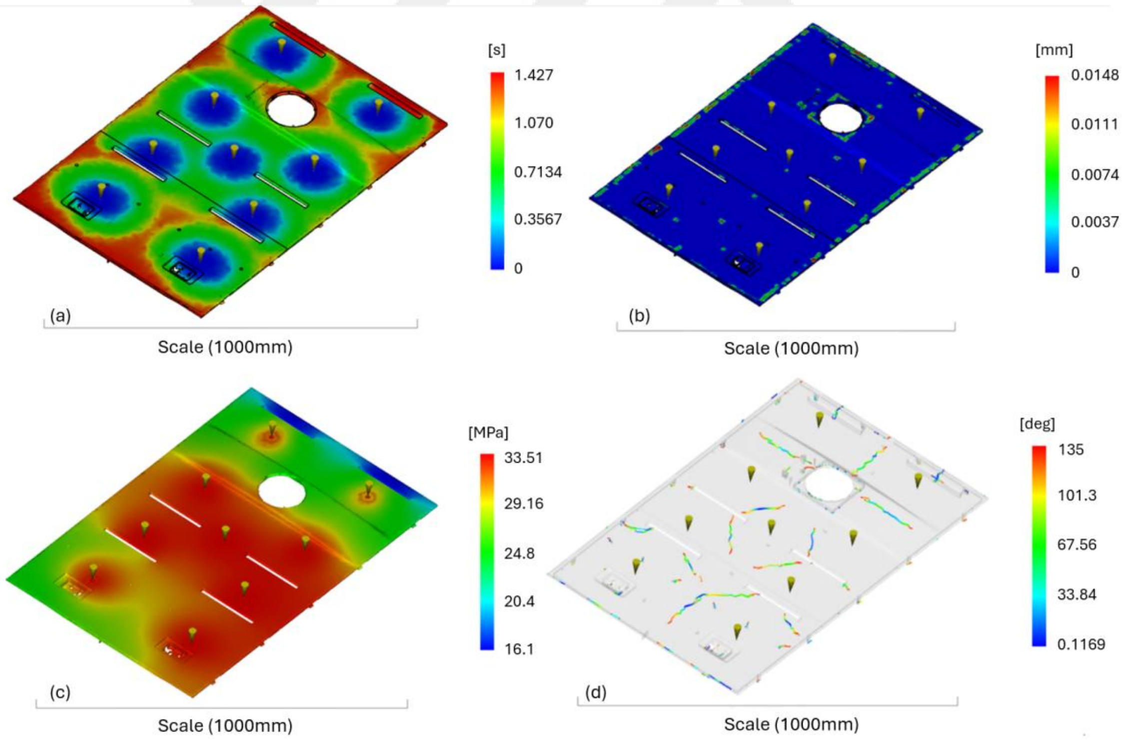

Figure 6.1: Simulation results of the inner beyond cover, (a) filling time, (b) sink mark, (c) pressure end of the filling, (d) weld lines

Based on the analysis, key areas where pressure had a significant effect on the part were identified. In Figure 6.2, the nine grey dots indicate the locations of the valve covers, while the three blue circles indicate the locations of the cavity pressure sensors installed inside the mold.

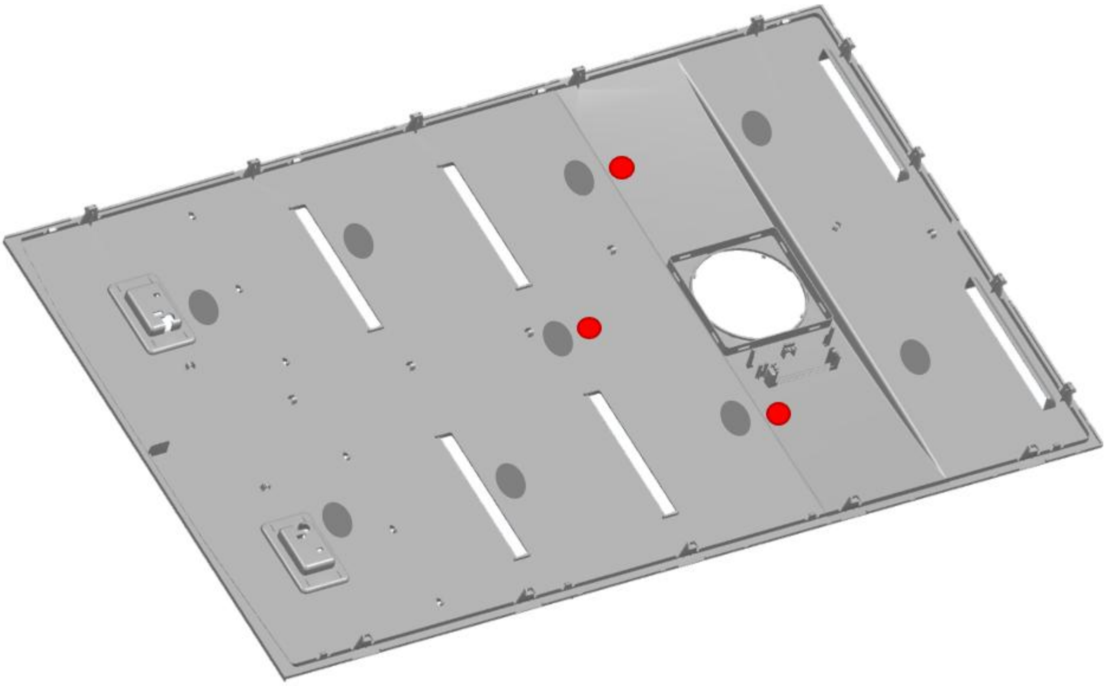

Figure 6.2: Placement of cavity pressure sensors on the refrigerator inner beyond cover with sensor locations marked in red and valve-gate positions highlighted in gray

Following sensor placement, DoE studies were initiated to define the safe machining zone. Since the part did not have specific mechanical performance requirements, visual inspection, shown in Figure 6.3, was used as the primary evaluation criterion throughout these studies and played a key role in determining the boundaries of the safe zone.

Figure 6.3: Visual inspections of the refrigerator's inner beyond cover, (a) example of quality standards, (b) example of flashes, (c) example of gate blush

Table 6.1: Refrigerator beyond cover's process parameters

Process Parameter	Unit	Value	Level	Total Changing Rate (± %)
Injection Pressure	bar	115	5	35
Injection Time	second	2.4	5	25
Injection Speed	mm/s	75	4	20
Holding Pressure	bar	85	5	37,5
Holding Time	second	2.4	5	50
Material Shot Volume	cm^3	1115	4	12
Barrel Temperature	C^0	250	-	constant
Back Pressure	Bar	22	-	constant

To define the reliable region and generate the dataset, a total of 200 production cycles were performed, 50 cycles for each predefined defect scenario, using the process parameters summarized in Table 6.1.

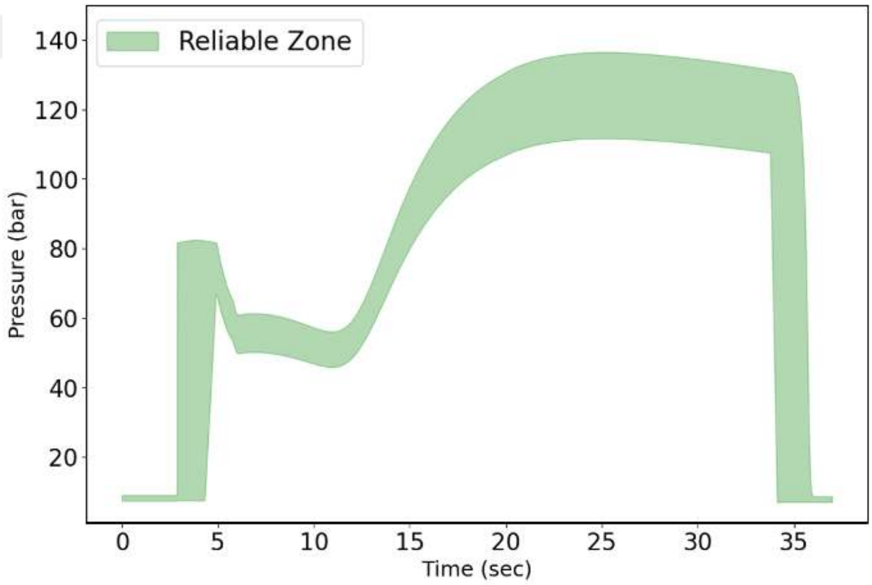

Figure 6.4: Reliable zone from refrigerator's inner beyond cover

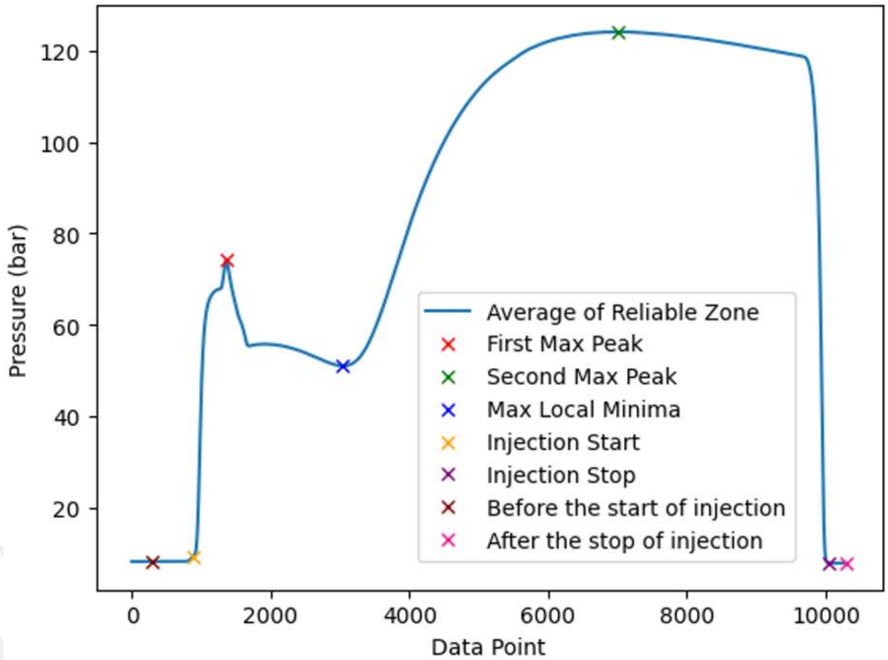

Figure 6.5: Significant features from the inner beyond cover

When examining the cavity pressure data for this use case, the resulting pressure curve is significantly different from that observed in other applications. This variation is due to several factors. Most importantly, using HIPS material on a visually exposed part requires extremely precise process control. As shown in Figure 6.6, the progression of the cavity pressure curve reveals distinct regional behaviors. In Region 1, the shift in acceleration is primarily due to the mold's sequential valve-gate system. Since the gates open sequentially, each activation and the timing between them directly affects the shape of the curve. This effect continues in Region 2, especially for the gates located farther from the pressure sensor, contributing to a greater change in acceleration.

The goal of using a sequential valve-gate system is to optimize gate opening and timing to eliminate weld lines on the part. While this strategy effectively addresses the weld line problem, it also introduces the risk of sink marks in the hot runner regions. To prevent this, a very high holding and packing pressure is applied, as seen in Region 3. Another important preventive measure involves maintaining this pressure throughout the cooling phase until the part cools below the critical temperature threshold, as shown in Zone 4.

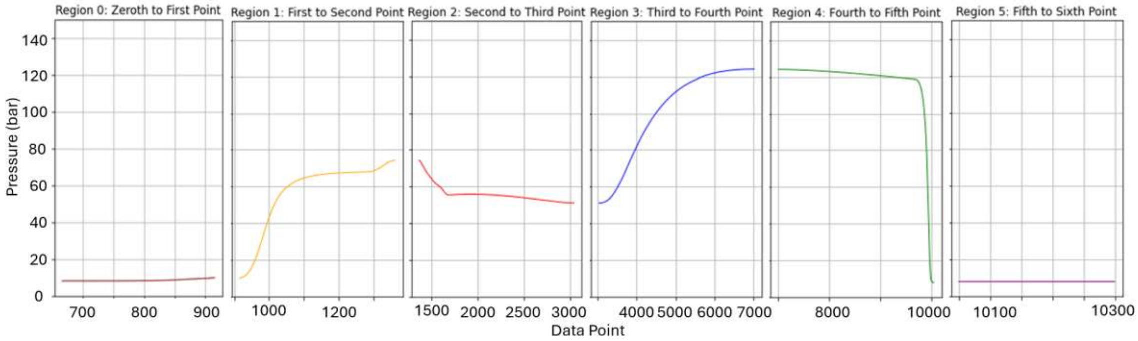

Figure 6.6: Divided regions of the inner beyond cover

The data collected from DoE studies were expanded through synthetic data generation as detailed in Section 4.2, yielding a total of 2,000 data points. After dividing these data into regions as shown in Figure 6.6, input matrices were generated based on the relationship formulas associated with the reliable region (Figure 6.4). These matrices were then fed into the learning model built on the basic knowledge learning framework explained in Chapter 5:, enabling effective task-specific knowledge adaptation.

When the test results were evaluated, the model achieved an accuracy rate of 93% for this part-specific cognition. More detailed findings can be seen in Figure 6.7.

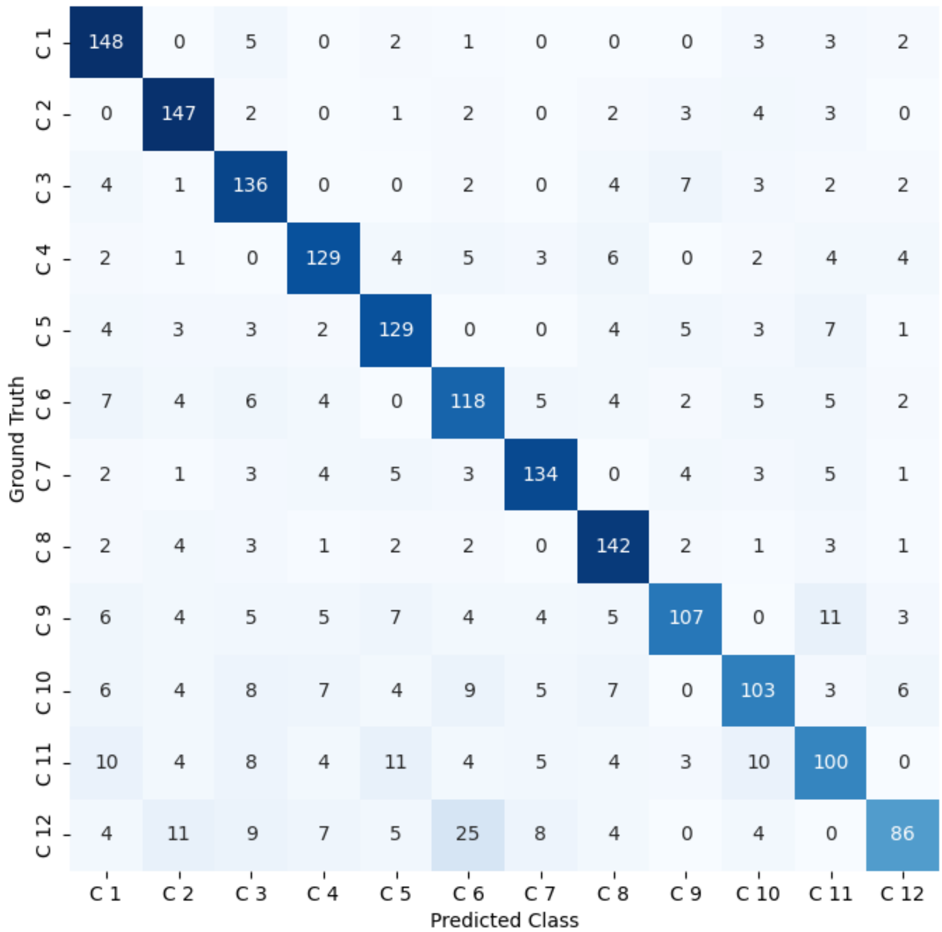

Figure 6.7: Results of the ML-based cognition for refrigerator's inner beyond cover

Chapter 7:
DEVELOPMENT OF ADAPTIVE VALVE-GATE CONTROL SYSTEM

7.1 Root Causes and Long-Term Impacts of Short Shot and Flash Defects

In the plastic injection molding process, particularly during the filling, holding, and packing stages, short shots and flash defects may occur when optimal pressure and valve-gate timing adjustments are not implemented. In such cases, beyond the rejection of defective products, additional time- and cost-related factors, such as new setup requirements and non-value-adding operations, emerge and significantly reduce production efficiency. Therefore, it is crucial to conduct a detailed root cause analysis of these frequently encountered issues, which may arise regardless of material or part structure, and to manage them autonomously, minimizing the need for human intervention.

A short shot defect typically occurs when molten plastic fails to fill the intended mold cavity. This defect, which results in the part being ejected before achieving its intended geometry, is primarily caused by insufficient mold pressure and, particularly in multi-runner systems, improper valve-gate timing. The likelihood of short shots increases in parts with thin walls, long flow paths, or complex geometries [43].

In contrast, a flash defect arises due to excessive mold pressure, essentially the opposite of a short shot. Under such high-pressure conditions, molten material escapes through the mold's parting lines, forming thin plastic protrusions. Unlike short shots, flash defects do not always necessitate scrapping the part. However, they still require non-value-adding secondary operations that may take two to ten times longer than the standard cycle time. Beyond the loss in production efficiency, flash defects contribute to structural wear and performance degradation in both the mold and the production machine. Over time, they can lead to mold deformation and a reduction in mold lifespan. On the production bench, repeated flash defects may cause stress accumulation in the clamping system, resulting in mechanical issues such as deviations in clamping force and wear of segmented components during operation [44].

7.2 *Effect of the Scraps on the Cavity Pressure & Contol System*

During the DoE studies, the process settings of which are detailed in Table 3.1, it was observed that short shot and flash defects were related to cavity pressure. An analysis of the defects and their root causes revealed that they occurred at two distinct boundaries of the reliable zone. Specifically, excessive pressure in the mold (i.e., attempting to inject too much material) led to flash, while insufficient pressure (i.e., insufficient material) resulted in short shots. This phenomenon initially arises from the improper adjustment of process parameters for the specific part. However, as stated in Section 1.3, process settings involve numerous interdependent factors, and optimizing pressure during the filling–holding–packing stages alone is insufficient to resolve such defects. To reduce complexity at this stage and establish a more fundamental control mechanism, an automatic feedback control system operating on the valve gate timer was selected as a solution.

The measurements obtained from the cavity pressure sensor were analyzed, and features indicative of short shot and flash defects were extracted. As illustrated in Figure 7.1 these two types of defects are observed within the time interval between the peak of the cavity pressure curve and the point at which it returns to its initial value (i.e., when no additional pressure is being applied to the mold). One of the critical indicators within this interval is the difference between the integrals of the actual cavity pressure and the defined reliable zone (Equation 8). The sign of this difference—whether positive or negative—is crucial for distinguishing between short shot and flash defects.

$$Pressure\ Difference = \int_{t_1}^{t_2} \big(reliable(t) - actual(t)\big)dt \tag{8}$$

$$where\ t_1 = \arg\max_{t} reliable(t),$$

$$t_2 = \min\{t > t_1 \mid reliable(t) = reliable(t_0)\}$$

Another critical factor is the time difference between the point at which the cavity pressure curve returns to its initial value and the point at which the reliable zone returns to its initial value. This time discrepancy serves as an indirect input for the re-adjustment of the valve gate timer.

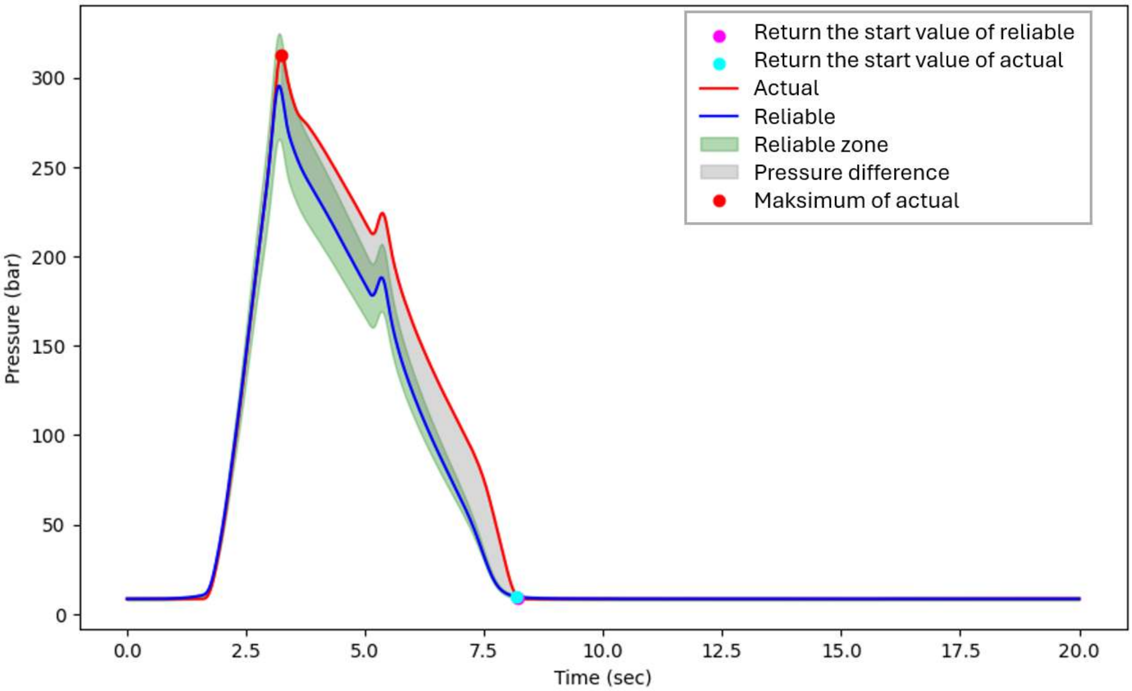

Figure 7.1: (a) Visualization of the method for flash defect

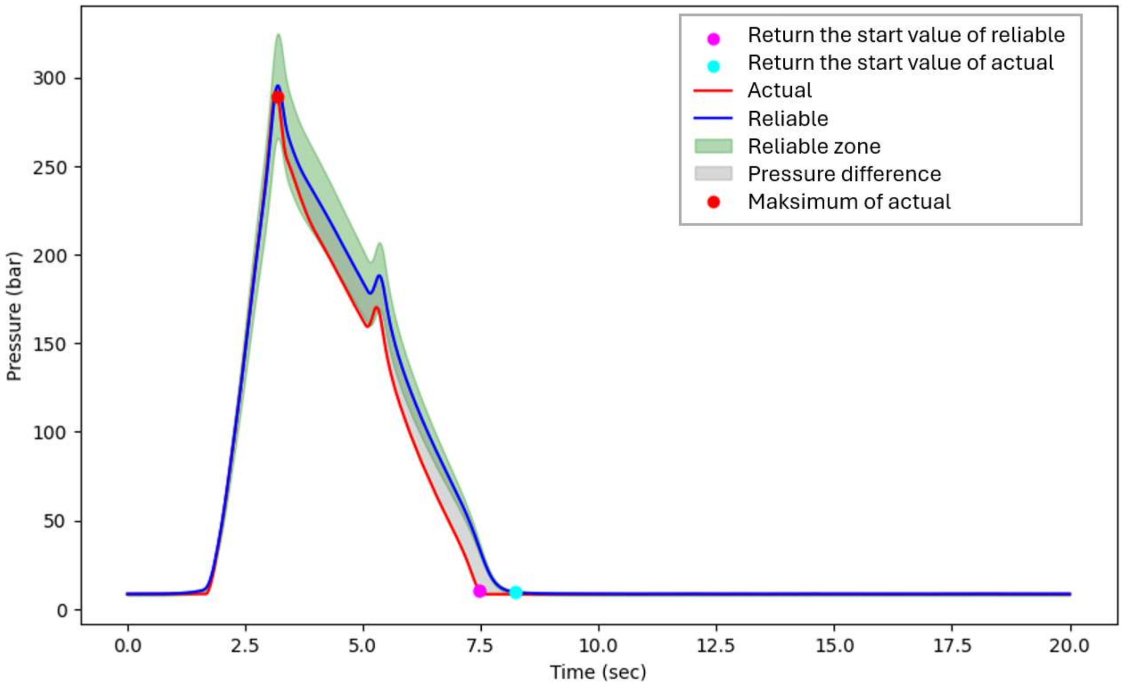

Figure 11: (b) Visualization of the method for short shot defect

In light of the information obtained, instead of using the sequential valve-gate controller integrated with the plastic injection molding machine, a PLC was employed to communicate with the machine, while a mini-PC was used to run the adaptive feedback control system code. To prevent the development of an overly aggressive control system that may be sensitive to changes in batches, seasons, or other environmental factors, the proposed method ensures a gradual convergence of the actual cavity pressure curve toward the reliable zone. As a result, abrupt transitions between the two defect types, which represent opposite conditions, are avoided. Moreover, the actual cavity pressure curve doesn't need to deviate significantly from the reliable zone to trigger adaptive valve-gate controller; even relatively minor deviations can be prevented. In this way, the system can autonomously converge back to the reliable zone before any visible defect occurs. With this stepwise methodology, the pressure curve typically returns to the reliable zone within a maximum of three steps (Figure 7.2) and prevents visible defects in just two.

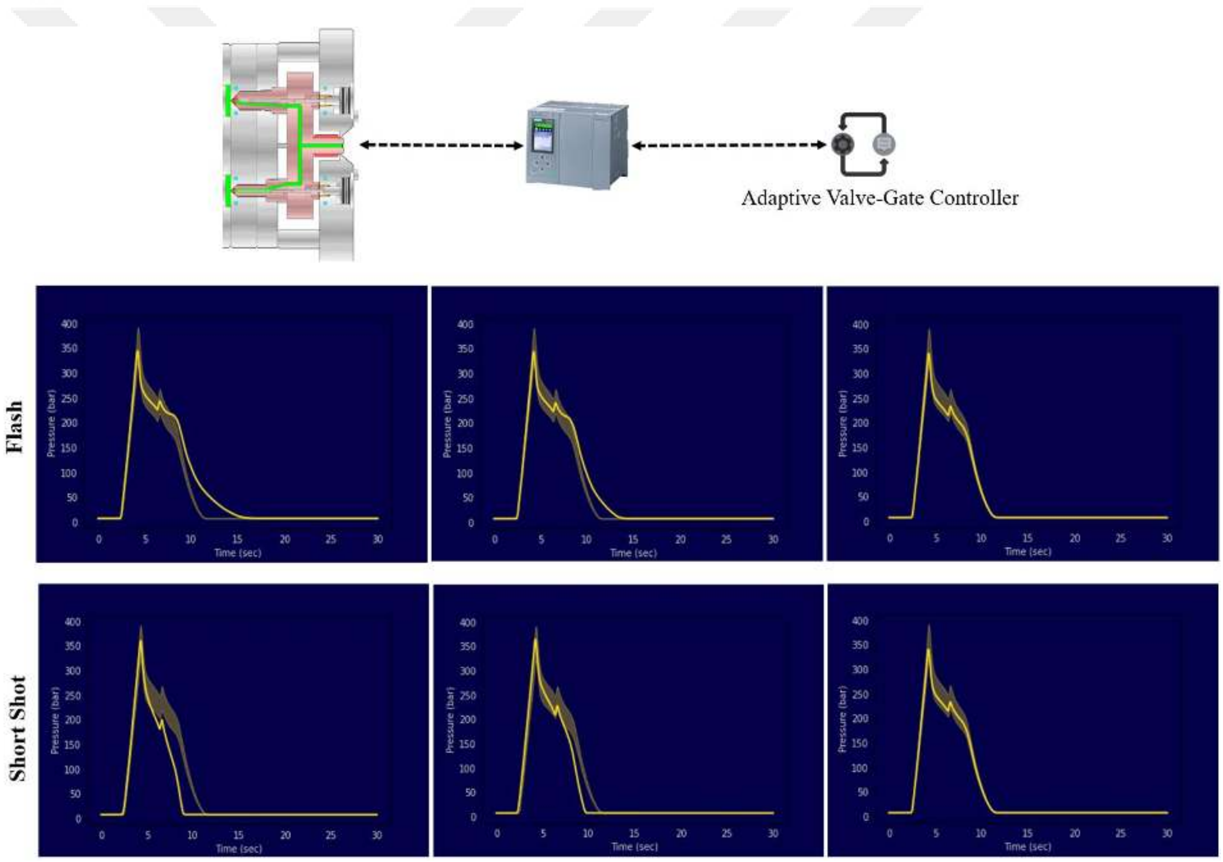

Figure 7.2: Adaptive valve-gate controller with stepwise visualization

Chapter 8:
RESULTS AND DISCUSSION

8.1 Real-World Deployment: The Influence of ML-Driven Cognition on Advanced Injection Molding Production Lines

The use cases outlined in Chapter 5 and Chapter 6 were actively implemented by Beko Corporate and its supplier network over a six-month period. During this time period, both scenarios delivered significant improvements, particularly in vital areas such as increasing business transparency and strengthening production monitoring capabilities.

These improvements not only improved operational visibility but also contributed significantly to increasing overall production efficiency and reliability.

In the case of the dishwasher bottom cover part, the application of this approach enabled the determination of an optimum production range. By keeping the production process within the reliable zone created specifically for the part, cycle times during mass production were reduced by 18%. In addition, thanks to the instant detection of errors that occur during production and the optimum suggestions provided for the actions to be taken for solution, a reduction of 800PPM in scrap rate was achieved. The study reduces the scrap rate in the part, paving the way for more product production in a shorter time. This also paves the way for inventory reduction and reduces assembly line downtime by approximately 500 minutes. Thus, a significant bottleneck in the mass production process has been eliminated.

For the refrigerator's inner beyond cover part, the visual defects caused by system instability were completely eliminated after a 6-month application. Thus, the scrap rate during the production process was reduced by 52%. Furthermore, thanks to the optimal process setting independent of the operator and the decision support algorithm, scrap generated during production start-ups was also reduced by 49%. This highlights the robustness and stability of the implemented solution, ensuring consistent quality from the very beginning of the production process.

The study highlights the successful outcomes of integrating the improved pressure signal-based ML-based cognition into a real-world production environment. The improvements made within the scope of the study ensure stable product output with high quality. In addition, it contributes to cost savings, shorter cycle times, and a more sustainable mass production environment. This creates a significant competitive opportunity for implementers.

8.2 *Review of Methodological Advantages, Limitations, and Future Directions*

Thanks to the proposed approach, an ML-based cognition for advanced plastic injection molding was developed, and an average accuracy of 95% was achieved.

The two-stage model structure (first a basic knowledge learner, then a task-oriented adaptor) proved to be particularly effective during implementation. This design made it possible to achieve high accuracy even with relatively small datasets during the wider deployment of the model.

To prepare the model's input, each parameter was referenced against its reliable zone and normalized between 0 and 1. This strategy allowed the model to remain robust, even though the cavity pressure curves varied significantly from part to part.

The model also performed successfully in mass production trials. Still, a closer look at class-level accuracy shows that the lowest performance occurred in the "material shot volume" class. This drop in accuracy seems to stem from overlapping features with other classes, specifically "injection pressure" and "holding pressure."

For instance, in the case shown in Figure 8.1(a), the correct classification should have been "material shot volume decrease." Instead, the model misclassified it as a drop in injection and holding pressure. While these alternative suggestions might still help maintain part quality, they reduce the method's overall efficiency. A reverse case can be seen in Figure 8.1(b), highlighting how this overlap can also work in favor of the outcome.

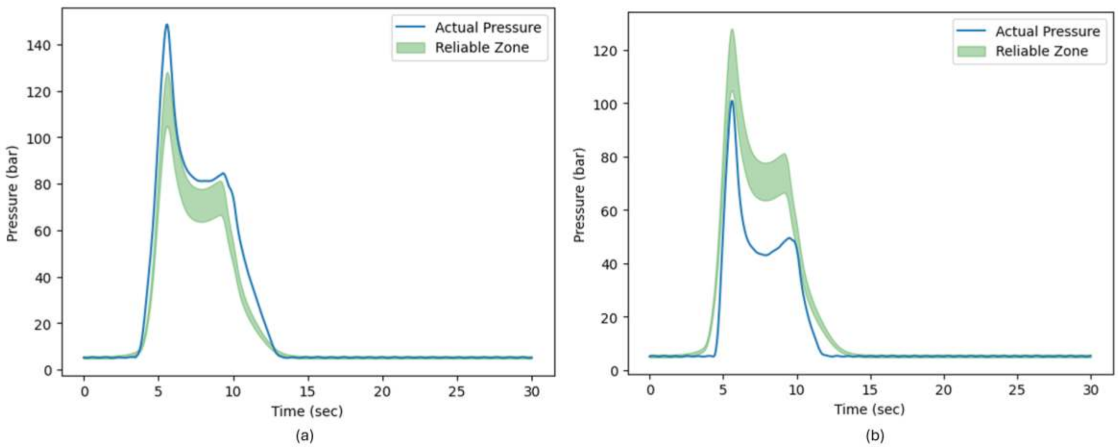

Figure 8.1: Example of class "material shot volume", (a) decrease, (b) increase

A critical solution to overcome this problem could be to increase the number of features in the input matrix. As seen in mass production trials, the performance of the proposed method may decrease slightly as the complexity of the part increases, and hence the gap pressure curve increases. In such cases, the pressure curve can be divided into more than six regions to improve the prediction accuracy.

Another possible improvement is to redefine the segmentation strategy. Instead of using only critical points as boundaries, it may be more effective to define larger regions that include these points, for example Figure 8.2. Although the current study shows that separation by critical regions is effective, future research can investigate this alternative method in more depth.

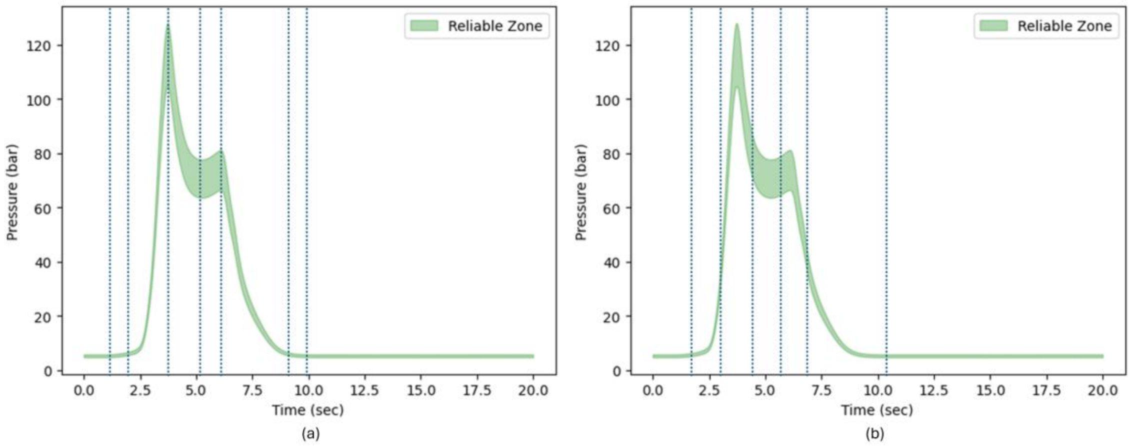

Figure 8.2: Dividing to regions of reliable zone, (a) purposed method, (b) future work

One of the main limitations of the proposed methodology is the use of both CAE and DoE studies to determine the reliable zone. If this reliable zone could be determined using only CAE, it would greatly improve the scalability and ease of implementation of the method, especially during widespread adoption, without the need for physical trials involving materials and workmanship.

Currently, the proposed method marks increases or decreases in six key machine parameters that drive the process. In future direction, this can be expanded to suggest specific target values for each parameter. As a result, a closed-loop control system can be developed where these adjustments are fed back to the plastic injection molding machine in real time, eliminating human dependency.

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