Quality Failure Detection Technique in Simultaneous and Sequential Multi-Valve Plastic Injection Molding

by

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Koç University

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Dedicated to my family who always supports me exceptionally.

ABSTRACT

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The plastic injection (PI) process has the nonlinear and time-varying complex dynamic characteristics of the batch processes, and the continuity of the process depends on the long-term experienced and skilled operators. The increase in the design complexity requirements, the use of new materials to reduce environmental effects, and energy consumption minimization requirements increase the control studies about PI. Failure detection in the PI process is critical for increasing the automation level of the process and reducing the scrap rate. In recent years, quality failure detection methods and smart injection strategies have been developed and utilized in PI to increase control over the process. This thesis mainly focused on developing failure detection techniques for simultaneous and sequential multi-valve PI molding. Three main criteria are questioned in the proposed method: high quality failure detection rate, sustainability in the production, and feedback substructure. Different trials are conducted, and an iterative approach is used to construct the method. Confusion matrices and hypothesis evaluation metrics such as accuracy (Acc), precision (Pr), and sensitivity (Sn) are used to measure the proposed technique's success. An iterative approach is used to satisfy the criteria, and studies started with time series-based approaches. Time series approaches neither have feedback substructure nor sustainability. Therefore, data windowing approaches are implemented, and criteria are satisfied. Cavity sensors (CS) and valve timings are the primary sources of information, and the only collected input from the injection molding machine (IMM) is the injection start signal. Thus, a failure detection method that is independent of the IMM is proposed in this study.

Quality failure detection in multi-valve PI molding is presented in this study. Timings of the valves are collected via a programmable logic controller (PLC), while sensor outputs are collected with a custom-developed data acquisition device (ADCR). Collected sensor profiles and timing information are matched and transferred to the electrical panel, which can store, analyze, and configure the upcoming data. Labeled data is used to construct a learning-based failure detection algorithm and valve time feedback. The study focuses on analyzing the cavity pressure (CP) sensor and derivative profiles with the sliding data windowing technique. Additionally, the labeled time series CP profile is analyzed with Python's Time Series Feature Extraction on Basis of Scalable Hypothesis library (TSFRESH), and the most critical parameters are evaluated and selected for the learning algorithm. To evaluate the quality of the product, features are extracted from the windowed CP sensor profile, windowed pressure derivative profile, cavity temperature (CT) sensor, valve opening times, and TSFRESH. Different learning algorithms such as k-nearest neighbor (KNN), support vector classifier (SVC), and logistic regression (LR) are used for failure detection. Thus, a learning algorithm is created, and a new method that has high quality failure detection rate, sustainability in production, and feedback substructure is proposed for multi-valve PI processes.

ÖZETÇE

Çok Yolluklu Eş Zamanlı ve Sıralı Plastik Enjeksiyon Kalıplarında Kalite Hatası Bulma Tekniği
Burak Tosun
Makine Mühendisliği, Yüksek Lisans
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Plastik enjeksiyon prosesi lineer olmayan ve zamana bağlı değişen, kompleks dinamik bir karakteristiğe sahiptir ve prosesin devamı tecrübeli ve eğitimli operatörlere bağlıdır. Dizayn kompleksliğindeki artışlara, çevresel etkiyi azaltmak için kullanılan yeni malzemelere ve enerji harcamalarını düşürme gerekliliklerine bağlı olarak plastik enjeksiyon üzerine olan kontrol çalışmalarının sayısı artmıştır. Plastik enjeksiyonda hata bulma çalışmaları otomasyon seviyesini arttırdığı ve hurda oranını azalttığı için kritiktir. Son yıllarda giderek artan sayıda kalite hata bulma sistemleri ve akıllı enjeksiyon stratejileri geliştirilmiştir. Bu tez genel olarak çok yolluklu sıralı ve eş zamanlı plastik enjeksiyon kalıplarında kalite hatası bulmaya odaklanmıştır. Ortaya koyulmaya çalışılan metodun başarısını ölçmek için üç ana kriter kullanılmıştır: kalite hatalarını yüksek oranda bulma, üretimde sürdürülebilirlik ve geribildirim altyapısı. Metodu geliştirmek için çeşitli denemeler yapılmış ve tekrarlı bir yaklaşım kullanılmıştır. Hata matrisleri, doğruluk, kesinlik ve hassaslık gibi hipotez değerlendirme kriterleri önerilen tekniğin başarısını ölçmek için kullanılmıştır. Kriterleri sağlamak için tekrarlayan yaklaşım tercih edilmiş ve çalışmalara zaman serisi bazlı yaklaşımlarla başlanmıştır. Zaman serisi bazlı yaklaşımların ne geri bildirim altyapısına ne de sürdürülebilirliğe sahip olmadığı görülmüştür. Bu sebeple, veri pencereleme yaklaşımları uygulanmış ve kriterler sağlanmıştır. Kalıp içi sensörler ve yolluk zamanları verilerin ana kaynağıdır ve enjeksiyon kalıplama makinesinden alınan tek sinyal enjeksiyon başlama sinyalidir. Böylece, enjeksiyon makinesinden bağımsız bir hata bulma metodu bu çalışmada ortaya atılmıştır.

Bu çalışmada, çok yolluklu plastik enjeksiyon proseslerinde hata bulma çalışmaları sunulmuştur. Yollukların zamanlamaları bir programlanabilir akıllı kontrolör aracılığı ile toplanırken, kalıp içi sensör verileri geliştirilmiş olan veri toplama sistemi ile toplanmıştır. Elde edilen sensör profilleri ve zamanlama bilgileri eşleştirilmiş ve elek-

trik paneline depolama, analiz ve kontrol amacı ile transfer edilmiştir. Etiketlenmiş veri, öğrenme bazlı hata bulma algoritması ve yolluk zaman geri bildirimi için kullanılmıştır. Çalışma kalıp içi basınç sensörü ve onun türevini veri pencereleme tekniği ile analiz etmektedir. Ek olarak, kalıp içi basınç sensörünün profili bir Python kütüphanesi olan zaman bazlı parametre çıkarma ve hipotez testi (TSFRESH) ile analiz edilmiş ve en kritik parametreler öğrenme algoritması için seçilmiştir. Parçanın kalitesini analiz etmek için pencerelenmiş kalıp içi sensör profilinin ve profilin pencerelenmiş türevinin yanında kalıp içi sıcaklık sensöründen, yolluk zamanlarından ve TSFRESH'ten parametreler çıkarılmıştır. K-en yakın komşu (KNN), destek vektör makinesi (SVC) ve lojistik regresyon (LR) gibi öğrenme algoritmaları hata bulma metodu için kullanılmıştır. Böylece bir öğrenme algoritması geliştirilmiş ve yeni metot yüksek kalite hatası bulma oranına, üretimde sürdürülebilirliğe ve geri bildirim altyapısına sahip bir metot olmuştur.

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ABBREVIATIONS

PI	Plastic Injection
CS	Cavity Sensors
IMM	Injection Molding Machine
PLC	Programmable Logic Controller
ADCR	Data Acquisition Device
CP	Cavity Pressure
CT	Cavity Temperature
KNN	K-nearest Neighbor
SVC	Support Vector Classifier
LR	Logistic Regression
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Acc	Accuracy
Pr	Precision
Sn	Sensitivity

Chapter 1

INTRODUCTION

1.1 Overview

One of the world's most extensively utilized plastic production method is PI. Injection-molded plastics market size is estimated to be USD 265.1 billion in 2020 and USD 284.7 billion in 2021 (Grand View Research, 2020). Aside from that IMM and molds are worth billions of dollars. The primary reason is that plastic injection is often acknowledged as the most efficient method for producing plastic goods.

The material, the injection machine, and the mold are three distinct factors that shape the plastic injection process. Each of them requires specialized knowledge, and they must collaborate well in order to maximize profits. Batch-to-batch consistency is the leading cause of production problems, and facilities have been fixing this inconsistency for decades using long-term experienced, skilled operators. Injection machine manufacturers, on the other hand, used a variety of sensors to improve machine control (Zhang et al., 2015). Critical parameters such as injection pressure, injection speed, injection temperature, backing pressure, screw position, and clamping force can be obtained via sensors in the injection machine. However, there is a complicated relationship between them, and modifying one can have an impact on the others. Several studies have been carried out to investigate the relationship between the parameters and their impact on the product. However, the plastic injection process has nonlinear and time-varying complex dynamic characteristics of the batch process (Chang and Faison, 2001, Wen et al., 2014, Song et al., 2020, and Zhang et al., 2015).

The plastic injection process is a mass production method widely used in numerous industries since it allows for the manufacture of both disposable and complicated industrial goods with high accuracy criteria (Li et al., 2021). Injection-molded parts can be used as visual parts, such as an automobile's instrument panel, or as functional parts, such as a dryer chassis. Apart from that, injection molded parts have a variety of characteristics, such as UV resistance, hygiene, packaging, wear resistance, vibration emission, and high-temperature resistance (Timur and Kılıç, 2021 and Chien et al., 2004) Multifarious characteristics can be achieved with plastic injection because thousand of materials are commercially available nowadays. Engineers are developing new materials for increasing the usage of injection molded parts and taking advantage of plastic injection in their process. Additionally, parts not made of plastic are produced with plastic injection after the material and technology improvements.

1.2 Materials of Plastic Injection

Plastics are the world's most common artificial materials, and the plastic production rate has increased from 2 million metric tons in 1950 to 367 million metric tons in 2020 (Tsakona and Rucevska, 2020). The plastic injection raw material's market size is valued at $44.6 billion (Grand View Research, 2020). However, only four types of raw materials are dominating the market which are polypropylene (PP), acrylonitrile butadiene styrene (ABS), high-density polyethylene (HDPE), and polystyrene (PS) (Dizon et al., 2019). Material is the essential factor in determining the characteristic of the end product. Mainly, PP is leech resistant, ABS is lightweight, HDPE is flexible, and PS is impact resistant (Huszar et al., 2015). In addition, different ingredients such as stabilizers and plasticizers are added to common plastics to achieve better characteristics according to the requirements of the process.

Material type is not a variable of plastic injection because the material is selected before designing the part and mold. However, the material characteristic is an essential parameter because the characteristics of the material are changed from producer to producer and batch to batch. Controlling the material characteristic in every cycle is necessary for modern production environments because further automation cannot be installed before handling this issue. Several studies concentrated on evaluating material features before injection, but material features depend on the machine and environment parameters, and it increases the complexity of the control (Lockner and Hopmann, 2021 and Rosli et al., 2020).

Pressure and temperature are the main factors affecting the material's characteristics inside the machine and the mold. The aim of the plastic injection is to fill the mold cavity with molten plastic, and in order to achieve that, plastic must reach the desired fluidity behavior. Changes in the machine and environment parameters may affect the material's behavior in the mold cavity and cause various production defects such as short shots, flow lines, and sink marks.

Another important aspect of plastic materials is the environmental effects because only 18% of the plastics are recycled. On the other hand, 58% of the world's plastic is expired and stored as waste (Chamas et al., 2020). As mentioned above, the production of plastic is increasing annually, and the rate of recyclable plastics is not increasing as desired. The main reason is that recyclable plastics or bioplastics are not as stable as petroleum-based plastics. Therefore, their usage is still limited. Increasing the control over the plastic injection process can increase the usage of bioplastics and can decrease the global effects of plastic usage in the future.

1.3 Machine of Plastic Injection

The plastic injection machine was first invented in 1872, and the process has become an efficient mass production method (Middleman et al., 1977). The machine consists of two main parts: the injection unit and the clamping unit (Figure 1.1). Mainly, plastic injection machines are defined by tonnage and driving system. Various applications and products need machines of different power; therefore, the tonnage of a plastic injection machine may vary between 30 tons to 4200 tons. The driving system can be hydraulic, mechanic, electric, or servo-hydraulic. Hydraulic machines are widely used; however, electric and servo-based drivers have higher accuracy and consume less energy.

The first purpose of the injection unit is homogenizing the molten plastic along the reciprocating screw and then injecting the molten plastic into the mold with

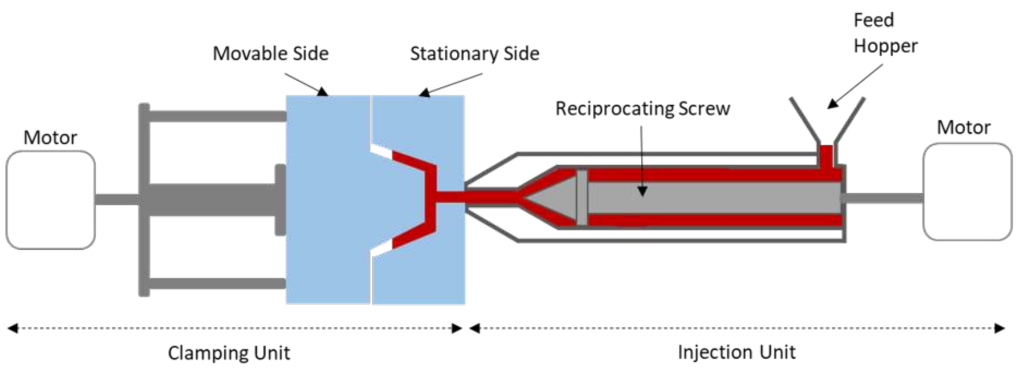

Figure 1.1: Plastic injection machine scheme.

controlled pressure and velocity. The screw moves forward and backward in every cycle for injection and feed. The nozzle is the part where injection happens, and the hopper is the part where feed happens. The screw goes forward in the filling stage of the process and comes back in the cooling stage to feed and start the new cycle.

The task of the clamping unit is to hold the mold closed until ejection. The clamping unit generates the counter force to keep the mold closed and eject the finished product with ejector pins. One side of the mold is attached to the stationary platen, and the other is attached to the clamping unit's movable platen. Other parts of the clamping unit are tie rods for alignment and cylinder controllers.

1.4 Mold of Plastic Injection

The mold is a pair of steel plates with cavities that molten material filled and took the shape of the final product. The mold's stationary side is named cavity and connected to the stationary platen and nozzle. The movable side of the mold is named as core and connected to the movable platen of the clamping unit. When the mold is closed, injection starts. Thus, molten material starts to fill the cavity. The filling phase is followed by packing, holding, cooling, and ejection. Mold stays closed until ejection and opens in the ejection phase. While the mold is opening, the final product stays with the core. Then, mounted injection pins pushed the product to a robotic arm or production line.

As presented in Figure 1.2, industrial molds have a complex structure, and a mold can have multiple cavities, runner systems, complex cooling channels, injection pins, and movable inserts. Multiple cavities can have the same product for increasing the manufacturing speed or different parts, such as the rear and front tub of the washing machine. Runner systems have two types which are cold and hot runner systems. In cold runners, molten plastic in the runner freezes and ejects out with the product. However, hot runner systems keep the material hot and molten until the next cycle. Thus, material in the hot runner is injected into the cavity in the start of the next cycle.

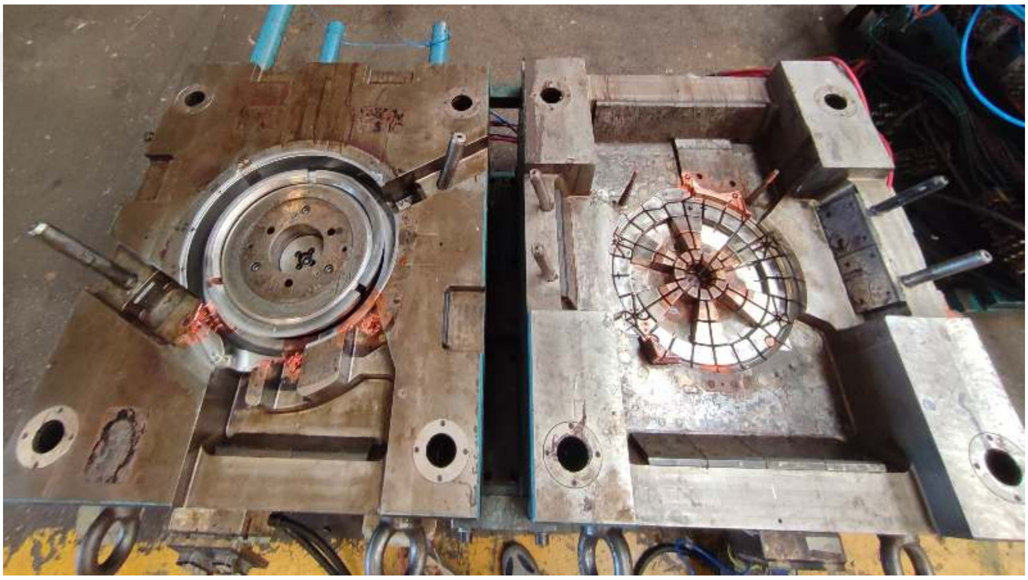

Figure 1.2: Exemplary industrial plastic injection mold.

The molten plastic temperature in the nozzle and hot runners are set to be fixed due to the consistency of the cycle. However, the mold cavity's molten material needs cooling to freeze. Cooling channels reticulate the mold cavity on both sides to provide efficient and homogenized cooling to prevent imperfections.

Holes, grooves, and negative draft angles are used in industrial designs, and these features may not eject successfully from the mold. Therefore, movable inserts are used in the electrical system. Thus, the cavity can be filled with necessary features, and problems in the ejections can be prevented.

Valves are the connection between the runner system and the cavity. The cavity can be filled with one valve gate; however, filling with multiple valves can benefit

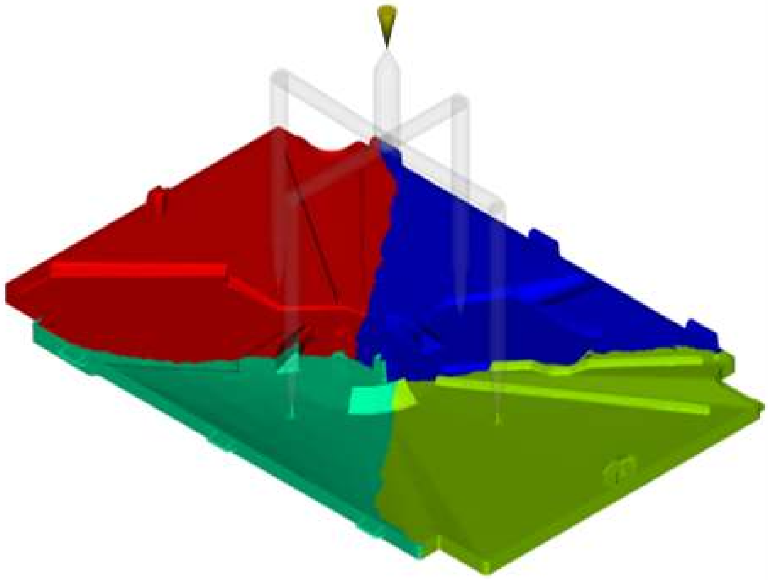

Figure 1.3: Four valve regional filling.

large parts and multi-cavity molds. Multiple valves increase the consistency in multi-cavity mold injection because filling starts simultaneously for each cavity. Multiple valves can also be beneficial for large parts because it increases the control over filling by starting to fill in multiple sides of the cavity. As observed in Figure 1.3, concurrent four valves are opened simultaneously, and quarters are filled with different valve gates simultaneously. Thus, the material flow distance in the filling is reduced. Starting and operating time of the valve can be arrangeable and increases the flexibility of the design. Additionally, valve-gate timing reduces the required injection power because the part is filled regionally in order instead of single shot.

1.5 Cycle of Plastic Injection

The plastic injection cycle consists of four stages: clamping, injection, cooling, and ejection (Figure 1.4). Clamping and ejection are related to mold closing at the start and mold opening at the end. Therefore, these are not the aim of this research. This research aims to investigate the injection and cooling phases because the process is a black box, and if the inputs are not linked with the product outputs, sustainable control may not be achieved. The injection phase is the shortest stage of the process and consists of two main parts: filling and packing. The cooling phase is the longest stage and starts with the holding.

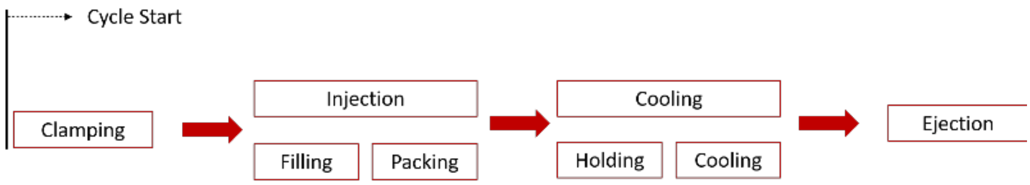

Figure 1.4: Stages of plastic injection cycle.

Injection phases start when the valves are opened, and the reciprocating screw of the machine applies injection pressure to the molten plastic. Pressurized molten plastic starts to fill the mold cavity with regulated injection velocity. Thus, the first filling stage is controlled by velocity-controlled screw movement, and the corresponding pressure graph in the nozzle can be observed in Figure 1.5. When the part is volumetrically filled (90-99%), the switchover from velocity to pressure-controlled screw movement happens, and packing starts. Packing is the second part of the filling stage (Fan-Jiang et al., 2021). The packing aims to compensate for the shrinkage and compress the plastic to increase density uniformly. After that, the holding phase starts, and the machine applies lower injection pressure until the gates freeze. Thus, molten material freezes and forms the cavity without defects. Packing and holding phases have very similar characteristics and can be classified as a single step. However, screw motion continues in the packing phase, and the set pressure can be different from the holding pressure. Therefore, packing is the last step of the filling while holding is the initial part of the cooling.

Material, plastic injection machine, and mold are the essential part of the process, as stated in the previous sections. However, pressure in the nozzle or other machine parameters do not give information about the process inside the mold. Repeatability and traceability of the machine parameters can increase the control over the process, but information from mold can show the combined effects of the parameters on the product. Gathering and analyzing the pressure and temperature profiles inside the mold gives information about the material characteristic, machine parameters,

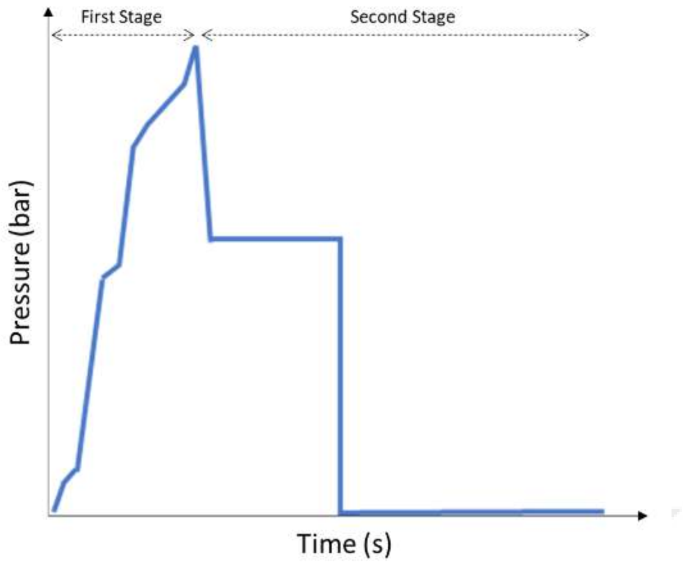

Figure 1.5: Injection pressure graph in the nozzle.

cooling, and product quality. Therefore, cavity pressure and temperature sensors are beneficial tools to track the plastic injection cycle.

An exemplary cavity pressure profile is given in Figure 1.6. Cavity sensors are positioned on the mold and directly in contact with molten plastic. Thus, sensors show the combined material, machine parameters, and cooling performance results. Consistency and quality can be traced with cavity sensors; however, if the tracking of the process depends only on the cavity sensors without any other input, profile changes may not be interpreted correctly in the production environment. Therefore, supporting cavity sensor outputs with data from the process is widely used in the researches to increase the success of the study.

The cavity pressure profile depends on the process setup and process variables. Process setup is affected by the mold design, machine, and placement of the sensors. The effect of these parameters is constant; however, it determines the expected profile and outputs of the cavity sensors. The profile of a near-gate and a far-gate sensor output is not the same and does not give the same output (Figure 1.7). The cavity sensor close to the valve contains more information about the cycle and increases the possible trackable parameters (Papathanasiou et al., 2022). On the other hand, process variables may change from cycle to cycle and affect the sensor

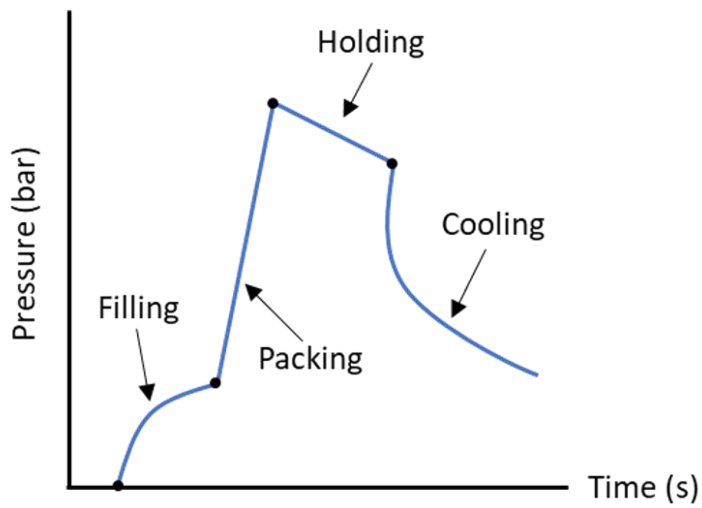

Figure 1.6: Exemplary cavity pressure sensor output.

output. Therefore, the aim of the cavity sensors is to track the process variables.

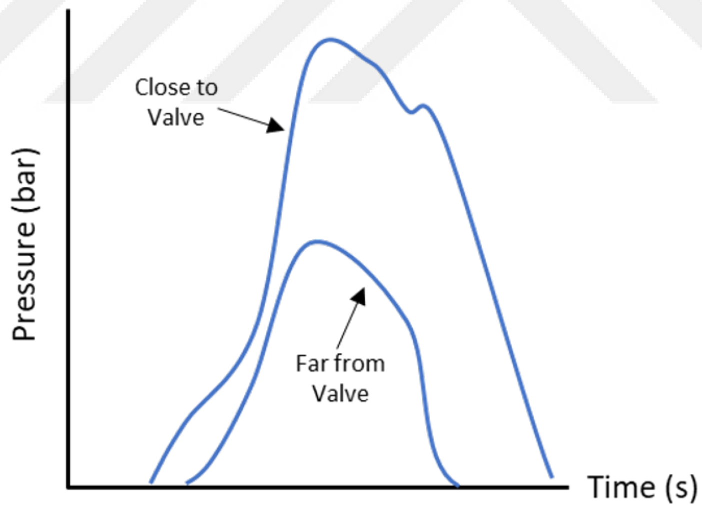

Figure 1.7: Comparison of near-gate and far from gate cavity sensor profiles.

Plastic injection cycles can be interpreted from different perspectives according to the aim of the study. Cavity sensors will be used in this study to evaluate the product's quality and track the process. Therefore, the filling stage of the process is emphasized and explained in detail.

1.6 Objective of the Research

Cavity sensors are used in industry and academia to track plastic injection. Their usage aims to analyze the desired process profile and evaluate the final product's quality. Additionally, some systems give feedback to machine parameters and operators when there is a failure. However, academic studies primarily focus on parameter relations and test specimen production systems. Complex industrial parts have multiple valves, and valves can be opened sequentially or simultaneously. Therefore, this study focuses on the usage of cavity sensors in complex industrial molds and generating a novel quality failure detection and feedback algorithm substructure by using valve timer unit in order to increase the overall equipment efficiency and reduce the scrap rate.

Simultaneous and sequential opening of a multi-valve system is required in production centers. Material characteristics, environmental changes, and machine parameter fluctuations cause quality failures such as short shots, warpages, and sink marks. Experienced operators use machine parameters, timer settings, and hot runner temperature settings to prevent errors and maintain production. The changes in the production conditions are inevitable; however, preventing failures and increasing the automation in the process are achievable. The objective of this study is to propose an automated quality failure detection method with a feedback substructure to prevent failures and increase the automation level of the process. This study proposes a novel data windowing technique, and generated technique is independent of the injection molding machine except for the injection start signal.

1.7 Thesis Outline

Chapter 1 gave general knowledge about the plastic injection process. The material, the machine, and the mold are explained with ground details in order to increase the understanding of the thesis. The plastic injection cycle part gives the scope of the cycle and explains the reason for choosing the topic.

Chapter 2 provides a literature review on the topic. The first part of the literature review focuses on the found machine parameter – cavity sensor relations. The second part summarizes the studies about data analysis and feedback mechanisms. Most related researches are investigated; however, other sections use additional citations.

Chapter 3 provides an explanation of the data acquisition system, software, sensor fusion, and feedback mechanism. The constructed system is independent of the research aim and beneficial for industrial and academic purposes.

Chapter 4 explains the preliminary study of cavity sensors and shows the potential of cavity sensors in failure prediction studies. The washing machine rear tub part is used in this chapter, and the viscosity tracking system is used for failure detection. This section aims to propose a failure detection method for simultaneous multi-valve molds.

Chapter 5 provides a detailed explanation of the failure detection technique in sequential multi-valve plastic injection molding. Different approaches are used to increase the success of the system and the developed system uses the data windowing technique. The study was conducted in the chassis part of the tumble dryer, and cavity sensors are used with timer information. Machine parameters or signals are not used in this study except for the injection signal. Therefore, the proposed method is independent of the machine and only depends on the mold. This chapter is submitted as a journal article and is currently under review.

Chapter 6 summarize the research done in this study and points out important contributions to academia. Additionally, further research topics are proposed in this chapter.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

CS have been used in academia and industry for more than a decade however benefit of the technology is still questionable. Most academic results are specific to a case; however, some researchers found generally accepted results. The literature review focuses on parameter-CS relations and the usage of CS for giving feedback to the process. This study aims to construct a failure detection method and valve timing feedback substructure for plastic injection using CS outputs. Relevant research in the literature will be investigated in detail.

2.2 Cavity Sensor – Machine Parameter Relations

The quality of the developed technology depends on the sensitivity to changing conditions. Researchers and developers investigated the correlation between the machine parameters and CS to understand the effects of process parameters on CS outputs. Hassan (2012) conducted a comprehensive study and analyzed the relations between CS and important process parameters: cooling time, injection pressure, packing pressure injection temperature, and injection time. The study used two different materials to observe the effect of material change. According to Hassan, CP increases with packing pressure, injection pressure, injection temperature, and packing time for both materials. Increasing the injection time decreases the cavity pressure. Study shows that injection time has 3 times greater impact on cavity pressure than packing time. On the other hand, Sykutera et al. (2018) focus on the relation between collected parameters and material properties. Sykutera et al. discovered that CP and CT sensors allow for the calculation of shear rate, shear stress, and apparent viscosity in the mold. This rheological study demonstrates that properly placed pressure and temperature sensors enable the generation of essential process parameters and aid in the control of process quality.

Obregon et al. (2021) collected 30 important machine and mold parameters to observe the relation between parameters and product quality. Holding pressure, injection speed, and clamping force are changed to find the relations, and results showed that the quality of the part is classified with more than 99% success by seven different classification algorithms. According to studies, parameter changes directly affect product quality, and CS are sensitive to parameters. Guerrier et al. (2017) used CS for flow visualization and simulation during the plastic injection in another study. According to Guerrier, temperature sensors react to contact with molten plastic. Thus, temperature sensors can give the exact material arrival time, and filling status can be tracked online. Gim et al. (2015) conducted a study on a multi-cavity mold and proposed a method for filling imbalance detection. Similar to Guerrier, Gim used temperature sensors for tracking resin-arrival-time. However, researchers used indirect pressure sensors, and the pressure signal did not produce reliable results according to their findings. In another study, Gao et al. (2014) used sequential temperature and pressure sensors to calculate the viscosity in the cavity. The formula depends on detecting the molten plastic contact with the temperature sensor. The time between injection start and temperature sensor contact is used to find pressure change. Thus, viscosity is calculated and used as an online quality index.

Indirect CP sensors cannot produce trusted results, but direct cavity pressure sensors produce reliable outputs and can show a reliable correlation with important machine parameters. Tsai and Lan (2015) conducted a study and investigated the correlation between runner pressure and cavity pressure. According to their results, runner pressure and cavity pressure are directly correlated, but the relative position of the valve and sensor affects the quality of the output. Different valve positions are used to investigate this effect, and results are compared. The closest distance between runner and sensor gave the most detailed results. Additionally, the team conducted experiments to investigate the effect of process parameters on the CP sensor. Effects of injection pressure, switchover timing, cooling time, melt temperature, packing pressure, and injection speed are investigated for different valve locations. The study shows that parameters have 0.9 or more correlation between cavity pressure except for packing time.

2.3 Quality Failure Detections and Feedback Mechanisms for Plastic Injection

Understanding the parameter relation with the sensor is followed by investigating the results in production. Complex interrelations of the machine, material, and environmental parameters in plastic injection environments cause failures. CS with machine parameters were used in the production to detect the failure signals and give feedback to the process. The simplest method to give feedback is rule-based; however, complex production methods do not have direct relations in most cases. Kumar et al. (2020) constructed a control boundary for the process with labeled data. Flow rate, packing pressure, packing time, melt temperature, and coolant temperature are used to give feedback, and feedback decisions are decided with thresholds and rules. On the other hand, Hopmann et al. (2017) conducted a study and used model-based self-optimization to achieve desired cavity pressure profile. Iterative learning controlled the holding pressure to reach desired cavity pressure profile. This unique approach used a reference CP profile and changed the reference according to the past cycles.

Chen et al. (2019) found that maximum clamping force is a good indicator of the final product quality. In their research, cavity sensors are coupled with the tie-bar strain sensors and showed the relations between sensor profiles and switch-over timing. Research shows that tie-bar strain and cavity sensors give similar profiles for varied injection speeds, switch-over timings, and holding pressures. Chen et al. (2021) implemented simple strain gauges on tie-bars in the following study to observe peak clamping force without using cavity sensors. A rule-based control system controls switch-over timing and holding pressure to prevent failures. The study proves that giving feedback on the process is achievable by just using the sensors from the mold. A similar study was conducted by Rao et al. (2017), and clamping force measurement with tie-bar strain sensors is used to regulate the partial load on tie bars. When the partial load rate of the tie bar exceeds the setting value, the system arranges the partial loads and the tie-bar balance is achieved. Thus, the quality of the product is sustained.

Quality prediction of the part is the main aim of PI studies, and several studies are conducted. Zhou et al. (2017) created a quality prediction model by monitoring key process parameters. The team investigated the changes in pressure integral and discovered that pressure integral is strongly linked to product weight. As a result, the model uses pressure integral changes to predict product quality. In another study, Moayyedian et al. (2018) developed a multi-objective quality evaluation model which attempted to correlate frequent quality defects to process parameters. The Taguchi method is used to assign weight to parameters. As a result, researchers devised a practical method for determining the operation's process parameters. Nasiri and Khosravani (2019) collected data from the machine parameters and constructed a Fuzzy case base reasoning (CBR) fault detection system. Thus, the team predicted the failures and recommended adjustments for the parameters. Nasiri categorized the collected 19 parameters to 5 and gave different weights to increase accuracy. The resultant accuracy of the system reached 80% with the developed model. On the other hand, Kozjek et al. (2017) proposed a data-driven holistic approach to fault prognostics. The team used real industrial data from five injection machines within six months. High-dimensional data is used to construct quality fault detection, and a failure prediction method is proposed. The resultant method predicted 22% of unplanned machine stops with 86% probability.

2.4 Conclusion

Reviewed studies show that cavity sensors can be a reliable source of information in plastic injection quality failure detections because sensor outputs correlate with the process parameters and can give information about the success of the cycle. On the other hand, data-driven studies focused on more sophisticated prediction methods than the sensor outputs, increasing the methods' complexity. Additionally, some of the research is fully conducted in laboratories, and implementing these systems can be challenging in the industrial environment.

This study aims to construct a quality prediction method that can be appropriate for both simultaneous and sequential multi-valve mold operations in industrial facilities. The method must have high failure detection rate, sustainability, and feedback substructure to increase the production's automation level and reduce the scrap rates. This literature review shows that cavity sensors can be the primary source of information for constructing a quality failure detection algorithm.

Chapter 3

METHODOLOGY

3.1 Overview

Quality and production control are the main aim of production centers, especially for net-shape mass productions such as molding and extrusion. Quality control is performed offline in net shape productions when the part is produced. Even though sensing technologies are developed, cycle-based control over processes is still challenging. Machine producers developed control mechanisms to control processes in each cycle; however, achieving success without taking data from the mold is not achievable. CS are the essential tools for tracking production and gathering data from the mold.

Various companies such as Kistler, Priamus, and Futaba make industrial-level CP and CT sensors. However, these sensors come up with high cost and nonconfigurable software. Usage of CS is depended on the problem that needs to be solved. Pressure and temperature sensors are used sequentially to evaluate viscosity (Gao et al., 2014). Thus, researchers followed the molten material's fluidity characteristic to estimate the final part's quality. Another approach is putting pressure sensors in the most probably problematic position (Guerrier et al. 2017 and Gim et al., 2015). Filling quality is controlled for this specific position and quality failure detection is achieved with this strategy. Another common approach is using the pressure sensor profiles, which are placed close to the valve. This method follows pressure profile changes, and action is taken if the pressure curve goes out of the limit (Hassan, 2012). Configurable software makes it possible to implement existing and possible solutions.

Data acquisition and online monitoring systems are required to use CS effectively. This chapter presents the constructed system and components in detail. Sensor selection and placement, data acquisition, data storage, and visualization will be explained.

3.2 Sensor Selection and Placement

An average industrial mold can run millions of cycles. Therefore, desired cavity sensor has to have a high lifetime. Additionally, the pressure inside the cavity can reach several hundred bars, and melt temperature can reach 300 °C for high tonnage plastic injection machines and various materials. Lifetime and range of senses are the main two constraints for the selection of cavity sensors. The sensing method, sensitivity, linearity, and size are additional consideration points. After careful evaluations and discussions with the firms, Kistler 6157C (Figure 3.1a) and Priamus 6002B are chosen for the pressure sensor. On the other hand, Kistler 6192B (Figure 3.1b) and Priamus 4008C are selected for the temperature sensor. Pressure sensors use quartz with piezoelectric behavior, which deforms after mechanical load and generates an electrical charge. When force is applied to the front of the sensor, pressure is transmitted to the quartz measuring element, which produces a proportional electric charge. Temperature sensors are simple K-type or N-type capsulated thermocouples. The cables of the sensors are delicate and mostly not replaceable. Therefore, the cables should be protected from external damage while the machine is working.

(a) (b)

Figure 3.1: (a) Kistler 6157C pressure sensor, and (b) Kistler 6192B temperature sensor.

Placement of the sensor in the mold is challenging because sensors and cables are delicate. Producers developed tools and methods to place sensors; however, disassembly is not possible with the existing methods. Placement tools are also designed for a maximum of 70 mm, but the molds used in this study have a minimum 75 mm mold core. Therefore, a new assembly method has been developed to make assembly and disassembly easier and safer. In the new method, sensors are placed inside an insert, and then the insert is assembled into the mold (Figure 3.2). This method has two advantages. Firstly, assembly of the sensor on deep molds is safer and more accessible because screwing operation inside the mold is not required in this method. Secondly, sensors are dissembled easily if the mold needs to be repaired. Additionally, the machining process is more straightforward because precise machining is applied to a simple insert instead of the mold core.

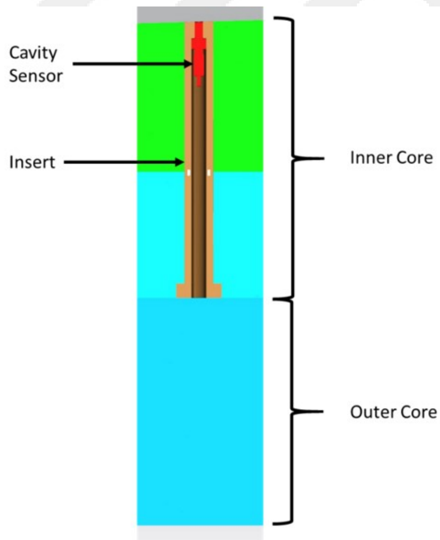

Figure 3.2: Sensor placement to the mold with insert.

The next step of the cavity sensor implementation is connecting the cables to the data acquisition device, which is positioned on the mold. Cable channels are machined on the surface of the inner core to transfer the cables inside the mold. Cables from different sensors have connected to each other and come out of the mold at one point, as represented in Figure 3.3.

Cable road and insert fasten the position of the sensor in the mold and increase

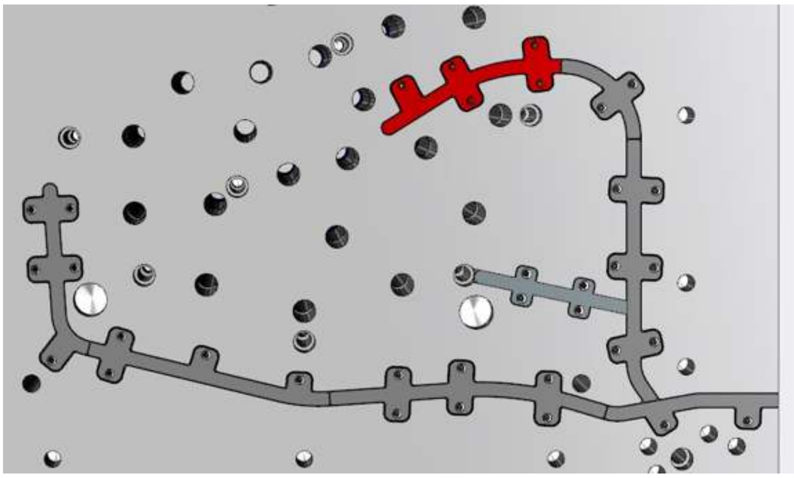

Figure 3.3: Cable channels on the inner core's surface.

the safety. Cable roads stayed between the inner core and outer core, which means the data acquisition box may be positioned in the middle of the mold. On the other hand, insert and sensor can be observed on the surface of the mold (Figure 3.4).

Figure 3.4: Insert and sensor on the surface of the mold.

3.3 Data Acquisition

Produced proportional electrical charges by CP sensors are transferred to the data acquisition system. The ADCR is designed to collect upcoming data from the sensor with up to 5 kHz sampling rate. The device converts proportional electric charges to voltage, which means the measured voltage is proportional to the cavity pressure. Thus, the measured electric charge with the unit of Pico coulomb is amplified and converted to the desired output, cavity pressure.

The ADCR is placed on the mold, and cavity sensors are connected to the device. The device is capable of collecting data from 4 pressure and 4 temperature sensors with 5 kHz sampling rate and transmits the data to electric panel in order to store, analyze and visualize. As portrayed in Figure 3.5, the device has magnets to hang on mold. Sensor cables follow the cable channels in the mold and are connected to the data acquisition box when it gets out of the mold. The device's output side has one ethernet port, and incoming data is transferred via ethernet cable to the electrical panel.

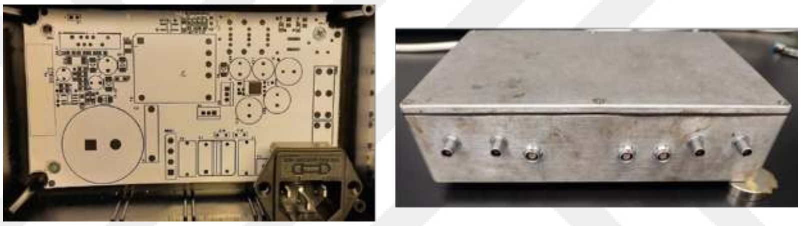

Figure 3.5: Electronic board and cover of the data acquisition device.

An exemplary placement of the device on the mold is illustrated below in Figure 3.6. The upper side of the mold is the most appropriate position to put the device because the sides of the mold have electric motors and cooling water inlets-outlets.

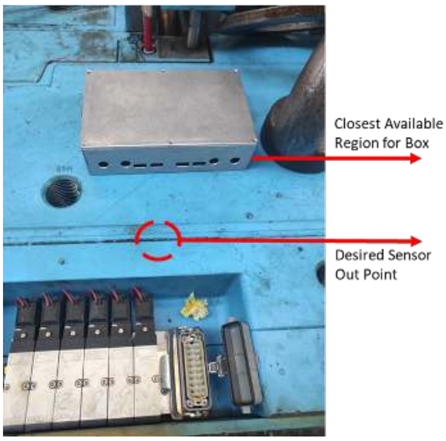

Figure 3.6: An exemplary data acquisition device placement on mold.

Additionally, placing the device on the stationary side of the mold is advantageous because movement in each cycle can harm the cables. However, the device and sensors must be placed on the same mold's side. Therefore, if sensors are placed on both sides of the mold, each side of the mold needs a data acquisition device

3.4 Electrical Panel

The ADCR aims to amplify the sensor output and safely transmit data to the electrical panel in real-time. The electrical panel takes the data via ethernet cable and the upcoming data stored in it. The electrical panel is installed on the machine with four magnets for swift and steady installation. The components of the electrical panel are the power supply, router, edge pc, and PLC.

The router is equipped to provide stable and independent internet from the local environment. The ethernet cable that comes from the ADCR is also connected to the router. Edge pc is connected to the router for internet connection and data transfer. Gigabyte BRIX Barebone edge pc is selected and used in this study. Additionally, a Siemens S7-1200 series PLC is used to gather valve timings from the timer and control the valve timings in the mold. Other than the electrical panel, a touchscreen monitor is used in this study to visualize results for field operators and on-site observations. Similarly, the monitor is equipped with magnets for stable and flexible installation. The constructed electrical panel is illustrated in Figure 3.7.

Figure 3.7: An exemplary electrical panel.

PLC is equipped if the mold has sequential valve openings and gathers information from the timer. PLC sends the timing information to the edge pc with timestamps. According to the pc's output, regulated or the exact valve timings are sent to the mold. PLC type sequential valve timer arranges valve-gate timing, and the unit is embodied in Figure 3.8a. The unit is set the start and operating time of the valve-gates. As also shown in Figure 3.8b, the output of the used timer is transferred with an 18-pin connector, and the connector is connected to the panel before mold.

(a) (b)

Figure 3.8: (a) PLC-type sequential valve timer, and (b) valve timer input and output connections

The electrical panel collects the CS output and valve timer information, and sensor fusion is handled via the upcoming timestamps. Thus, the information sources are calibrated according to each other. Consequently, constructed project scheme is represented below in Figure 3.9.

3.5 Visualization

The system collects valve timing signals and CS outputs in real-time. Software is written to store, analyze, and visualize the data every cycle. CP and CT sensors give information from inside the mold. The primary output of the sensors is the profile; however, profiles may not be meaningful if not interpreted. A PI cycle consists of

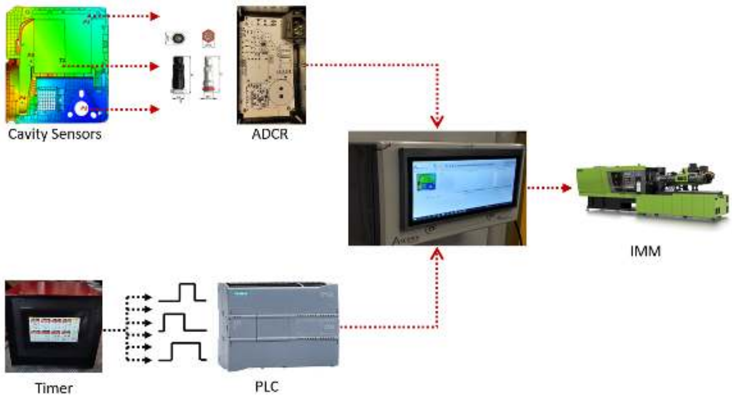

Figure 3.9: System scheme.

four stages: clamping, filling, cooling, and ejection. CS outputs are mostly related to the filling stage because the filling stage is the only dynamic stage of the molten plastic and takes 10-15% of the cycle time. Valve timing signals give the exact time of the filling signal. Therefore, the visualized data in the software takes from valve signal to 25% of the total data for detailed visualization. Shortened data is used in visualization and data analysis studies to reduce the required computational power. An exemplary interface of the software is represented in Figure 3.10. The interface is showing CS outputs and locations. Limiting lines can also be added in the interface by the user. Software is labelling the cycles according to the limit lines. Additionally, labelling can be done by a learning algorithm or viscosity calculation.

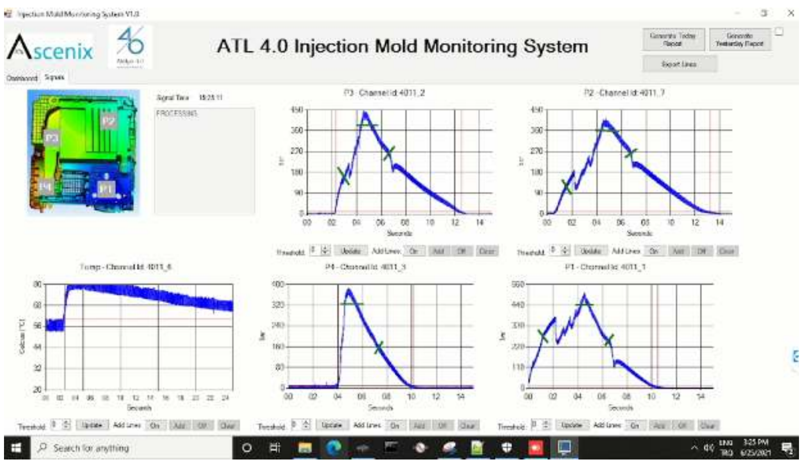

Figure 3.10: Software interface.

3.6 Conclusion

This study aims to construct failure detection methods for plastic injection in industrial environments. To ensure sustainability for data collection and visualization, the constructed system must be autonomous and continuous. The system is responsible for valve timings and valve management errors can halt production. Therefore, the system is stabilized with several tests and another electric source powers programmable logic controller. Thus, programmable logic controller continues to send valve timings independent of the data acquisition device and electrical panel.

Collected data must be stored systematically and collected data from valves and sensors must be synchronized. Computer time of the cycle is used to name the data output files and valve timings with the quality label of the cycle are written to a text file as a line at the same time. Thus, sensor output, valve timings, and cycle labels are paired, and outputs become ready for further studies.

Chapter 4

SIMULTANEOUS VALVE GATE OPENING FAILURE DETECTION

4.1 Overview

Failures in the PI cycles can be caused by machine parameter variations, material characteristics, or changes in the mold. However, due to the complex nature of the process, analyzing and tracking the factors may not result in a generic solution. The characteristic of molten plastic can show the cumulative effect of the parameters because it is affected from the machine parameters and material characteristic. Therefore, the behavior of the molten plastic inside the mold shows the process variation's overall effect on the filling. Thus, tracking and comparing the molten material characteristic may increase the overall efficiency of the process.

One key feature of molten plastic is viscosity, which depends on chemical structure, composition, and process conditions. Temperature, shear rate, and pressure also affect the plastic's viscosity, which means that viscosity can be a resultant parameter of the cycle and shows the effect of material, machine, and mold.

This chapter uses CS to evaluate the viscosity of the washing machine's rear tub part. Pressure and temperature sensors are located in the injection mold. For every cycle, the viscosity of the molten plastic in the filling is evaluated, and end products are labeled according to the quality. Thus, the relation between viscosity and part quality is investigated in the study.

4.2 The System

The washing machine's rear tub is used in this study to analyze relations between part quality and calculated viscosity. The rear tub is 4.5 kilograms and has several connection points such as springs, dampers, and electric motor connections for dynamic functions (Figure 4.1a). Additionally, drum, cover, and water inlet-outlet connections are located on the rear tub for static functions and impermeability of the part. The rear tub is both performing static and dynamic functions. Therefore, changes in the part's weight or shape can cause destructive consequences. It is important because increasing the packing time or the amount of injected plastic are not an option in the production of the rear tub part.

(a) (b)

Figure 4.1: (a) The rear tub part of the washing machine, and (b) the 2000-ton Chen Hsong plastic injection machine.

The mold uses three valves with a hot-runner system for filling the part, and the valves are opened simultaneously at the start. The valves are positioned to fill approximately one-third of the cavity; however, the filled volumes do not have similar characteristics because of the non-symmetrical industrial design. The machine used in this study is a 2000-ton Chen Hsong IMM (Figure 4.1b), and the reason behind using a 2000-ton powerful machine is the mold has two cavities. The mold is designed to produce a rear tub and cover every cycle; therefore, required machine power is increased. Another thing that increases the needed machine power is the timing of the valves because the machine needs to fill the 4.5 kg cavity in 4 to 5 seconds.

The mold is equipped with one temperature (Kistler 4008C) and one pressure (Kistler 6002B) cavity sensors. The sensors placed in the same one-third of the part that filled by the same valve. Pressure sensor is placed close to the valve in order to increase the detail of the upcoming data. On the other hand, temperature sensor is placed at the very end of the filling region to collect filling status and time. Sensors are connected to ADCR for amplifying the signals and then, data is transferred to the electrical panel.

The pressure and temperature data for each cycle is used to evaluate the viscosity of the molten material. Calculated viscosity is compared with the material's properties for validation. The material used in this study is Leonidt which is a polypropylene based recycled plastic material. Leonidt's melt temperature range is between 220°C to 270°C and viscosity graphs of the Leonidt for different melt temperatures is shown in Figure 4.2.

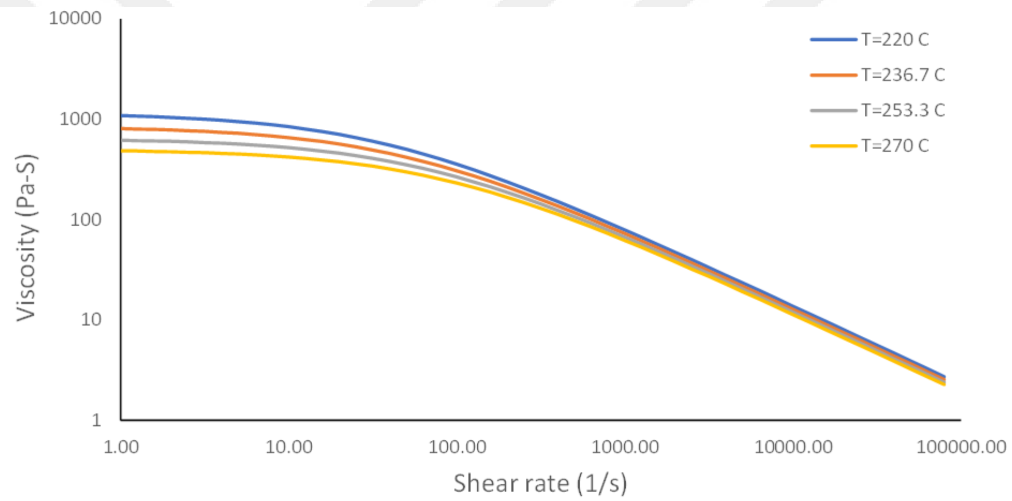

Figure 4.2: Leonidt's viscosity graph.

4.3 Viscosity Calculation

Molten plastic's viscosity is a resultant parameter of the process and different methods are developed by the researchers. Velocity and viscosity are linked parameters, and different methods are proposed to measure them. Ultrasonic sensors (Doğan et al., 2000), capacitive sensing methods (Chen et al., 2004), and electromagnetic probes (Suh and Lee, 2000) are used to evaluate the cavity velocity of the plastic. However, proposed methods have limitations and depend on assumptions. On the other hand, different methods are proposed to measure the viscosity of the plastic, such as the capillary method and rotating cylinder method, but the implementation of these methods in the cavity is not possible for the rear tub. Therefore, nozzle pressure is linked with viscosity because viscosity is defined as the ratio of shear stress to shear rate. Nozzle pressure directly relates to the melt shear stress, and flow rate directly relates to the shear rate. If the flow rate of the process is assumed to be constant, the viscosity will only depend on the nozzle pressure (Kim et al., 1998). Another method is proposed by Gao et al. (2014), and CS are used in their model. In Gao's model, the flow of molten plastic in the cavity is assumed as an incompressible viscous flow between two fixed parallel plates as showed in Figure 4.3.

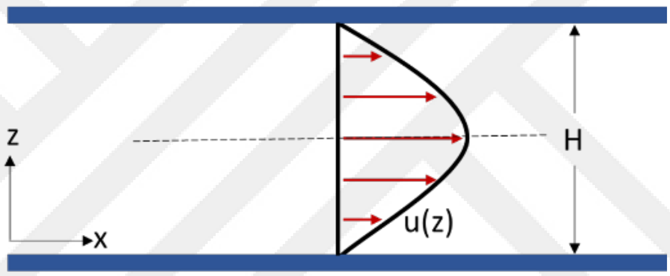

Figure 4.3: Incompressible viscous flow between two fixed plate.

When μ is the viscosity and g_x is the gravitational acceleration constant, the Navier-Stokes equation for the x direction gives:

$$\rho(\frac{du}{dt} + u\frac{du}{dx} + v\frac{du}{dy} + w\frac{du}{dz}) = -\frac{dp}{dx} + \rho g_x + \mu(\frac{d^2u}{dx^2} + \frac{d^2u}{dy^2} + \frac{d^2u}{dz^2}) \tag{4.1}$$

If v and w assumed to be zero, the equation can be solved in two-dimensional space. If the gravitational force is also neglected, equation can be simplified as:

$$\frac{dp}{dx} = \mu\frac{d^2u}{dz^2} \tag{4.2}$$

When boundary conditions are applied to the equation 2, final equations will be:

$$\frac{dp}{dx} = \frac{12\mu v_x}{H^2} \tag{4.3}$$

Derivative of x-position is not related to the CS outputs; however, if the both sides are divided to time derivative, related equations can be found:

$$\mu = \frac{H^2}{12v_x^2}\frac{dP}{dt} \tag{4.4}$$

If velocity term is converted to distance-to-time ratio, viscosity formula is derived where ΔP is pressure difference, Δt is time difference, H is the distance between the plates and L_i is the distance between reference points (Gao et al., 2014).

$$\mu = \frac{\Delta P \Delta t H^2}{12L_i^2} \tag{4.5}$$

Equation 4.5 will be used to calculate viscosity of the product. Sequential CP and CT sensors are used in this formula while H was 3 mm, and L was 120 mm. CT sensors are started to increase when the molten plastic contacts them. Temperature increase time and pressure increase until this time is used in this formula, and experimental viscosity is calculated for tracking the changes in material characteristics inside the mold. Viscosity values will be tracked for every cycles and abnormalities will be matched with the viscosities in next section.

4.4 Results of Study

Environment and material characteristics affect the plastic injection cycle and cause failure. If a failed product is sent to the production line from plastic injection, failed products can be produced. Quality control for plastic injection is mostly operated offline by operators. Therefore, quality control is crucial for plastic injection to increase automation and reduce operator dependency. Viscosity tracking is a promising solution for online quality monitoring and can increase the success rate of production.

Calculation of viscosity will be done by CP and CT sensors output. The last ten successful cycles are used as a reference for the next product, and the 10% range is defined. The rule-based approach checks the viscosity value of the cycle and labels

Table 4.1: Confusion matrix of the viscosity tracking.

		Predicted: Failed - 1	Predicted: Successful - 0
Actual	Failed - 1	422	110
	Successful - 0	141	21029

the product accordingly. The system labels the products as a failure if the viscosity value exceeds the limit.

On the other hand, a button is placed near the operator's working area, and failed cycles are labeled by the operators. The comparison between the labels is used for validation of the system. The labeling system is used for ten days, and labels are compared accordingly. To define the success of the classification methods, confusion matrices are used. In confusion matrices, true positives (TP) represent correctly classified failed products, and true negatives (TN) represent correctly classified successful products. False negatives (FN) are the misclassified failed products, while false positives (FP) represent misclassified successful products. Accuracy (Acc), precision (Pr), and sensitivity (Sn) performance metrics are used for comparison between methods. Acc is the ratio of correctly classified products (TP and TN) to the total number of products. On the other hand, Pr shows the ratio of correctly classified failed products (TP) to the total products predicted as failures (TP and FP). Lastly, Sn evaluates the ratio of correctly classified failed products (TP) to the total number of failed products (TP and FN). Sn result is the main aim of this study because misclassified failed products cause problems in the production lines and prevent the automation level enhancement effort. On the other hand, Pr is problematic for the IMM because misclassified successful products will cause unnecessary feedback to the system. Viscosity-based labels are compared with the production data, and Table 4.1 is constructed.

According to Table 4.1, Acc is 98.84%, Pr is 74.96%, and Sn is 79.32%. Resultant ratios are promising; however, this method does not ensure sustainability due to the

10-products-based limiting method. The main result of the proposed method is that cavity sensor outputs can be useful for online failure detection and increase the automation level of the process.

4.5 Conclusion

CT and CP sensors are used in this study to evaluate molten plastic's viscosity. Viscosity is the measure of molten plastic's resistance to flow and can explain the behavior of the plastic in the cavity. The viscosity formula developed by Gao et al. (2014) is used in this study to evaluate viscosity. Sequential pressure and temperature sensors measure the pressure and time difference between two sensor locations. Thus, viscosity is calculated.

The results of this study prove that CS can be promising for online failure detection. Viscosity calculation gives promising results; however, the method's sustainability depends on just one value. Therefore, more comprehensive approaches are needed to ensure sustainable quality failure detections.

Chapter 5

FAILURE DETECTION TECHNIQUE IN SEQUENTIAL MULTI-VALVE INJECTION MOLDING

5.1 Overview

Sequential multi-valve plastic injection molding is widely used in industry due to the complex shape of the final products. Multi-valve molds are used to fill cavity from different points. The part in Chapter 4 is filled from 3 valves and valves opens at the same time. However, valves can be opened at different times with timers. Timers are programmable logic controller (PLC) based signal generation units that control the operation time of the valves. Timers can be an integrated unit of the injection molding machine or can be an external unit. Sequential multi-valves are beneficial for complex shapes because filling volume of each valve can be optimized. Welding positions can also be arranged with optimized valve timings. Therefore, sequential multi-valve operations are widely used in industry especially for axisymmetric and complex parts.

In this chapter, a novel failure detection technique in sequential multi-valve plastic injection molding using cavity sensors will be proposed and investigated in detail. In this technique, cavity sensors and valve timings are used as the source of information, and failure detection algorithms for sequential multi-valve molds are generated. Derivative of the cavity pressure sensor profile is also used to analyze the responses of the cavity pressure against valve opening, packing, and holding. Most essential time series features are extracted from Python's Time Series Feature Extraction on Basis of Scalable Hypothesis library (TSFRESH). Valve timings and critical parameters from the cavity temperature sensor are added to extracted features. The resultant feature set is independent of the changes in plastic injection parameters, and learning algorithms are implemented. The method is constructed and validated in the production environment, and the valve timing feedback substructure is successfully implemented. The novelty presented in this chapter is the use of cavity sensors with valve timings and constructing a quality failure detection method for sequential multi-valve molds.

This chapter starts with introduction and continue with explanation of system and methods. Results of iterative study for constructing a failure detection technique will be examined in the fourth section. Evaluation of the results and further research opportunities will be covered in the discussion and conclusion sections.

5.2 Introduction

The plastic injection (PI) process has the nonlinear and time-varying complex dynamic characteristics of the batch processes, and the continuity of the process depends on the long-term experienced and skilled operators (Dubay et al., 1997). The increase in the design complexity requirements, the usage of new materials for reducing the environmental effects, and energy consumption minimization requirements increase the control studies about PI (Rao et al., 2017 and Zhao et al., 2020). Generally, the heuristic approaches are used to determine the optimal process parameters such as filling time, injection pressure, injection temperature, packing pressure, and packing time (Pervez et al., 2016). However, the process's complex dynamic depends on three branches and variations in them: the material, the machine, and the mold. Even after determining the process parameters with the heuristic approach, the parameters only work for the designated process conditions, which means variabilities in the process, such as changes in material characteristics and environment, and fluctuations in the machine parameters can halt the production. Therefore, implementation of process control strategies and increasing the control over the process is inevitable and required to ensure the sustainability of the process and quality.

Quality and production control are the main aim of production centers, especially for net-shape mass productions such as molding and extrusion. Quality control is performed offline in net shape productions when the part is produced. Even though sensing technologies are developed, cycle-based control over processes is still challenging (Kozjek et al., 2017). The PI cycle consists of four stages: clamping, injection, cooling, and ejection (Figure 5.1). However, clamping and ejection are related to mold closing at the start and opening at the end. Therefore, process control studies aim to track and analyze the injection and cooling phases. The injection phase is the shortest stage of the process and consists of two main parts: filling and packing. In the filling, the molten plastic fills the mold cavity until the cavity is volumetrically filled (95-99%) with velocity-controlled screw movement. To compensate the shrinkage and distribute density uniformly, screw movement control is switched over to pressure, and the molten plastic continues to fill the cavity in the packing phase. When screw movement is done, injection phase is terminated. First part of the cooling phase is named as holding and screw pressure is applied to the mold cavity in this phase. The holding phase lasts until the gates solidify. The cooling phase starts with holding and lasts until the molten plastic solidifies totally. Injection and cooling phases occur inside the closed mold, and results are not trackable until the mold is opened. To track the cycle and control the consistency of the production, various inline data acquisition and control strategies are proposed by the researchers, which can be investigated in two categories.

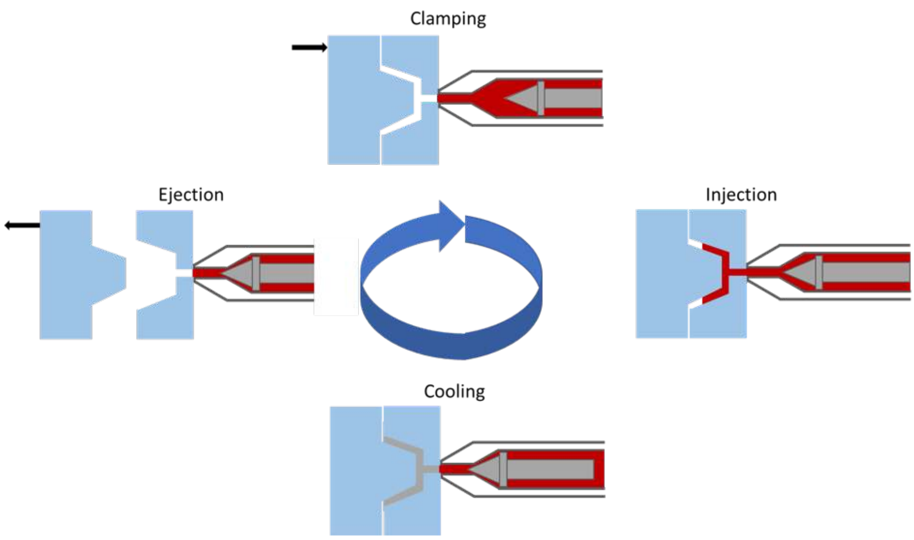

Figure 5.1: Stages of plastic injection cycle.

In the first category, critical process parameters are collected from the machine, and labeled production data is used to construct rule or learning-based control mechanisms. Kumar et al. (2020) formed a control boundary for the process with labeled data. Flow rate, packing pressure, packing time, melt temperature, and coolant temperature are used to give feedback, and feedback decisions are decided with thresholds and rules. In another research in the literature, Nasiri and Khosravani (2019) collected the machine parameters and constructed a fuzzy case base reasoning fault detection system. Thus, the team predicted the failures and recommended adjustments for the parameters. Categorization of the parameters and weight adjustments increased the system's accuracy and reached 80% with the developed model. Their works propose new methods which can be applied to industry and increase the control over PI process. However, the changes in the material characteristics, machine parameters, and environment are affecting the behavior of the molten plastic inside the mold. Therefore, the machine parameter-based approach suffers from gathering information from the changes inside the mold.

For the second category, sensors are placed inside the mold, and data from the mold is used chiefly with machine parameters. Cavity pressure (CP) and cavity temperature (CT) sensors are the most common sensors; however, strain gauges (Guan and Huang, 2013) and ultrasonic sensors (Michaeli and Starke, 2005) are also used for gathering information from the mold and the molten plastic. In their research, Chen et al. (2019) coupled machine parameters with cavity sensors and strain sensors. The study investigated the relationship between sensor profiles and critical process parameters and showed that clamping force is a good indicator of the final product quality. As a continuation of the study, Chen et al. (2021) implemented simple strain gauges on tie-bars to observe peak clamping force without using cavity sensors. A rule-based control system gave feedback on switch-over timing and holding pressure to prevent failures. Study proves that giving feedback to the process is achievable by just using the sensors from the mold.

This study proposes a straightforward process failure detection method based on CP and CT sensors. This research is the first study in the literature to predict failures in a PI process with sequentially opened multi-valves molds with CS, according to the authors' best knowledge. Timings of the valves are collected via a programmable logic controller (PLC), while sensor outputs are collected with custom developed data acquisition device (ADCR). Collected sensor profiles and timing information are matched and transferred to the electrical panel, which can store, analyze, and configure the upcoming data. Labeled data is used to construct a learning-based failure detection algorithm and valve time feedback.

The paper focuses on analyzing the CP sensor and derivative profiles with the sliding data windowing technique. Additionally, the labeled time series CP profile is analyzed with Python's Time Series Feature Extraction on Basis of Scalable Hypothesis library (TSFRESH), and the most critical parameters are evaluated and selected for the learning algorithm. The mold has six valves, and timing information for all is added to the extracted features; however, the study uses the CP sensor close to the first opening valve. To evaluate the quality of the product, features are extracted from windowed CP sensor profile, windowed pressure derivative profile, CT sensor, valve opening times, and TSFRESH. Thus, a learning algorithm is created, and a new method is proposed.

5.3 System and Methods

5.3.1 Moldflow Analysis and Sensor Positioning

Moldflow simulation software (Autodesk Inc.) is useful for analyzing the plastic injection process and reducing manufacturing failures. Filling results, potential short shot locations, weld line locations, and cooling phase can be investigated by using Moldflow. In this study, Moldflow analysis is used to determine appropriate CS locations. Arranged process conditions for Moldflow simulation are shown in Table 5.1.

Internal pressure (Figure 5.2) is analyzed and found that internal pressure is dropping to 13.49 MPa in a weld line location. CT sensor is positioned in this region to control the welding position. Welding locations with low internal pressure can cause short shot quality failures. CT sensors can be beneficial because temperature sensors react to molten material contact, and weld line position can be tracked with temperature sensor profile changes.

Table 5.1: Process parameters for Moldflow simulation.

Injection Pressure	165 bar
Initial Injection Velocity	75 mm/s
Packing Pressure	70 bar
Holding Time	2.00 s
Mold Temperature	40 °C
Melt Temperature	190 °C
Maximum Shear Stress	0.25 MPa
Maximum Shear Rate	100000 1/s
First Valve Opening Time	0 s
Second Valve Opening Time	2.2 s
Third Valve Opening Time	3.0 s
Fourth Valve Opening Time	3.5 s
Fifth Valve Opening Time	4.0 s
Sixth Valve Opening Time	4.1 s

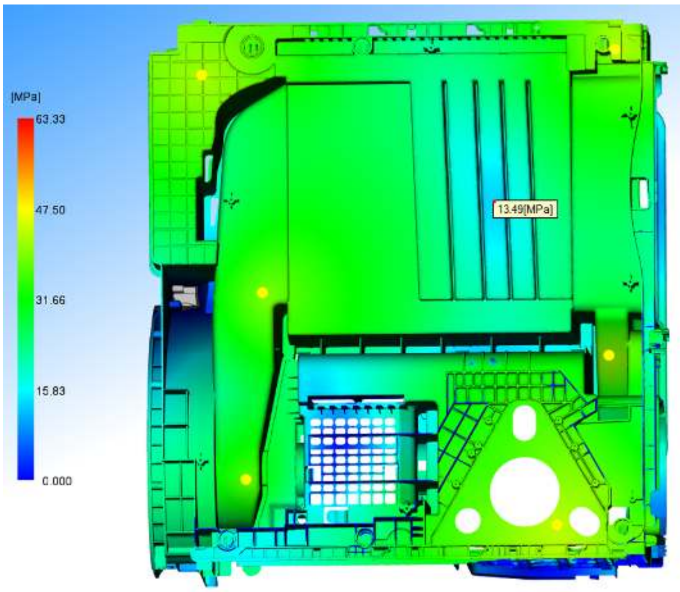

Figure 5.2: Internal pressure results.

Near valve locations are chosen for the CP sensor positioning; however, cooling channels and inserts reduce the potential sensor placement locations. Four points are selected according to the availability of the mold. CP profiles are plotted for the first valve (Figure 5.3a), third valve (Figure 5.3b), fifth valve(Figure 5.3c), and sixth valve (Figure 5.3d) in Moldflow to understand potential behavior in the mold. CP sensors are implemented in these locations to increase the detail of upcoming data. According to the plots, maximum pressure is between 35 MPa to 40 MPa except for the first opening valve. The pressure reaches 55 MPa for the first opening valve because injection pressure is applied to the position more than the other valves.

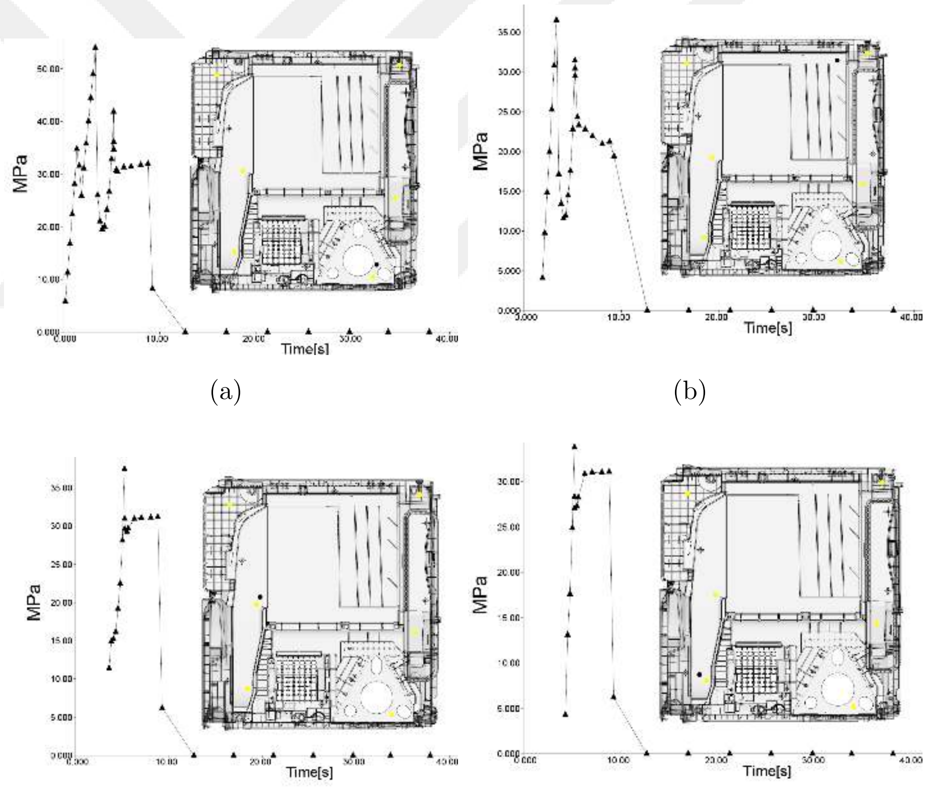

Figure 5.3: Moldflow simulation results of cavity pressure profiles for (a) first opening valve, (b) third opening valve,, (c) fifth opening valve,, and (d) sixth opening valve,.

5.3.2 Process and System Setup

Injection process is a nonlinear cyclic process, and complex parameter relations make it difficult to create a generic solution (Obregon et al., 2021). In their study, 30 critical process parameters are collected, and relations between parameters and product quality are observed. Seven different classification algorithms are used to classify results, and classification is succeeded with 99% accuracy. Another important finding of this study is that cavity sensors are sensitive to parameter changes and product quality.

Usage of cavity sensor is depended on the problem that needs to be solved. CP and CT sensors are used sequentially to evaluate viscosity (Gao et al., 2014). In this study, researchers followed the molten material's viscosity and compared it with the product quality. A different approach is putting pressure sensors in the most potentially problematic position (Lawrence et al., 2004). With this strategy, filling status and quality are controlled for this specific position (Guerrier et al. 2017 and Gim et al., 2015). Another common approach is using the CP sensor profiles, which are placed close to the valve (Hassan, 2012). In this method, sensor profile changes are followed, and action is taken if the readings exceed prescribed limits. Additionally, the method is used in this paper, and 4 CP sensors are located close to the valves in order to increase the detail of the upcoming profile. According to Tsai and Lan (2015), CP sensor close to the valve can measure the switchover, filling, and holding times while measuring the pressure more precisely. The CP profile also reacts to changes in machine parameters.

Table 5.2: Material parameters of PPHO. E: elastic modulus; v: poisson's ratio; ρ_{melt}: melt density; ρ_{solid}: solid density; MVI: Moldflow viscosity index.

$\boldsymbol{E}$ **(GPa)**	$\boldsymbol{v}$	$\boldsymbol{\rho_{melt}\ (g/cm^3)}$	$\boldsymbol{\rho_{solid}\ (g/cm^3)}$	$\boldsymbol{MVI}$
6.105	0.406	1.124	1.2788	VI(179)0140

The bottom chassis part of the tumble dryer is selected for this study. The part is 3.3 kilograms and has 4 CP (Priamus Co, 6002B) sensors with 1 CT (Priamus Co, 4008C) sensor (Figure 5.4a). 43% Calcite (CaCo3) reinforced propylene homopoly-

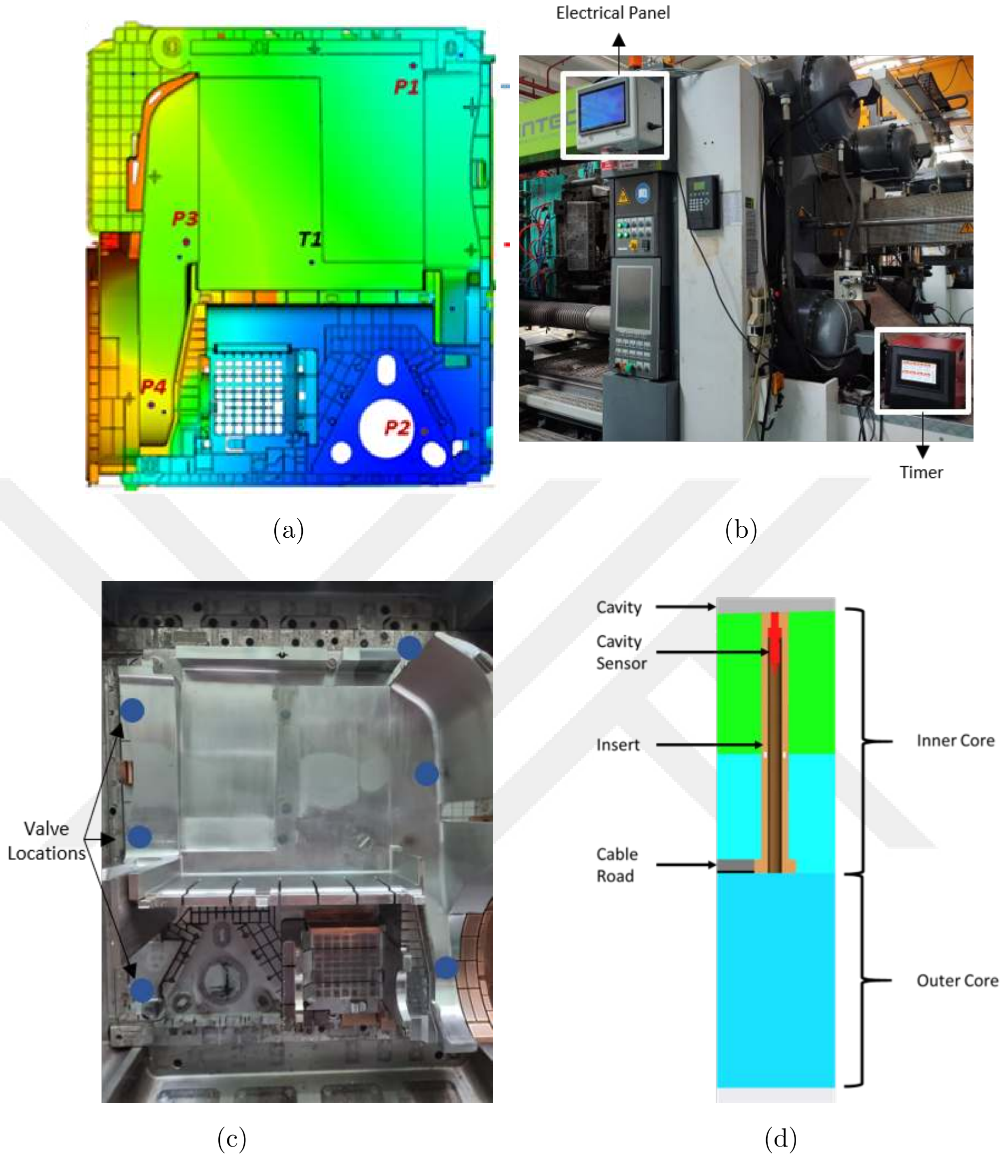

Figure 5.4: (a) Bottom chassis part of dryer with CS locations, (b) 1500-ton Wintec IMM, (c) mold of the bottom chassis part with valve locations, and (d) design details and implementation of the insert.

mer (PPHO, Vatan Plastic Co.) is used for the production, and Table 5.2 shows the key material properties of the material which is taken from Moldflow Material Database. PPHO has a higher strength-to-weight ratio, chemical resistance, and impact resistance than propylene copolymers and is suitable to use in chassis parts. As presented in Figure 5.4b, the machine used for the production is a 1500-ton Wintec IMM. Sensors are placed on the stationary side of the mold. The mold has

6 valves which illustrated in the Figure 5.4c. Insert design and sensor placement detail is shown in Figure 5.4d. Inserts are used to protect the sensor and facilitate the implementation.

CP sensors use quartz with piezoelectric behavior, which deforms after mechanical load and generates an electrical charge. On the other hand, CT sensors are K-type or N-type capsulated thermocouples. Generated signals are transferred via cables (Figure 5.4d) and reach the ADCR on the mold (Figure 5.5a). The ADCR is designed to collect upcoming data from the sensor with up to 5 kHz sampling rate and is able to collect from four CP and four CT sensors. However, 4 CP and 1 CT sensors are used in this study with 250 Hz. Collected and amplified signals are transferred to electrical panel for analysis, storage, and visualization. The electrical panel (Figure 5.5b) consists of an edge PC, a router, and a Siemens S7-1200 PLC. PLC is equipped to gather the opening time of valves from the timer. The timer is a PLC-based signal generation unit that controls opening and operation time of several channels with voltage differences. The timer's output is connected to the electrical panel (Figure 5.5c). PLC can collect the timer data and manipulate the time settings according to the analysis result. The output of the ADCR and PLC is synchronized in the edge PC. The flow chart of the process is visualized in Figure 5.5c.

Synchronized CS profiles and valve times are used to track production and detect failures. Valve times can be configurable at this point; however, valve feedback is not covered in this study, and research is limited to failure detection in production. Due to the complex nature of the PI process and IMM, critical process parameters change in a range. When there is a failure, skilled operators change critical process parameters in this observed range. Critical process parameters are provided in Table 5.3. PI parameters are recorded during the production, and products are labeled. As observed in Table 5.3, operators change parameters according to their experience. Packing pressure and the first valve's opening time are the only constant variables during the tracked productions. Therefore, the CP sensor close to the first valve is this study's most trusted source of information.

In a PI cycle, CP starts to increase after the filling is started and continues to

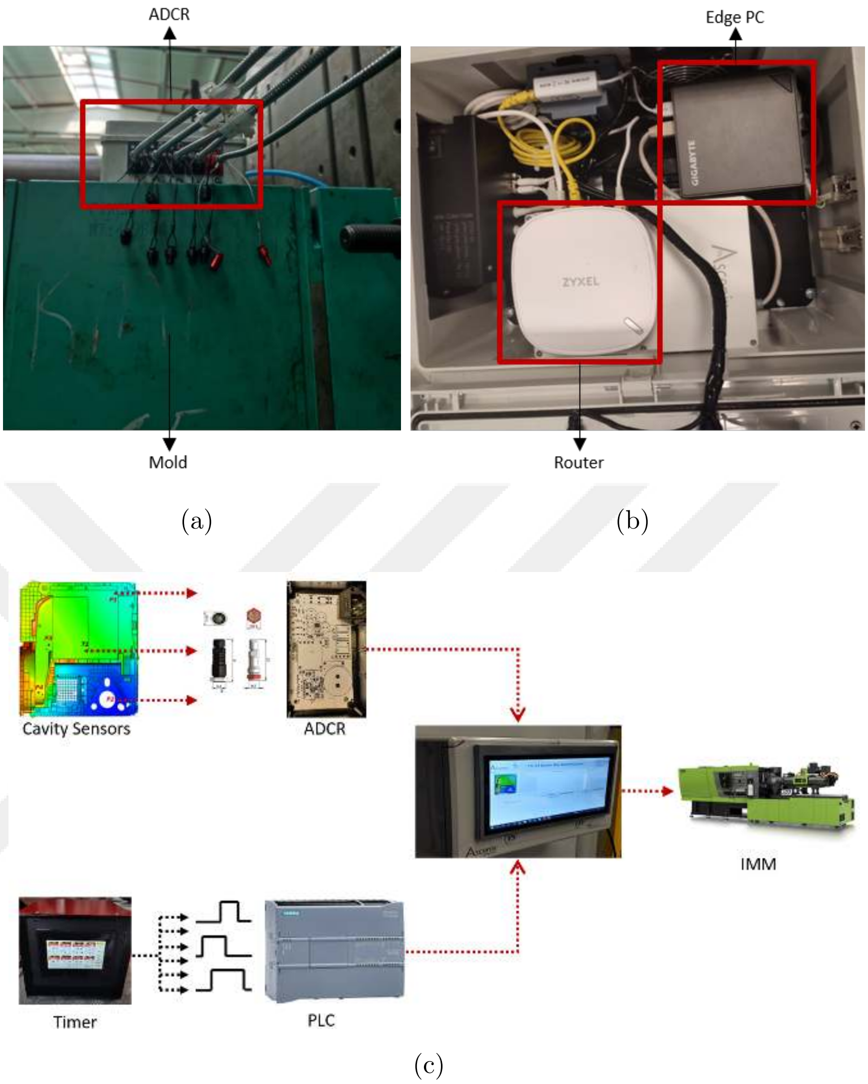

Figure 5.5: (a) Data acquisition device (ADCR) on the mold, (b) constructed electric panel, and (c) flow chart of the study.

increase until packing is completed. CP starts to decrease in the holding phase and becomes zero in the first seconds of the cooling (Figure 5.6a). Since tracking and visualizing the entire cycle is unnecessary, the first 20 seconds of the cycle are tracked for this study. Shortened CP profiles (Figure 5.6b) demonstrate more details, especially for on-site observations; however, tracking the changes is still challenging because of the predominant effect of the filling. Derivative of the shortened CP profile (Figure 5.6c) is used for exaggerating the changes and observing the effects more accurately.

Table 5.3: Range of critical process parameters.

Injection Pressure	155 – 175 bar
Initial Injection Velocity	65 – 80 mm/s
Injection Time	5.62 – 6.01 s
Packing Pressure	62 – 70 bar
Packing Amount	26 – 34 mm
Holding Time	2.00 – 2.50 s
Mold Temperature	35 – 45 °C
Melt Temperature	180 – 210 °C
Cycle Time	65.00 – 71.00 s
First Valve Opening Time	0 s
Second Valve Opening Time	2.2 – 2.6 s
Third Valve Opening Time	2.9 – 3.1 s
Fourth Valve Opening Time	3.0 – 3.6 s
Fifth Valve Opening Time	3.5 – 4.2 s
Sixth Valve Opening Time	4.0 – 4.6 s

Valves are electro-mechanical systems that open after the signal comes from the timer; however, the opening of a valve is not instant due to the pressure of the molten plastic and mechanical operation time. When the second valve is opened, cavity pressure is decreased in the first valve because the molten plastic finds an easier way to flow inside the cavity. This effect is observed better in the derivative profile because cavity pressure increase is the predominant trend until packing is completed, and the effect of another valve's opening is limited, especially for the CP profile. Additionally, the end of packing and holding are detectable in the derivative plot (Figure 5.6c). Dotted black lines are the timings of the valve openings, and five pressure drops are observed between the second valve's opening and the end of packing. These pressure drops are the effects of valve openings on the CP. On the other hand, the CT sensor profile (Figure 5.6d) gives the exact time of contact with the molten plastic and the temperature profile inside the cavity.

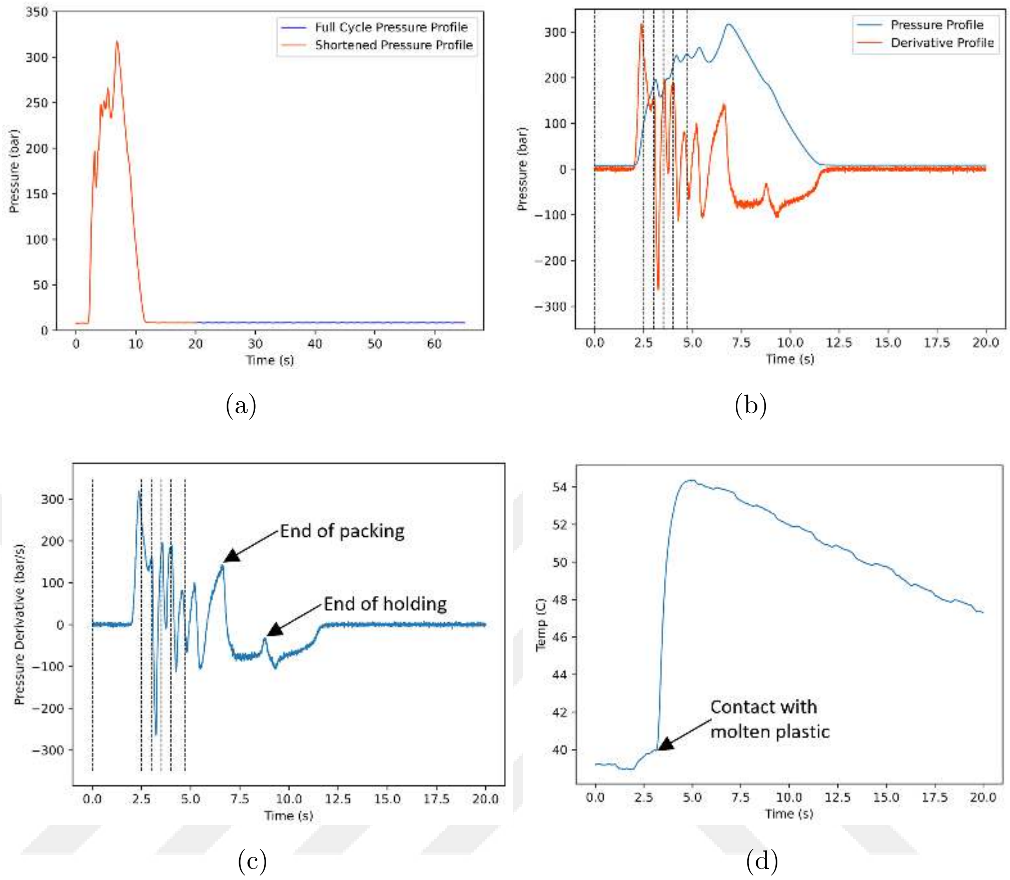

Figure 5.6: (a) Shortened and full cycle pressure profiles, (b) shortened pressure and derivative profiles with valve openings, (c) derivative profile with valve openings, and (d) shortened temperature profile.

5.3.3 Classification and Feature Extraction on CS Profiles

Failure detection in the sequential valve PI process is not a topic that has been studied extensively in the literature. Therefore, the authors carried out an iterative study to construct a method. Failure detection success rate, sustainability, and feedback substructure are considered while evaluating the success of a method. The desired feedback mechanism depends on finding the valve that is able to rectify the fault because the constructed system can modify the timing of the valves. On the other hand, sustainability depends on working in changing production environment. To ensure sustainability, algorithms must be able to collect the same features in different system parameter settings, which listed in Table 5.3.

The success of the failure detection depends on detecting the small changes in the profiles and using the 5000 (20 seconds with 250 Hz sampling rate) data points of shortened data is not giving promising results. Therefore, the profiles are considered time series data, and feature extraction methods are used. TSFRESH is a Python library used in signal processing and computing 794 features (Christ et al., 2018). However, the feedback substructure is not obtainable with the features extracted from TSFREH because features are not related to the PI, and interpretation is not possible.

As observed in Figure 5.6b and Figure 5.6c, the CP profile and its derivative have local extremum points around valve openings, end of packing, and end of holding. Also, pressure increasing point, amount and time of the maximum pressure are the characteristic parameters of the cycle that can be tracked. However, as listed in Table 5.3, parameters being changed in the production environment and local extremum points are not detectable for every cycle. The direct feature extraction method has neither a high failure detection success rate nor sustainability. To extract critical process features, the data windowing technique is used. Valve opening times and maximum pressure time are used to define windows. Separately extracted features from the windowed data have promising failure detection rate; however, due to the same reason as the direct feature extraction method, sustainability is not possible even by adding the derivative profile.

Windowing the data with valve opening times is not sustainable, but the windowing method is appropriate for feedback substructure and has high failure detection rate. The windowing technique should not be affected by process parameter changes to achieve sustainability in the method. Therefore, evenly windowed data is used, and data is divided into half-second segments. Thus, desired process parameters are collected independent of the process parameter changes, and all three conditions are achieved. Lastly, the most distinguished features from TSFREH are investigated with the analysis of variance (ANOVA) f-test method and 19 parameters, which have 0.5 or higher scores, are selected. 19 TSFREH parameters, valve opening times, and CT parameters (temperature increase time, maximum temperature time, maximum temperature, and temperature at the end) are added to extracted features from the

CP profile.

5.4 Results

5.4.1 Cyclic Approach

PI is a cyclic process and the output of CS are evaluated as time series data at the start of method generation. The data set that consists of 1850 labeled cycles is used in this study, and data is collected from the production center without interference. Support vector classifier (SVC), K-nearest neighbors (KNN), and logistic regression (LR) are used for binary classification. To define the success of the classification methods, confusion matrices (CM) are used. In CM, true positives (TP) represent correctly classified failed products, and true negatives (TN) represent correctly classified successful products. False negatives (FN) are the misclassified failed products, while false positives (FP) represent misclassified successful products. Accuracy (Acc), precision (Pr), and sensitivity (Sn) performance metrics are used for comparison between methods. Acc is the ratio of correctly classified products (TP and TN) to the total number of products. On the other hand, Pr shows the ratio of correctly classified failed products (TP) to the total products predicted as failures (TP and FP). Lastly, Sn evaluates the ratio of correctly classified failed products (TP) to the total number of failed products (TP and FN). Sn result is the main aim of this study because misclassified failed products cause problems in the production lines and prevent the automation level enhancement effort. On the other hand, Pr is problematic for the IMM because misclassified successful products will cause unnecessary feedback to the system.

The CP sensor profile is used in the first trial; the results are shown in Table 5.4. While Acc is 94.59% due to the high number of TN, Pr and Sn are less than 65%. The direct time series method is sustainable; however, the method does not have a high failure detection rate and is not appropriate for the desired feedback mechanism.

Secondly, TSFRESH is used to extract features from the CP profile, and the resultant data set is cleaned by removing columns with null and identical values.

Table 5.4: Results of direct time series method.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	332	18	9	11	94.59%	66.67%	62.07%
KNN	334	17	7	12	94.86%	70.83%	58.62%
LR	335	18	6	11	95.41%	75.00%	62.07%

The resultant feature set is used, and the results are represented in Table 5.5. TSFRESH method is not successful for failure detection, but the statistical approach is beneficial for failure detection.

Table 5.5: Results of TSFRESH method.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	327	19	14	10	93.51%	57.58%	65.52%
KNN	330	13	11	16	92.70%	54.17%	44.83%
LR	331	17	10	12	94.05%	62.96%	58.62%

ANOVA f-test is used to evaluate TSFRESH parameters, and parameters that have 0.5 or more scores are selected for another trial. Eventually, the results are improved except for the SVC's Sn (Table 5.6), and the resultant parameter set is saved for future methods.

Table 5.6: Results of TSFRESH selected parameters.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	331	17	10	12	94.05%	62.96%	58.62%
KNN	331	13	10	16	92.97%	56.52%	44.83%
LR	334	18	7	11	95.14%	72.00%	62.07%

The direct time series method has promising results; however, generating the feedback substructure is challenging due to the required data for multi-class classification. Therefore, the feature extraction method is used. Firstly, descriptive statistics are extracted from the CP profile, and the results are analyzed in Table 5.7.

Table 5.7: Results of CP feature extraction.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	314	28	27	1	92.43%	50.91%	96.55%
KNN	332	14	9	15	93.51%	60.87%	48.28%
LR	340	0	1	29	91.89%	0.00%	0.00%

CP feature extraction method has perfect results for Sn, but ACC and Pr results are not promising. To increase the overall results, the derivative profile is also used to extract descriptive statistical features and added to CP profile features (Table 5.8). Thus, overall results are improved for SVC and KNN.

Table 5.8: Results of feature extraction for CP profile and profile's derivative.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	319	26	22	3	93.24%	54.17%	89.66%
KNN	331	18	10	11	94.32%	64.29%	62.07%
LR	340	0	1	29	91.89%	0.00%	0.00%

5.4.2 Data Windowing Approach

Time series approaches suffer in catching local extremum points because the number of local extremum points and their detectability are changing due to the process parameter variations. The data windowing approach is implemented to the CS output to increase the detail of collected parameters. At first, valve opening times and end of packing time are used to window the data, but valve times are changed during the production (Table 5.3), and the regional approach fails when a region disappears. Variability in the number of regions violates the desired method's sustainability requirement. Therefore, evenly windowing technique (0.5 s) is used to ensure sustainability, and features are extracted from every data window. Thus, the resultant feature set will be steady. The results of the evenly windowing approach are shown in Table 5.9.

Table 5.9: Results of evenly windowing approach.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	334	23	7	6	96.49%	76.67%	79.31%
KNN	333	16	8	13	94.32%	66.67%	55.17%
LR	335	16	6	13	94.86%	72.73%	55.17%

To increase the Sn ratio, selected TSFRESH parameters and CT features are added to the model. The results of the final model are represented in Table 5.10, and SVC gives the best results for Acc and Sn.

Table 5.10: Results of final model.

	TN	TP	FP	FN	ACC	Pr	Sn
SVC	332	24	9	5	96.22%	72.73%	82.76%
KNN	333	16	8	13	94.32%	66.67%	55.17%
LR	335	19	6	10	95.68%	76.00%	65.52%

5.5 Discussion

Failure detection in the PI process is vital to increasing the level of automation and reducing the dependency on operators. Changes in material characteristics, fluctuations in machine settings, and environmental effects cause failures, and CS profiles are the essential tools for tracking the results of factors. Alternatively, experimental studies (Park et al., 2013 and Moayyedian et al.,2018) and machine parameter tracking studies (Zhou et al., 2017 and Zhang et al., 2015) have been proposed and given promising results for process control and failure detection. However, most studies are conducted for test specimens with single-valve molds. On the other hand, an industrial mold with six sequentially opened valves is studied in this study. The study is conducted in a production facility due to the high cost of constructing a similar setup in a laboratory. CS are used to observe the impacts of factors inside the mold, and CS profiles are examined in detail. The constructed method uses basic classification algorithms such as KNN, SVM, and LR but focuses on extracting features from CS in detail.

Another advantage of the proposed method is the independency of the machine because the only input taken from the machine is the injection start signal which is identical for all machines. The proposed method also prepares the substructure of valve time feedback which reduce the dependency on operators. Hopmann et al. (2017) have a similar approach and proposed a control method for CP profile which controls actuators. However, control over CP profile is not studied because the success of such complex control systems can be challenging in production environment. The aim of this study is to detect the failure at the current stage and rectify the failure at the next stage.

The proposed method uses the derivative of the CP profile, TSFRESH features, and valve timings. Derivative of the CP profile contains information about the packing phase, holding phase, and valve openings. The data windowing technique is used to standardize the extracted feature and eliminate the changes in process parameters. TSFRESH features are used to increase the Sn ratios. The final method aims to maximize the Sn ratio with optimum Acc and Pr ratios at this stage because misclassifications of failed products can cause stoppages in the production line. Consequently, process conditions are changing due to PI's production environment, and the proposed method can adapt to the changes. Future work will use this method and develop a valve timing feedback mechanism to reduce the scrap rate. A classification method will be implemented in the system to find the start of failure and according to the resultant window, the appropriate valve will be arranged. To increase the success of the feedback structure, the Pr ratio will be the focus on further studies.

5.6 Conclusion

In this chapter, the multi-valve molds with sequential opening are analyzed via cavity sensors for failure detection and constructing the feedback substructure. The critical novelty of this study is the data windowing technique and usage of the cavity pressure profile's derivative. The constructed method is also unique for detecting failures in sequential valve operations. Cavity pressure sensor is the primary source of information, and selected TSFRESH parameters are also used in this study to increase the accuracy and sensitivity ratios. Additionally, the method collects valve opening times and evaluates the opening effects of valves on the cavity pressure profile. Data collection and labeling are conducted in an industrial environment, and the method satisfies the failure detection rate, sustainability, and feedback substructure criteria. Extracted sets of features are evaluated with learning algorithms such as k-nearest neighbor, support vector classifies, and logistic regression. As a result, the final method has 96.22% accuracy ratio and 82.76% sensitivity ratio in a dynamic industrial environment. Implementation of such a method aims to increase the automation level of the plastic injection process and reduce the scrap rates. The constructed system is independent of the machine and suitable for feedback.

Chapter 6

SUMMARY AND CONCLUSIONS

6.1 Summary

The plastic injection process has the nonlinear and time-varying complex dynamic characteristics of the batch processes, and the continuity of the process depends on the long-term experienced and skilled operators. The increase in the design complexity requirements, the usage of new materials for reducing the environmental effects, and energy consumption minimization requirements increase the control studies about the plastic injection. Failures in the plastic injection cycles can be caused by machine parameter variations, changes in material characteristics, or environmental conditions. However, due to the complex nature of the process, analyzing and tracking the factors may not result in a generic solution. The characteristic of molten plastic can show the cumulative effect of the parameters because it is affected by the machine parameters and material characteristics. Therefore, the behavior of the molten plastic inside the mold shows the process variation's overall effect on the filling. Thus, tracking and comparing the molten material characteristic may increase the overall efficiency of the process. However, molten material tracking requires destructive sensor implementation inside the mold, and constructing a mature data acquisition system is challenging, especially for industrial molds in production sites.

Industrial cavity sensors are used in this study with a developed placement technique with inserts. Developed data acquisition device placed at the top of the mold, and sensor data is transferred to electrical panel for storage, analysis, and visualization. Production tracking is not accurate without an injection start or end signal. Sequential and simultaneous multi-valve molds are also covered in this study. Valve timings are collected for injection start time and increase the knowledge about the cycle. Machine parameters are not tracked in this study due to the limitations of the machine producers, and valve timings are the possible way of giving feedback to the system.

This thesis contains a systematic approach for developing a failure detection method for simultaneous and sequential multi-valve plastic injection moldings. In Chapter 1, plastic injection is introduced and explained in detail. The literature review is summarized in Chapter 2. Different approaches are investigated in chapter 2. Failure detection in plastic injection is a topic that researchers from different points of view investigate. Researchers examined the relations between cavity sensor outputs and machine parameters. Thus, linear and complex relations are found; however, mold changes and environmental conditions are mostly neglected. On the other hand, cavity sensors and machine parameters are used to construct failure detection and feedback mechanisms. Rule-based parameter tracking, material characterization formulations, and complex learning algorithms are implemented in the systems. Insights gained from Chapter 1 and Chapter 2 showed that multi-valve sequential and simultaneous molds are not covered in the literature.

The designed methodology is explained in Chapter 3. The constructed system consists of industrial cavity sensors, an insert for placement, a data acquisition box, and an electrical panel. The aim of the system is to acquire synchronized data from valve timings and cavity sensors. Different failure detection methods, parameter tracking techniques, and feedback substructures are evaluated with the system.

Simultaneous multi-valve molding is used for large and symmetric parts. Several valves are opened at the same time and fill the cavity. Cavity pressure and cavity temperature sensors are used sequentially, and the viscosity calculation formula from the literature is used to track product quality. The characteristic of the molten material inside the mold depends on the viscosity; if viscosity exceeds a prescribed limit, quality failures can happen. Simultaneous multi-valve molding quality tracking study is explained in Chapter 4. Promising results are achieved with viscosity tracking, but the main output of Chapter 4 is quality failure detection can be achieved with using cavity sensor outputs.

Sequential multi-valve molding is used for large and asymmetric parts. Several valves are opened at different times and fill the cavity. The timing of the valves are arranged according to the simulation results and the operator's experience. Based on the observations, valve timings are used to rectify the faults, especially for short shots and warpages, because timing changes do not affect the cycle time and can increase the filling quality of the desired region. Therefore, a programmable logic controller is added to the system to control valve timings. A novel failure detection technique with cavity sensor outputs and valve timings is developed in Chapter 5. This chapter is also sent to journals for publication.

6.2 Conclusions

The study presented in this thesis proposed a novel quality failure detection method for sequential multi-valve plastic injection molding. The method is used cavity sensor outputs and valve timings. Three main criteria are questioned in the proposed method: high quality failure detection rate, sustainability in the production, and feedback substructure. Different trials are conducted, and an iterative approach is used to construct the method. Confusion matrices and hypothesis evaluation metrics such as accuracy, precision, and sensitivity are used to measure the proposed method's success. Trials are started with time series approaches and feature extractions, but the criteria are not satisfied. Therefore, the data windowing approach is used, and cavity pressure profiles are analyzed as segments. TSFRESH, feature extraction library of Python, is also used, and statistically important features are added. Thus, the proposed method satisfies all the criteria.

A novel method is proposed to detect the quality failure in sequential multi-valve plastic injection molding with high quality failure detection rate, sustainability in production, and feedback substructure. Implementation of data windowing technique is increased the sustainability of the method because techniques is segmenting the cavity pressure data independent of the valve timings and machine parameters. Effects of non-initial valve openings are investigated in detail with data windowing technique. Feature extraction from the cavity pressure derivative profile, temperature sensor outputs, important TSFRESH parameters, and valve timings increase the failure detection rate. Feedback substructure depends on the valve timing control and high failure detection rate enables to give feedback to the system. Different classification algorithms will be implemented to segmented data of failed cycles for evaluating the feedback amount and related valve region.

6.3 Future Work

In this study, a sustainable failure detection algorithm and appropriate feedback substructure are developed using cavity sensors. Feedback structure will be studied in future works. Due to the limitations of machine producers, machine parameter feedback is excluded from the feedback studies. According to the author, there are two options for giving feedback on the plastic injection process: valve timing control and mold temperature control because these two settings can be controlled independently from the machine, and separate units are used to control these parameters.

The timer is explained in this study and considered for future feedback studies. The data windowing approach will be used to detect feedback needed valve region, and the timing of the valve will be changed according to the result. However, if feedback needed valve region is the first opening valve, valve timing feedback will not be an option. Therefore, mold temperature control is also required to develop a feedback substructure working in any situation. Future work will be focused on finding the feedback needed region and giving the required feedback.

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