DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

PLASTIC INJECTION PARAMETER OPTIMIZATION STRATEGIES FOR MOLD SET-UP REDUCTIONS VIA SOFT COMPUTING TECHNIQUES IN A MULTI PRODUCT SYSTEM

by
Mahmut Kemal KARASU

February, 2018
İZMİR

PLASTIC INJECTION PARAMETER OPTIMIZATION STRATEGIES FOR MOLD SET-UP REDUCTIONS VIA SOFT COMPUTING TECHNIQUES IN A MULTI PRODUCT SYSTEM

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Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"PLASTIC INJECTION PARAMETER OPTIMIZATION STRATEGIES FOR MOLD SET-UP REDUCTIONS VIA SOFT COMPUTING TECHNIQUES IN A MULTI PRODUCT SYSTEM"** completed by **MAHMUT KEMAL KARASU** under the supervision of **PROF. DR. LATİF SALUM** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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ABSTRACT

For changeover time reduction, the famous methodology, named single minute exchange of dies (SMED), introduced by Shigeo Shingo, has been applied in production plants for years in lean manufacturing scope. The main philosophy of this technique can be summarized as "make it simple and keep it simple". However, this simplification is not possible for all the steps of a changeover. In the last part of a changeover, which is also named as trial runs and adjustment, injection parameters are manipulated to resolve quality issues that occur during trial productions after the mold is changed. This session requires a deep knowledge and experience, hence, only dedicated personnel called setup experts can handle this session.

In this dissertation, two popular soft computing techniques, fuzzy inference system (FIS) and multilayer neural networks (MLNN), are used to capture this domain expertise. The primary objective is to distribute the domain experience to non-expert plastic injection personnel to eliminate expert scarcity and to increase flexibility. A systematic elimination of defect cases is presented to define the core scope that handles all the possible quality issues and their solutions with fewer rules.

Proposed soft computing solutions are implemented in a well-known international wiring device manufacturing plant together with a project team of setup experts and production staff. The results show that both FIS and MLNN could generate correct defect resolution actions on injection parameters.

Keywords: Plastic injection molding, quick changeover, parameter setting, expert system, fuzzy inference system, multilayer neural networks

ÇOKLU ÜRETİM SİSTEMİNDE KALIP HAZIRLAMA SÜRELERİNİ AZALTMAK İÇİN SOFT COMPUTING TEKNİKLERİ YARDIMIYLA PLASTİK ENJEKSİYON PARAMETRE OPTİMİZASYON STRATEJİLERİ

ÖZ

Kalıp değişim sürelerinin kısaltılmasıyla ilgili olarak Shigeo Shingo tarafından ortaya atılan ve kısaca SMED (on dakikanın altında kalıp değişimi) olarak adlandırılan meşhur yöntem, yıllardır yalın üretim kapsamında uygulana gelmektedir. Bu tekniğin temel felsefesi "basitleştir ve basit kalmasını sağla" olarak özetlenebilir. Ne var ki, kalıp değişiminin tüm adımları basitleştirilebilir değildir. "Deneme üretimi ve ayar" olarak adlandırılan kalıp değişiminin son adımında kalıp değiştirildikten sonra yapılan deneme üretimlerinde ortaya çıkan kalite problemleri, enjeksiyon parametreleri ayarlanarak giderilmeye çalışılır. Bu işlem derin bir bilgi birikimi ve tecrübe gerektirdiğinden sadece bu alanda uzmanlaşmış bir ekip tarafından yürütülür.

Bu tez çalışmasında, bulanık çıkarım sistemi ve çok katmanlı yapar sinir ağları kullanılarak bahsi geçen uzmanlık bilgisi elde edilmeye çalışılmıştır. Temel amaç, uzmanlık bilgisinin diğer enjeksiyon personeli tarafından kullanılmasını sağlayarak uzman sayısındaki kısıdı azaltmak ve üretimde esnekliği arttırmaktır. En az sayıda kuralla bir kalıp değişiminde karşılaşılabilecek tüm kalite problemlerine çözüm üretebilmek için tasarlanan sistematik vaka eleme yöntemi çalışma içinde verilmiştir.

Önerilen esnek hesaplama sistemleri, uluslararası bir elektrik cihazları üreticisinin üretim tesisinde, enjeksiyon uzmanları ve üretim personelinden oluşan bir ekiple beraber uygulanmıştır. Çalışma sonuçları, hem bulanık çıkarım sistemi hem de çok katmanlı yapay sinir ağlarının, enjeksiyon hatalarını gideren çözümler üretebildiğini göstermiştir.

Anahtar kelimeler: Plastik enjeksiyonla kalıplama, hızlı kalıp değişimi, parametre ayarlama, uzman sistem, bulanık çıkarım sistemi, çok katmanlı yapay sinir ağları

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CHAPTER ONE
INTRODUCTION

1.1 Motivation

Small lot production is an important element of lean manufacturing that reduces variability in the system. Lot size directly affects inventory levels, scheduling activities, lead time to customer and quality of the product. The biggest challenge in lot size reduction is the cost of setup. In order to decrease the setup cost, setup times must be reduced.

SMED is the most popular technique in changeover time reduction which mostly uses simplification and standardization logic. However, not all of the steps of changeover could be simplified by SMED. The last step, named trial runs and adjustment, is a quite complex session wherein a dozen of quality issue is resolved by injection parameters manipulation. Although Shingo emphasized the magnitude of this session, it slides over the problem by assuming “as long as preceding improvements are applied properly, adjustments will be easier”. It is true up to a point; however, eliminating the need for this session is not possible due to sensitive nature of molten plastic. Moreover, each changeover is a unique parameter setting problem that must be solved within minutes. In the application, this session is handled by a limited number of experienced personnel called setup experts. In the cases that the number of the molds waiting for changeover is more than the number of setup experts on a shift, either the machines are stopped or continue production until an expert becomes available. So, even SMED implementation is completed, changeover still remains unpleasant due to the expert scarcity.

On the other hand, knowledge is precious and should be recorded. It is not uncommon that once a setup expert decides to leave the job, production planning unit has to increase batch sizes to decrease the setup frequency which is the exact opposite of what lean philosophy says. Such a knowledge record should also be used as a training material for newcomers.

1.2 Gaps in the Literature and in Real Applications

Parameter setting is a hot issue for both practitioners and academicians; however, no study is presented from changeover perspective. Most of the studies in the existing literature focus on finding optimal injection parameters, also named as initial set, in the launching phase of a new mold to define the level of parameters that provides a defect-free product at a reasonable cost for a newly manufactured mold, or for a mold which is in the design phase yet.

Initial parameter setting is a tough task since it starts from scratch and the time to find the optimal set is less important than reaching it. But for parameter setting during a changeover, initial set is used as a starting point, and the aim is re-setting the optimal set which is shifted due to the uncontrollable factors. During a changeover, the challenge is the time limit that is not more than several minutes.

In initial parameter setting, the conditions are stable. The trials are done on the newly manufactured mold that has no wear, within the same period of the day, and the year, in the same environment (temperature and humidity), and on the same machine. Therefore, the data collected during the trials can be used in the design of experiment studies. However, once a new mold starts to be used in mass production, all of these conditions are subject to change. Parameter setting during a changeover is performed under these dynamic conditions that make each changeover a unique case.

The vast majority of the studies in the literature consider parameter setting to resolve one or two major quality issues. On the contrary, in changeover parameter setting, all possible quality issues should be considered at the same time and without leaving any unresolved issue.

1.3 Objective and Method of the Research

The primary objective of this dissertation is to capture the expertise of setup experts using soft computing techniques. The outcome is a user-friendly interface to be used by injection machine operators who will make changeover parameter setting instead of setup experts. The proposed solution is not targeting the elimination of current knowledge possessors, contrarily, aims to motivate them to lead the operators on the way to achieve a leaner production.

The secondary objective is to build quality awareness on the machine operators by drawing them in the consideration of understanding the relationship between product quality and production parameters.

Fuzzy inference system (FIS) and multi-layer neural networks (MLNN) are used to map this relationship based on the knowledge of setup experts. The performance comparison of both techniques is presented along with the pros and cons of their application.

1.4 Organization of the Dissertation

In Chapter 2, basic information about plastic injection molding from design to mass production is presented. The factors affecting the product quality are introduced and classified. The injection defects are briefly explained together with their root causes. In Chapter 3, the three parameter setting modes are introduced and a comprehensive literature review is presented to reveal the gap about handling changeover parameter setting. In the same chapter the challenges in the changeover parameter setting are explained. In Chapter 4, a quick overview of SMED is given to show its shortcomings about elimination of adjustments, and the reasoning mechanism of setup experts is explained. Fuzzy logic and fuzzy inference system (FIS) is briefly explained to build an expert system that captures the reasoning of setup experts. In Chapter 5, a real implementation of FIS for changeover parameter setting is presented with the performance statistics and with the results of real molding trials. In Chapter 6, the same case study is handled with multi-layer neural networks (MLNN) to evaluate the advantages and disadvantages over FIS and comparative results are given at the end of the chapter. Final remarks are given in Chapter 7.

CHAPTER TWO
PLASTIC INJECTION MOLDING

2.1 Molding Basics

Plastic injection molding (PIM) is one of the most favorite manufacturing techniques. One-third of total plastic consumption in the world belongs to the products produced by PIM (Rosato & Rosato, 2000). The capability of producing complex shapes, fine details with excellent surface finish and high dimensional accuracy at low costs and high production rates make this technique appealing. Moreover, in this type of production, scraps can be used by recycling. The biggest disadvantages of PIM are the high tooling and equipment cost and high know-how requirement in design and manufacturing.

PIM can be described as the repetitive process of injecting melted plastic into a mold which is held under pressure until the molten is solidified. This process has five main steps: (1) *clamping*: closing two halves of the mold securely by hydraulic clamping unit, (2) *plasticizing*: withdrawing the dried plastic granules from the hopper and melting through a heated barrel, (3) *injection*: injecting the melt using horizontal movement of the screw with a controller shot size, (4) *packing*: maintaining the melt under pressure for a specified time to prevent backflow and to compensate the volume loss during solidification, (5) *cooling and ejection*: waiting the melt inside the mold to solidify and ejecting the final product. The process cycle after clamping is depicted in Figure 2.1.

Injection molding machines (IMM) are composed of three main components: *injection unit, clamping unit,* and *mold* (Figure 2.2). *Injection unit* is responsible for both heating and injecting the plastic raw material (resin). The reciprocating screw located in the barrel gets the resin from the hopper (the open bottom storage bin) by both rotating and sliding axially. The resin is melted by pressure, friction and the heaters around the barrel while advancing through the mold. The melt is injected quickly through the nozzle at the end of the barrel and packing pressure is applied to avoid thermal shrinkage and volume losses. The reciprocating screw retracts after the material solidifies to get more resin from the hopper for the next injection cycle.

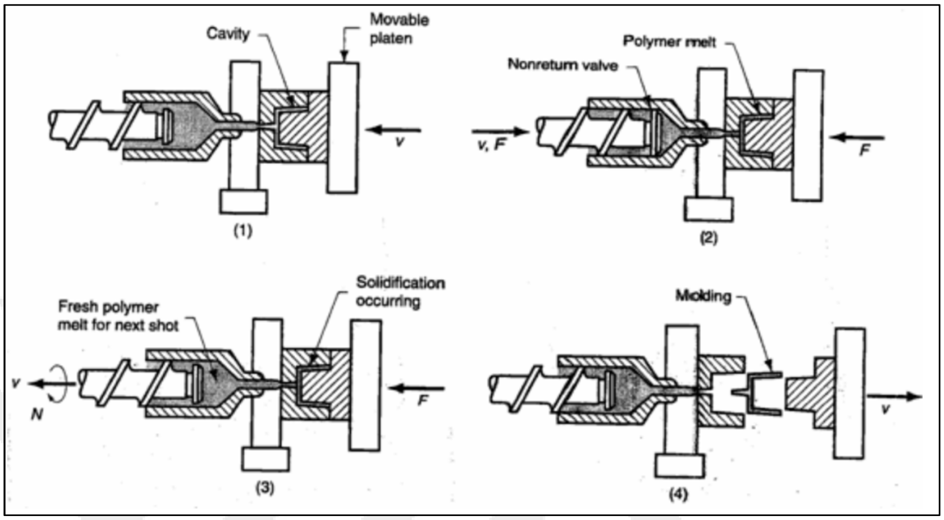


Figure 2.1 Plastic injection process cycle (Sinotech, 2017)

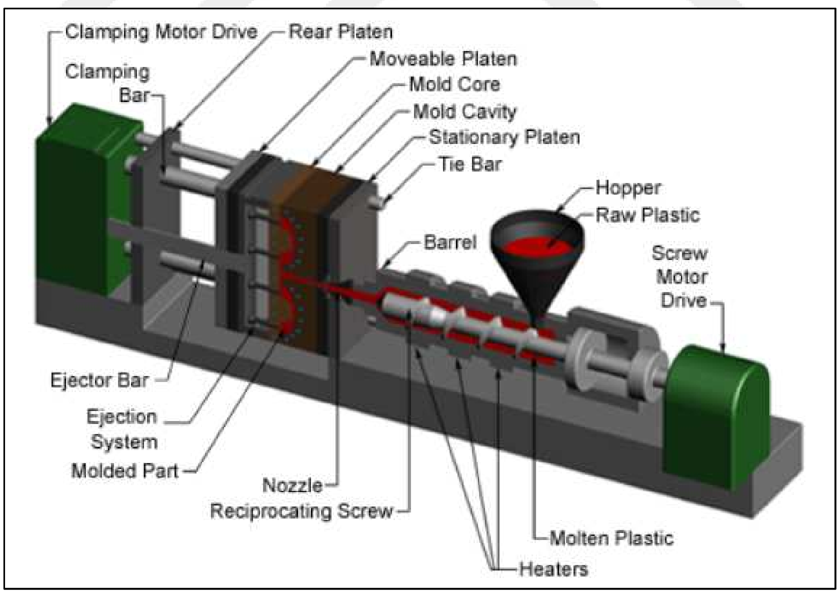


Figure 2.2 Plastic injection molding machine (Custompartnet, 2017)

Clamping unit is responsible for closing the mold halves securely and opening for ejection of the product. Each half of the mold is mounted to the plates of the clamping unit. One of these plates is fixed and the other is moveable. The mold half that has the cavities is attached to the fixed plate and is aligned with the nozzle. The other half called the mold core is attached to the moveable plate and slides through the bars. The ejectors are also located in this half. IMMs are classified based on the tonnage of the clamping force. Bigger parts require more tonnage. The viscosity of some resin may also require more tonnage. Clamping units are designed to cover a very large range of molds under several classes.

Molds are generally made of steel or aluminum. A mold has two halves named as mold core and mold cavity (Figure 2.3). These two parts constitute the part cavity when closed. Multi-cavity molds are used to produce more than one part at one injection cycle and these cavities may be similar or dissimilar. The entering point of the melt from the nozzle into the mold is named as sprue. The sprue is a kind of channel that is integrated with the additional channels transferring the melt into the mold cavities. These additional channels are named as runner and the ending point of these runners are called as gates. The mold has also water channels to solidify the melt before ejection.

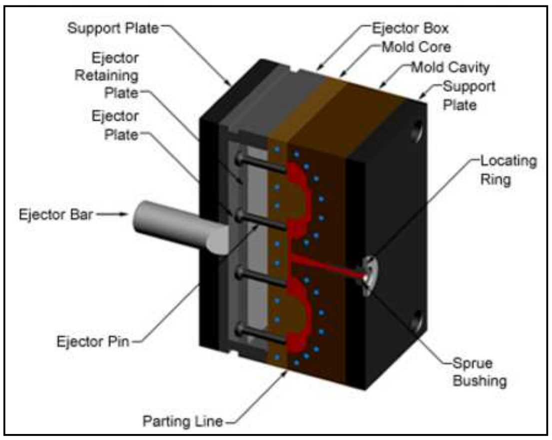


Figure 2.3 Plastic injection mold (Custompartnet, 2017)

Mold/part design is very crucial for successful production. The melt should flow through the cavities easily. The thickness of the part should be as thin as possible to decrease the cycle time by reducing the time needed for solidification. This will also help to reduce the material cost. The thickness of the part should be uniform in order to provide a uniform cooling and to reduce the defects. Sharp corners increase the stress on the part and cause defects so they must be rounded. For the ease of ejection, the part wall should have a draft angle. Ribs should be added for structural support instead of increasing the wall thickness. Bosses should be supported by ribs.

The most frequently used raw material in PIM is thermoplastics. Some thermosets and elastomers are also used. For colored products, either masterbatches are used by mixing during injection or self-colored raw materials may be preferred. Based on the expectations from the final product, different resins are chosen with different properties that also dictate the process parameters (pressures, temperatures, and durations). These technical properties of the resins are given in the datasheets provided by the suppliers. For example, ABS (Acrylonitrile Butadiene Styrene) is a strong, flexible resin with low shrinkage risk and low cost and used in automotive industry. PC (Polycarbonate) is a tough, transparent and temperature resistant resin. The viscosity of ABS and PC is different so a mold designed for ABS may cause problems if PC is fed instead. Property window of widely used resins is given in Figure 2.4.

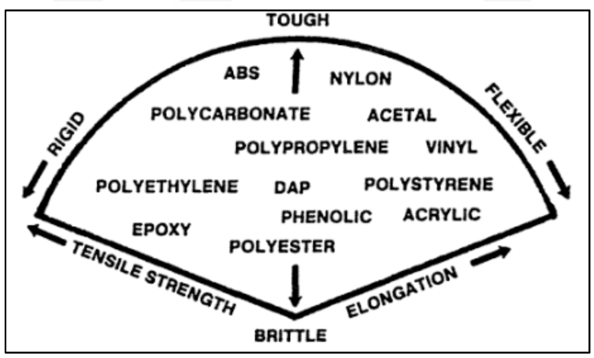


Figure 2.4 Range of resin properties (Rosato & Rosato, 2000)

2.2 PIM Process from Design to Mass Production

In order to provide smooth production throughout the life-cycle of the mold, a strict verification and validation process is followed before the mold is given to the plant for mass production (Figure 2.5).

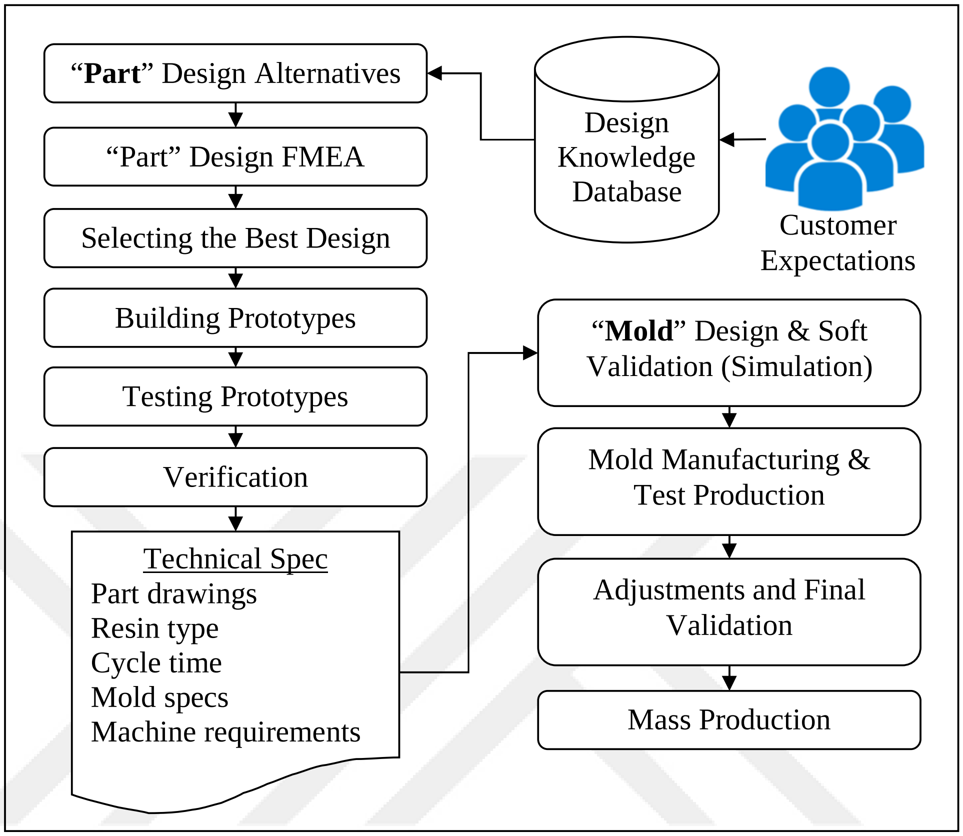


Figure 2.5 PIM process from design to mass production

In PIM, part (product) design and mold (tool) design are different but interrelated processes. At the very beginning of the journey, R&D department prepares design alternatives in accordance with the expectations from the product in terms of appearance, functionality, cost and volume of the demand. Failure mode and effect analysis (FMEA) is used to select the best design. Prototypes of selected design are manufactured using 3D printers, CNC machining or cheap, aluminum-made prototype molds. These prototypes are tested and if needed early design changes are made. With the approval, the part design verification is completed and technical specification for the mold of the part is defined. This specification includes the part drawings, measurements and tolerances, number of cavities, resin type to be used, the material of the mold, desired runner and gate design, desired cycle time and the capacity requirements of the injection machine.

The technical spec defined as the result of the part design process is used as the input in mold design studies. Again, based on the experience from previous projects and by using the important design rules, mold designers create 3D models in the virtual environment of special software. The 3D drawings are then uploaded into the simulation programs to predict the performance of the mold. Some of the capabilities of these programs are; draft analysis, thickness examination, undercut detection, geometry check, parting line recognition, flow simulation, cooling analysis and prediction of major injection defects like sink marks, weld lines, and some cosmetic defects.

Designing the product and designing the tooling (mold) of that product require different specialties. Product designers are mostly marketing oriented and they have lack of tooling background. In order to decrease the time of a product launch to the market by eliminating subsequent corrections on the design or modification of the currently manufactured mold, tool designers are invited to the part design process. With this concurrent engineering approach, expectations of customers can be interpreted in terms of moldability at the early design stage; an environment of cross training occurs that increases the abilities of both part and tool designers and tool designers can anticipate potential changes so they consider compatibility in tooling.

2.2.1 Drivers of Product Quality in PIM

Selection of the resin (plastic raw material) and selection of the injection machine are two important headlines that are as important as the design itself, and these three are directly cross-related. In this dissertation, they are named as “primary factors” to the molding performance. The expectations from the product dictate them simultaneously. As an example, if the product is expected to be sound, wall thickness of the part should be carefully examined and a resin that would provide the soundness should be selected and the machine should have enough clamping force to inject this resin into the mold. In an another example, if the annual demand is too high, the mold is designed with multi cavities and the total molding cycle time is set as short as possible, thus the resin should have high flow rate and quick cooling capability and the injection machine must have compliance with rapid production.

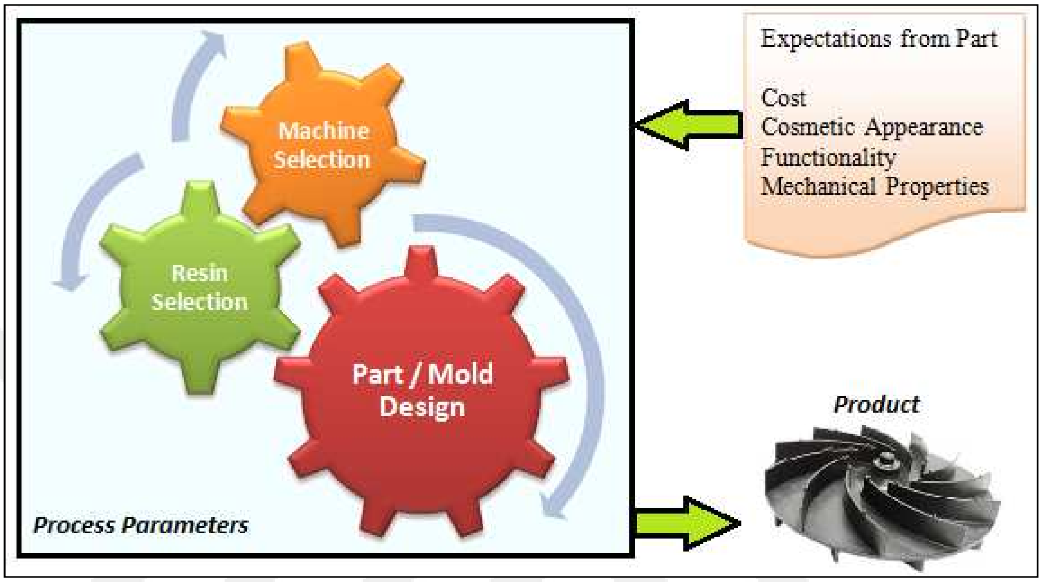


Figure 2.6 Drivers of product quality in PIM

The "secondary factors" affecting the product quality are the process parameters. Injection process parameter set is just like a "lubricant" in the gearbox (Figure 2.6) that helps the primary factors to work smoothly. These parameters are; *temperatures* (of melt, mold, nozzle, barrel etc), *pressures* (of injection, holding and packing), and *duration* (of injection, cooling, packing). Even if there is a great compatibility among design-resin and machine, the process fails to produce qualified products unless the process parameters are set properly.

The last type of factors that affects the product quality in PIM is the **"**organizational factors**"**. These factors are mostly observed in mass production and generally arisen from negligence. Hindering the periodic maintenance of the machine, equipment and tooling, poor warehousing and poor 5S tightens the noose and triggers the troubleshooting mode. These three groups of factors affecting the product quality can be summarized as in Figure 2.7.

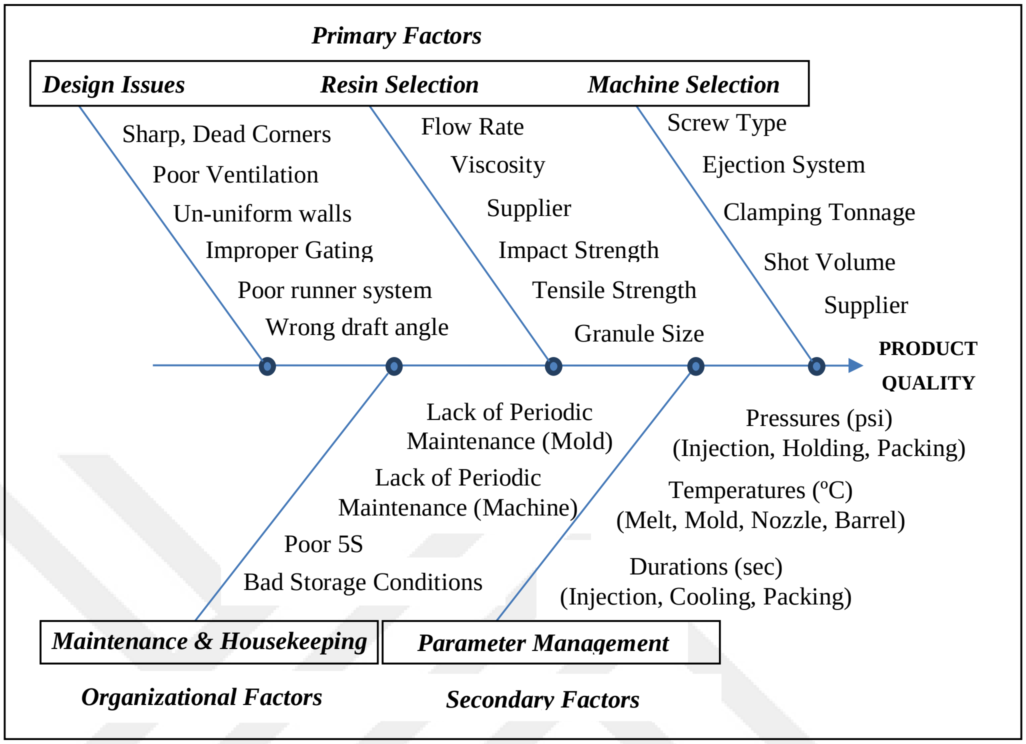


Figure 2.7 Cause and effect diagram for product quality in PIM

2.2.2 Plastic Injection Defects

Both in the design process and in real production, the type and severity of the defects give clear insights about the problem. Thus, understanding the mechanism behind an injection defect is crucial to take necessary actions. In this section, the types of the injection defects and the main root causes are briefly explained (see plasticportal.net). Each of the causes is addressed in parenthesis to one or several of the factors mentioned in the previous section.

2.2.2.1 Black Specks

The dark/black points on the molded part surface (Figure 2.8) are the result of either contamination or thermal damage. The basic source of contamination is poorly cleaned injection unit, oil leaks, uncovered raw material storage and dirty regrinds (maintenance). In order to prevent the black specks occurred due to thermal damage, the source of excessive heat should be taken under control (parameter). This is done by decreasing melt temperature, injection speed or pressures and reviewing mold design to reassess the sharp/dead corners which increase temperature by friction (design).

Figure 2.8 Black specks (Plasticportal, 2017)

2.2.2.2 Charring Streaks

Charring streaks are the silvery, splash-like appearance on the molded part surface due to excessive thermal damage that usually occurs in the regions which cause high friction like a small nozzle or narrow flow cross sections (Figure 2.9). The gaseous substance inside the melt creates bubbles which are transferred into the cavity and flow to the surfaces as charring streaks. Reduction in injection speed, barrel or nozzle temperature, screw speed, residence duration in the barrel or in back pressure is the proposals related to parameter management (parameter). Gate and runner design should be re-examined to avoid excess friction (design).

Figure 2.9 Charring streaks (Plasticportal, 2017)

2.2.2.3 Cold Slug

The tailed flows of a cold piece of plastic that is solidified between two shots in the nozzle, and is forced to enter into the cavity with the melt (Figure 2.10). This issue occurs due to poor sprue/runner design that has a lack of slug prevention (design) or low nozzle temperature (parameter). If the issue cannot be resolved by the increase of nozzle temperature, the runner design should be re-evaluated (design).

Figure 2.10 Cold slug (Plasticportal, 2017)

2.2.2.4 Colored Streaks

Colored streaks are the differences in color on the molded part surface (Figure 2.11). The sole reason is the non-uniform distribution of the color pigments. Homogeneity of the colored mixture should be increased mechanically by using smaller size granules (material) or changing the specifications of the screw (machine).

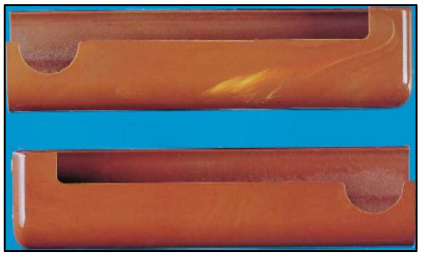


Figure 2.11 Colored streaks (Plasticportal, 2017)

2.2.2.5 Deformation on Demolding

Unsuitable or excessive application of ejection force may result in tears or fractures on the molded part (Figure 2.12). Unlike in warpage case, the deformation is mostly seen on ejection points or at the undercuts (the points which are hard to demold). Modification of the cooling time, or mold temperature (parameter), improving ventilation inside the cavities (design) or application of slip coating to the mold surface is proposed for the resolution.

Figure 2.12 Deformation on demolding (Plasticportal, 2017)

2.2.2.6 Delamination

Delamination means the case of facing peeling off of the molded part surface (Figure 2.13). The resin layers are bonded improperly due to excessive shearing of the cold melt in combination with intensive cooling of the mold. The possible reasons of delamination are; high injection speed and injection temperature (parameter) and un-uniform resin (material), which gets different crystal structures during cooling.

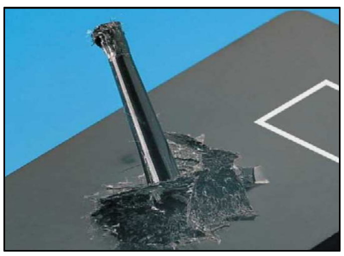


Figure 2.13 Delamination (Plasticportal, 2017)

2.2.2.7 Diesel Effect (Burn Marks)

Improper ventilation in the mold causes the air to be trapped by the melt flow. The entrapped air heats up so much and burns the part surface (Figure 2.14). For resolution, vents should be checked for contamination (maintenance), injection speed, melt temperature or back pressure is decreased (parameter), or the location of venting holes is re-considered (design).

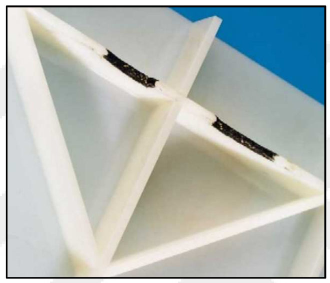


Figure 2.14 Burn marks (Plasticportal, 2017)

2.2.2.8 Ejector Marks

The marks in a form of depression or gloss difference or whitish discolorations may occur during ejection of the solidified product (Figure 2.15). The excessive ejection length (parameter), the small surface of ejectors (machine) may cause these marks. Insufficient cooling time or high back pressure may also create this defect (parameter).

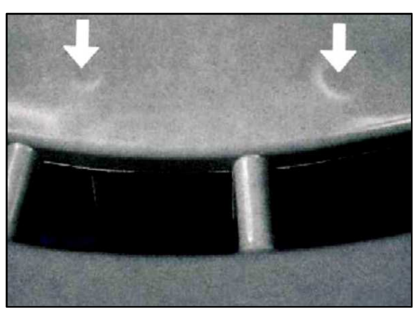


Figure 2.15 Ejector marks (Plasticportal, 2017)

2.2.2.9 Entrapped Air

Actually entrapped air is the root cause of burn marks or short shots, however, here the bubbles visible close to the surface of the part is mentioned (Figure 2.16). To prevent air from being trapped, flow pattern and gate design should be improved (design), any leakage between nozzle and sprue bushing should be checked (maintenance) and decompression via screw stroke should be reduced (parameter).

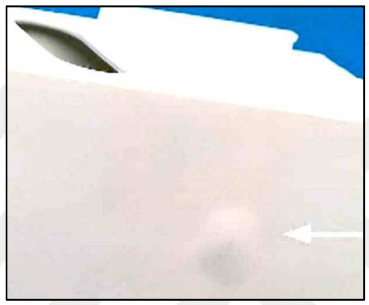


Figure 2.16 Entrapped air (Plasticportal, 2017)

2.2.2.10 Flash

Flash is the excessive plastic squeezed out perpendicular to the part (Figure 2.17). For resolution, clamping force should be increased, or injection speed, injection pressure, mold or melt temperature should be decreased (parameter), and/or the mold should be checked for wear (maintenance).

Figure 2.17 Flash (Plasticportal, 2017)

2.2.2.11 Glass Fiber Streaks

This defect may be observed with the use of a resin containing gloss fiber additives. Glass fiber particles tend to solidify quickly when meeting the mold surface. Due to different mechanical properties of resin and glass fiber, dull matt to a shiny metallic appearance on the molded part becomes visible based on the angle of light mostly due to the inadequate flow rate of the melt (Figure 2.18). For resolution, injection speed or melt temperature is to be increased (parameter) and the homogeneity of the resin should be ensured (material).

Figure 2.18 Glass fiber streaks (Plasticportal, 2017)

2.2.2.12 Gloss Differences

The gloss difference may be in different styles. The whole surface of the product may be either too glossy or too mat, or partial gloss differences are observed (Figure 2.19). This defect occurs mostly in the regions with different wall thicknesses. Un-uniform cooling and the un-smooth part surface may result in gloss differences (design). For resolution, mold or melt temperature or back pressure should be increased (parameter) or the surface of the mold should be shined (parameter) and the homogeneity of the resin should be ensured (material).

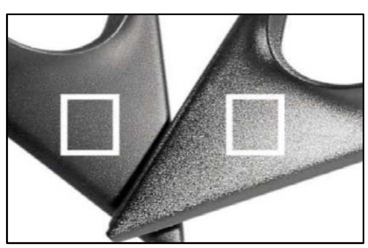


Figure 2.19 Gloss differences (Plasticportal, 2017)

2.2.2.13 Gramophone Effect

These are the marks on the flow direction parallel to each other in a form of furrowed structures (Figure 2.20). The main reason is the reduced flow speed of the melt front due to low mold temperature, low injection speed or low melt temperature. Increasing the temperature of the mold and melt, or increasing the injection speed is advised for resolution (parameter).

Figure 2.20 Gramophone effect (Plasticportal, 2017)

2.2.2.14 Incomplete Filling (Short Shot)

Short shot is the case of incomplete molded part due to insufficient material injection (Figure 2.21). Possible causes are, feeding insufficient resin to injection unit, leaky non-return valve that fails to prevent the melt slipping back over the screw from the cavity, insufficient pressure or high filling resistance due to the viscosity of the resin or mold/runner design. For resolution, amount of resin in the hopper should be checked, injection speed, mold or melt temperature (parameter) should be increased, the ventilation system should be improved to prevent from entrapped air, or runner/gate design that causes pressure losses is altered (design), or an easy flow raw material should be selected (material).

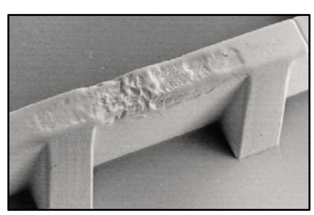


Figure 2.21 Short shot (Plasticportal, 2017)

2.2.2.15 Jetting

Jetting is a sneak-like pattern on the part surface, starting from gate due to undesirable turbulence and splitting of the flow front (Figure 2.22). The unique root cause is the high flow rate so the remedies advised are the reduction of injection speed, increasing melt temperature (parameter), enlarging the gate, and rounding the gate entry (design).

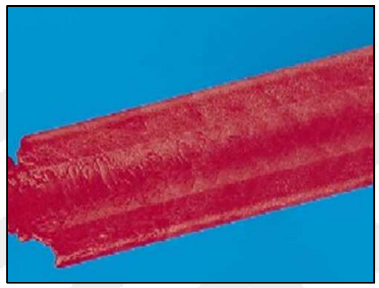


Figure 2.22 Jetting (Plasticportal, 2017)

2.2.2.16 Matt Areas

Low gloss surface on the product due to insufficient force to push the melt against the cavity wall (Figure 2.23). For resolution, the adequacy of injection pressure, mold and/or melt temperatures are checked (parameter), the design of ventilation system and gates should be reviewed (design), or an easy-flow material should be selected (material).

Figure 2.23 Matt areas (Plasticportal, 2017)

2.2.2.17 Moisture Streaks

If the resin is not dried properly or if there is any leakage from water channels (used for cooling) inside the mold (maintenance), small bubbles of water vapor occur (Figure 2.24). These bubbles burst on the surface of the mold while being pushed by the melt flow. For resolution, the drying conditions of the resin both in the storage area and inside the hopper should be controlled and the mold should be controlled for any leakage.

Figure 2.24 Moisture streaks (Plasticportal, 2017)

2.2.2.18 Mold Deposit

In the use of a resin containing additives, the deposit may be left due to high processing temperature (parameter) or poor ventilation (maintenance/design) (Figure 2.25). For resolution, temperatures in the process should be checked, ventilation system should be improved either via maintenance or design changes.

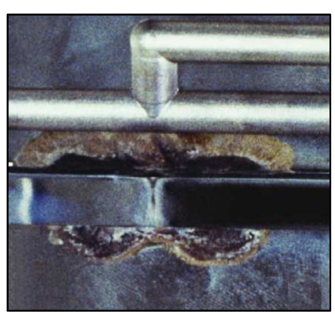


Figure 2.25 Mold deposit (Plasticportal, 2017)

2.2.2.19 Sink Marks

Sink marks are the depression on the part surface which can also be identified by a gloss difference (Figure 2.26). They occur in the regions where the melt accumulates and create excessive volume shrinkage by pulling the surface layer inwards. Sink marks may occur also after ejection. The remedies proposed are increasing back pressure, reducing melt/mold temperature or injection speed (parameter), or altering the wall/rib thickness or gate design (design).

Figure 2.26 Sink marks (Plasticportal, 2017)

2.2.2.20 Stress Cracking or Micro cracks

These kinds of cracks are visible as whitening and occur due to internal or external stress (Figure 2.27). External stress cracking may show up after days or weeks from production due to environmental effects. Inappropriate process parameters like high injection and back pressure, high injection speed and/or overheated melt increases the internal stress that results in cracking (parameter). Poor draft design (design) and/or wrong ejection system selection (machine) also increases the internal stress during ejection. Use of excessive mold release sprays also impedes proper bonding of the molecules and result in cracking.

Figure 2.27 Stress cracking (Plasticportal, 2017)

2.2.2.21 Tiger Lines

Tiger lines are the parallel melting pattern on the mold surface due to the use of multiphase blended resin as PC-ABS or ASA-PC (Figure 2.28). Increasing melt and/or mold temperature (parameter), enlarging the gates (design) or using an easy-flow resin is recommended (material).

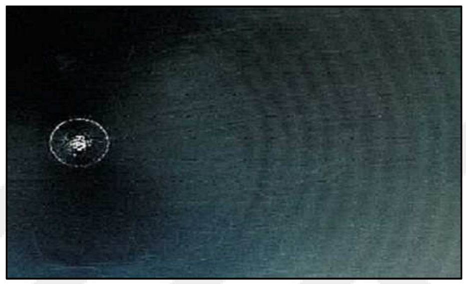


Figure 2.28 Tiger lines (Plasticportal, 2017)

2.2.2.22 Voids

During injection, air may be entrapped inside the melt. Unlike bubbles, voids always occur in the region of the core plastic (Figure 2.29). The main root cause is the volume shrinkage due to insufficient packing in the areas where the melt accumulates. For resolution, decompression should be reduced, the speed of back-return of the screw should be reduced, back pressure should be increased, the temperature of melt/mold or injection speed should be decreased (parameter), gates design should be improved, and thinner ribs should be used (design).

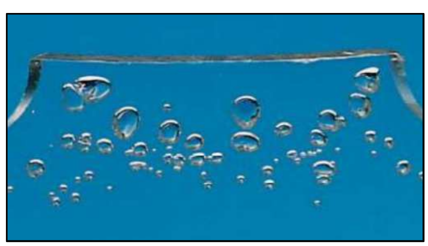


Figure 2.29 Voids (Plasticportal, 2017)

2.2.2.23 Warpage

Warpage is the dimensional distortion on the molded part as twists and turns (Figure 2.30). Differences in packing and resin orientation result in non-uniform shrinkage thus warpage occurs. For resolution, balance filling of the mold should be controlled to reduce the shrinkage differences and the wall thickness differences, and sharp corners should be avoided (design), or back pressure, injection pressure, or injection speed should be increased for a denser injection (parameter), or an easy-flowing and less shrinkable resin should be selected (material).

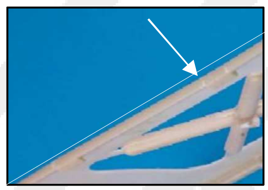


Figure 2.30 Warpage (Plasticportal, 2017)

2.2.2.24 Weld Lines

Weld lines occur due to the inability of two melt streams to knit together (Figure 2.31). The main reason is the early solidification due to inadequate temperature and pressure. This defect creates weak surfaces in terms of mechanical properties. For resolution, injection speed, back pressure or melt/mold temperature is increased (parameter) or ventilation and gate design is reevaluated (design).

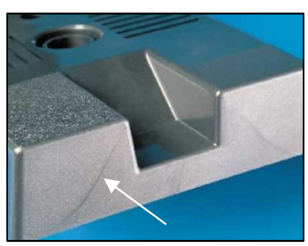


Figure 2.31 Weld lines (Plasticportal, 2017)

CHAPTER THREE
MODES OF PARAMETER MANAGEMENT AND CHANGEOVER PARAMETER SETTING

3.1 Three Modes of Injection Process Parameter Setting

Management of process parameters plays an important role to build a robust plastic injection process from initial design to mass production (Figure 3.1). In the design phase, aforementioned primary factor combinations are assessed by optimizing secondary factors for each case in virtual environment. In another words, the best design-machine-resin combination is evaluated under different process parameter set with the aid of molding simulation programs. This process is called **virtual parameter setting**.

With the soft validation, the mold is manufactured, thus primary factors are already defined and fixed. During injection molding, the plastic raw material is exposed to high rheological and thermo-mechanical changes (Kashyap & Datta, 2015). Due to the sensitive nature of plastic injection, the real molding performance differs from the expectations in simulation studies. To detect and resolve the molding issues in real production, the mold is transferred to the trial production team. The aim of this step is to define the optimal process parameters that recover injection defects and minimize the cost of molding under real production conditions. This step is called **optimal (initial) parameter setting**.

After the validation of the mold in trial production, the optimal set is recorded and the mold is launched to the mass production. For each changeover session during the mass production, the initial set should be modified because it shifts from its original point due to the noise factors, which are explained in the following section. Therefore, after mounting the mold of the next product in the production plan, the optimal set is recalled from the database and used as the initial set to redefine the shifted optimal set. The trial and error based parameter adjustment in this session is called **changeover parameter setting** wherein setup experts try to resolve the injection defects to start the mass production in a limited time.

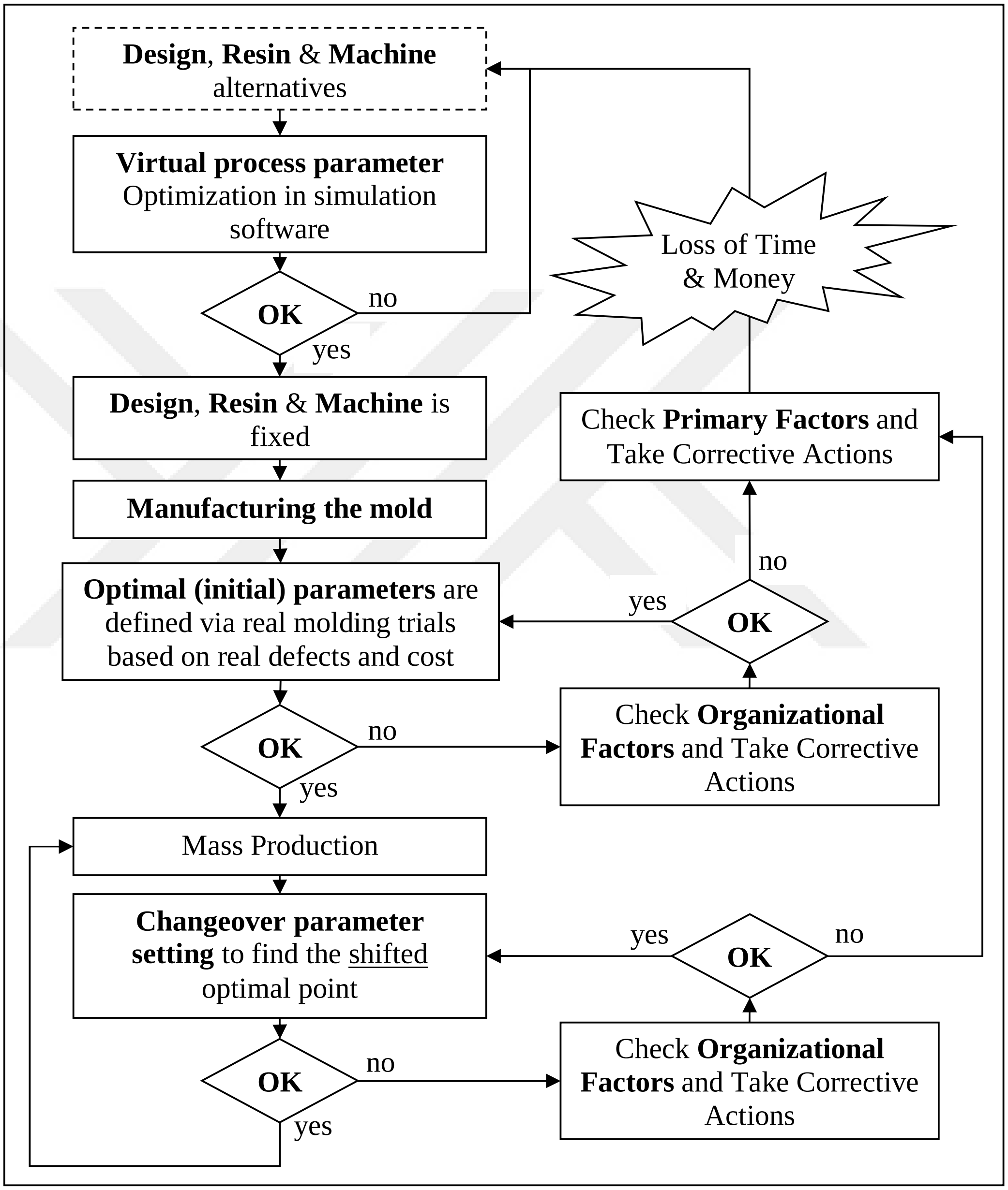


Figure 3.1 Parameter setting modes in the life time of a mold

In the cases that parameter setting is useless in resolving the quality issue, the troubleshooting mode is activated to find the real problem. If the root cause is one of the organizational factors, e.g., dirty mold surface, a corrective action is taken and parameters are re-adjusted. If re-adjustment still cannot resolve the issue, then the primary factors (design, resin, and machine) are re-considered. Observing a troubleshooting mode in an injection process reveals that the process is not well designed and/or periodic tasks are not followed up properly.

3.2 The Hot Topic: "Plastic Injection Parameter Optimization"

Many studies are presented in the literature to map the relationship between multiple-input vs. single/multiple output of PIM process and to optimize the process parameters that meet the expectations from the molded part. Plastic injection parameter optimization problem can be formulated as in Equation 3.1 (Kashyap & Datta, 2015).

Determine $$x = \left(x_j; j = 1,2, \dots, m\right)^T \tag{3.1}$$

To optimize $$Q(x) = \left(f_q(x); q = 1,2, \dots, n\right)^T \tag{3.2}$$

Subject to $$h_i(x, y) \leq 0; \quad i = 1,2, \dots, c \tag{3.3}$$

$$x_j^{(l)} \leq xj \leq x_j^{(u)} \quad j = 1,2, \dots, m \tag{3.4}$$

Where x represents process parameters, within the range of $(x_j^{(l)}, x_j^{(u)})$; Q is the overall quality characteristics expected from the product; h_i represents the limitations concerning cost, loss and efficiency and f_q represents the plastic injection defects.

In this section a comprehensive literature review is given (Table 3.1) with classification regarding the quality indices that are considered to improve process parameters, data collection method, the environment that the data is gathered from (real: actual molding trials, virtual: software programs like MoldFlow), model approximation method, the optimization method, the type of optimization, and the verification environment (real, virtual). Abbreviations used in process parameters are "D" for duration, "P" for pressure, "T" for temperature, "S" for speed, "VP" for transition from velocity to pressure, "$" for size and "#" for number. Abbreviations used in optimization methods are "ANN" for artificial neural networks, "ABC" for artificial bee colony, “DFP” for Davidon-Fletcher-Powel method, “DOE” for design of experiment, “EI” for expected improvement, “EPI” for enhanced probability improvement, “GA” for genetic algorithm, “PSO” for particle swarm optimization, “RSM” for response surface methodology, and “SQP” for sequential quadratic programming.

Table 3.1 Classification of the studies about plastic injection parameter setting

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Altan (2010)	Shrinkage	Tmelt, Pinj, Ppack, Dpack	Taguchi ANOVA	Real	ANN	(Taguchi Verif.)	Real	Meta-model
Alvarado Iniesta, García Alcaraz, & Rodríguez Borbón (2013)	Warpage	Tmelt, Tmold, Ppack, Dpack, Dcool	DOE	Virtual	ANN	ABC	Virtual	Meta-model
Chang & Faison (2001)	Shrinkage	Phold, Dhold, Tmold, Pinj, Tmelt, Pback, Dcool	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Chen & Kurniawan (2014)	Warpage & Length	Tmelt, Sinj, Ppack, Dpack, Dcool	Taguchi ANOVA	Real	1. ANN (Cpk), 2. ANN (Quality)	1. GA, 2. PSO & GA	Real	Meta-model
Chen, Cheng, Wang, & Chien (2005)	Warpage	Tmold, Tmelt, Sinj, Sgas, Pgas, Disp_inj, Delay_gas, Dpack	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Chen, Chuang, Hsiao, Yang, & Tsai (2009)	Warpage	Tmelt, Tmold, Sinj, Ppack	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Chen, Fu, Tai, & Deng (2009)	Length & Weight	Tmelt, Sinj, Pinj, VPswitch, Ppack, Dpack	Taguchi ANOVA	Real	ANN	GA	Real	Meta-model
Chen, Huang, & Huang (2013)	Warpage & Shrinkage	Dinj, Pinj, Dpack, Ppack, Dcool, Tcool, Dmold_open, Tmelt, Tmold	2-Phase Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Real	Taguchi
Chen, Huang, & Hung (2010)	Warpage & Shrinkage	Dinj, Pinj, Ppack, Dpack, Dcool, Tcool, Dmold_open, Tmelt, Tmold_surf	Taguchi ANOVA	Virtual	Dual RSM	(Output Prediction)	Virtual	Meta-model
Chen, Lai, Fu & Chen (2008)	Part Weight	VPswitch, Dinj, Ppack, Sinj	Taguchi ANOVA	Virtual	ANN	GA	Virtual	Meta-model
Chen, Lee, & Yu (1997)	Silver Streaks	Dfill, SO_fill/postfill, Sinj, Flow_Coolant, Dpostfill, Trunner, Phold, Tinj, Tmold, Dhold	2-Phase Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Chen, Liou, & Chou (2014)	Warpage & Length	Tmelt, Sinj, Pinj, Ppack, Dpack	Taguchi ANOVA	Real	1. ANN (Cpk), 2. ANN (Quality)	1. GA, 2. PSO & GA	Real	Meta-model

Table 3.1 continues

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Chen, Su, Chiou, & Chiang (2011)	Shrinkage	Sinj, Ppack, Tmold, Tmelt	DOE	Real	RSM	GA	Real	Meta-model
Chen, Wang, Chen, & Fu (2009)	Part Weight	VPswitch, Dinj, Ppack, Sinj	Taguchi ANOVA	Virtual	ANN	GA & DFP	Virtual	Meta-model
Chen, Zhou, Wang, & Wang (2010)	Warpage & min-max ink pressure	Tmold, Tmelt, Ppack, Dpack	DOE (Latin Hypercube)	Virtual	Kriging Surrogate	PSO	Virtual	Meta-model
Chuang, Yang, & Hsiao (2009)	Warpage & Tensile Stress	Tmelt, Tmold, Sinj, Ppack	Taguchi ANOVA	Real	RSM	(Output Prediction)	Real	Meta-model
Deng, Zhang, & Lam (2010)	Warpage	Tmold, Tmelt, Dinj, Ppack	DOE (Mode Pursuing Sampling)	Virtual	Kriging Surrogate	GA	Virtual	Meta-model
Farshi, Gheshmi, & Miandoabchi (2011)	Warpage & Shrinkage	Tmold, Tmelt, VPswitch, Ppack, Dpack, Tcoolant	DOE (Type is not given)	Virtual	-	Sequential Simplex	Virtual	Discrete
Gao & Wang (2008)	Warpage	Tmold, Tmelt, Dinj, Ppack	DOE (Rectangular Sampling)	Virtual	Kriging Surrogate	EI based opt	Virtual	Meta-model
Gao & Wang (2009)	Warpage	Ppack, Tmold, Tmelt, Dinj	DOE (Infilling sampling)	Virtual	Kriging Surrogate	EI based opt	Virtual	Meta-model
Gao, Turng, & Wang (2008)	Warpage	Tmold, Tmelt, Dopen, Dcycle, Dinj, Dpack, Ppack, VPswitch	DOE (Latin hypercube + Rectangular)	Virtual	Kriging Surrogate	SQP	Virtual	Meta-model
He, Zhang, Lee, Fuh, & Nee (1998)	Short shot, Flash, Sink Mark, Flow Mark, Weld, Cracking, Warpage	Pinj, Sinj, Tmelt, Fclamp, Dhold, Tmold, Phold, Pback, Dcool	Experts Interview & Molding Trials	Real	ANN *(for fuzzy rule generalization)*	(Output Prediction)	Real	Meta-model
Huang & Tai (2001)	Warpage	Tmold, Tmelt, Dfill, $gate, Ppack, Dpack	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Real	Taguchi
Hussin, Saad, Hussin, & Dawi (2012)	Warpage	Tmold, Tmelt, Dpack, Ppack, Dcool, Tcool, $runner	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Jan & O'Brien (1993)	Expert system that stores the initial operating conditions based on the part, resin and mold data and troubleshooting guide based on the experts' experience. System includes no approximation or optimization. (Too optimistic to expect the system to contain all possible combinations)						Real	Expert System

Table 3.1 continues

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Kamaruddin, Khan, & Foong (2010)	Shrinkage	Sinj, Tmelt, Pinj, Phold, Dhold, Dcool	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Kang (2014)	Warpage & Shrinkage	Dinj, Ppack, Dpack, Dcool	2-Phase Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Karasu, Cakmakci, Cakiroglu, Ayva, & Demirel-Ortabas (2014)	Warpage	Tmelt, Pinj, Ppack, Dcool	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Kenig, Ben-David, Omer, & Sadeh (2001)	Tensile Modulus	Tmold, Tmelt, Ppack, Sinj, Dcool	DOE *(Hadamard)*	Real	ANN	(Output Prediction)	Real	Meta-model
Kurtaran & Erzurumlu (2006)	Warpage	Tmold, Tmelt, Ppack, Dpack, Dcool	DOE & ANOVA	Virtual	RSM	GA	Virtual	Meta-model
Kurtaran, Ozcelik, & Erzurumlu (2005)	Warpage	Tmold, Tmelt, Ppack, Dpack, Dcool	DOE (Full Factorial) & ANOVA	Virtual	ANN	GA	Virtual	Meta-model
Kwong & Smith (1998)	Expert system that integrates Knowledge Sources – about production scheduling, mold selection, machine selection, cost estimation- in a Blackboard database and Case-Based Reasoning system to predict process parameters based on the similarity of the cases in the Blackboard database. (Limited to the number of available cases and similarities.)						Real	Expert System
Kwong, Smith, & Lau (1997)	Expert system that uses Case-Based Reasoning to propose process parameters based on the previous application stored in a database in accordance with the similarity of part-resin-mold-demand info. (Limited to the number of available cases and similarities.) Aim is initial process parameter setting.						Real	Expert System
Lam, Deng, & Au (2006)	Max Shear Stress & Cooling Time	Tmelt, Tmold, Dinj	DOE (orthogonal)	Virtual	-	GA & Gradient	Virtual	Discrete
Lau, Wong, & Pun (1999)	Part Length	Dsetup, Twarmup, Doperation, Poperation, Tsetup, Tcool	Experts Interview & Molding Trials	Real	ANN for fuzzy rule generalization	(Output Prediction)	Real	Meta-model
Li, Li, Si, & Rongji (2015)	Warpage	Ppack, Tmelt, Tmold, Dpack, Dcool, Pfill	DOE (orthogonal)	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Li, Zhou, Zhao, & Li (2009)	Short Shot, Flash	Tmelt, Tmold, Sinj, Pinj, Ppack, Dpack, Dcool	Simplified Equations & Experts Int.	Real	Fuzzy Inferencing	(Output Prediction)	Real	Expert System

Table 3.1 continues

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Liao, Chang, Chen, Tsou, Ho, Yau, & Su (2004)	Warpage & Shrinkage	Tmold, Tmelt, Ppack, Sinj	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Liao, Hsieh, Wang, & Su (2004)	Warpage & Shrinkage	Tmold, Tmelt, Ppack, Sinj	Taguchi ANOVA	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Lotti, Ueki, & Bretas (2002)	Shrinkage	Tmold, Tmelt, Phold, Rflow	DOE (C.Comp)	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Manjunath & Krishna (2012)	Shrinkage	Sinj, Tmold, Tmelt, Ppack	Regression Equation from others	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Mathivanan & Parthasarathy (2009)	Sink Marks	Tmelt, Tmold, Ppack, Rrib-wall	DOE (C.Comp)	Virtual	RSM	(Output Prediction)	Virtual	Meta-model
Mehat & Kamaruddin (2011a)	Strength & Modulus	Tmold, Tmelt, Dinj, Ppack, Dpack, Dcool	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Real	Taguchi
Mehat & Kamaruddin (2011b)	Strength & Modulus	Tmelt, Ppack, Dinj, Dpack	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Mehat & Kamaruddin (2011c)	Strength & Modulus	Tmelt, Ppack, Dinj, Dpack, Ratio_recycled_resin	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Mok & Kwong (2002)	Expert System of Case-Based Reasoning that uses Fuzzy Logic to define the similarity of the case with the cases in the database and uses ANN for case adaptation based on the part & mold design (inputs) data and process parameters (outputs). Aim is initial process parameter setting. Quality indices: Max shear stress, cavity temperature, shrinkage.						Real	Expert System
Mok, Kwong, & Lau (2000)	Expert System of Case-Based Reasoning that uses Fuzzy Logic to define the similarity of the case with the cases in the database and uses GA-ANN for case adaptation based on the part & mold design (inputs) data and process parameters (outputs). Aim is initial process parameter setting. Quality indices: Max shear stress, cavity temperature, shrinkage.						Real	Expert System
Mok, Kwong, & Lau (2001)	Max Shear Stress, Shear Rate, Cavity Temp., Shrinkage	Tnozzle, Tbarrel, Pinj, Phold, Pback, Fclamp, Sscrew, Dfill, Dhold, Dcool, Dcycle	Molding Database of a company	Real	GA-ANN	(Output Prediction)	Virtual	Meta-model
Oktem, Erzurumlu, & Uzman (2007)	Warpage	Dinj, Ppack, Dpack, Dcool	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Ozcelik & Erzurumlu (2006)	Warpage	Dinj, Pinj, Ppack, Dpack, Dcool, $channel, Dist_channel, #gate	Taguchi ANOVA	Virtual	ANN	GA	Virtual	Meta-model

Table 3.1 continues

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Özek & Çelık (2012)	Warpage & Shrinkage	Dpack, Tcool, Tmold, Tmelt, Ppack, Pinj, %_fiberglass	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Sadeghi (2000)	Soundness, Dfill, Dinj, Pinj	Tmold, Tmelt, Pinj, Resin_Grade, Rate_flow	DOE	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Shelesh-Nezhad & Siores (1997)	Expert System application using Case Based Reasoning to retrieve similar cases based on the resin type, part geometry, flow pattern, and Rule Based System to tune the parameters to resolve the defects occurring from the similar set. (Correction amount is not given)						Real	Expert System
Shen, Wang, & Li (2007)	Shrinkage	Tmold, Tmelt, Dinj,Dpack, Phold	Taguchi ANOVA	Virtual	ANN	GA	Virtual	Meta-model
Shi, Lou, Zhang, & Lu (2003)	Shear Stress	Tmold, Tmelt, Dinj, Pinj	DOE (Orthogonal)	Virtual	ANN	GA	Virtual	Meta-model
Shi, Xie, & Wang (2013)	Warpage	Tmold, Tmelt, Dinj, Dpack, Ppack, Dcool	DOE (Latin Hypercube)	Virtual	ANN	SQP	Virtual	Meta-model
Song, Liu, Wang, Yu, & Zhao (2007)	Part Filling	Sinj, Pinj, Tmelt, $metering, Thickness	Taguchi ANOVA	Virtual	-	(Taguchi Verif.)	Virtual	Taguchi
Spina (2006)	Shrinkage, Part Filling, Shear Stress, Part weight	Tmold, Tmelt, Sinj, Ppack	DOE (Full factorial)	Virtual	ANN	PSO	Real	Meta-model
Tang, Tan, Sapuan, Sulaiman, Ismail, & Samin (2007)	Warpage	Tmelt, Dfill, Ppack, Dpack	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Tsai, Hsieh, & Lo (2009)	Light Transmission, Surface Waviness*, Surface Finish	Tmelt, Sscrew, Sinj, Pinj, Ppack, Dpack, Tmold, Dcool	Taguchi ANOVA	Real	-	(Taguchi Verif.)	Real	Taguchi
Tzeng, Yang, Lin, & Tsai (2012)	Strength, & Impact resistance	Tnozzle, Tmelt, Ppack, Dpack, Tmold	Taguchi ANOVA	Real	Regression vs ANN	RSM vs GA	Real	Meta-model
Vagelatos, Rigatos, & Tzafestas (2001)	Sink, Flash, Shrinkage, Bad Finish, Short shot, Deformation, Warpage, Large Dimension, Burn, Gloss, Weight	Dcool, Tmold, Phold, Fclamp, Dhold, Tnozzle, Sinj, Pback, Pinj, Splast, Smoldopen1, Smoldopen2, OpenStroke, Tbarrel	Experts Interview	Real	Fuzzy Inferencing System	(Output Prediction)	Real	Expert System

Table 3.1 continues

Writers / Year	*Quality Indices*	*Process Parameters*	*Data Collection Method*	*Data From*	*Model Approx.*	*Optimization Method*	*Param. Setting Class*	*General Class*
Wang, Kim, & Song (2014)	Compression Strength	#gates, $gate, Tmold, Tmelt, Volswitch, VPswitch, Dcure	Numerical Simulation	Virtual	ANN	GA	Virtual	Meta-model
Wang, Zeng, Feng, & Xia (2013)	Shrinkage	Tmold, Tmelt, Dcool, Pinj, Ppack, Dpack	DOE (Fractional)	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Xia, Luo, & Liao (2011)	Warpage	Ppack, Dpack, Pinj, Tmelt, Dinj, Dcool	DOE (Latin Hypercube)	Virtual	Gaussian Process Surrogate	EPI	Virtual	Meta-model
Xu, Yang, & Long (2012)	Flash, Shrinkage and Part Weight	Tmold, Tmelt, Pinj, Dinj, Phold, Dhold, Dcool	Taguchi DOE	Real	ANN	PSO	Real	Meta-model
Yang (2006)	Wear Mass Loss, Friction Coefficient, Strain	Dfill, Tmelt, Tmold, Ppack	Taguchi DOE	Real	-	(Taguchi Verif.)	Real	Taguchi
Yin, Mao, & Hua (2011)	Warpage & Max Clamp Force	Tmold, Tmelt, Ppack, Dpack, Dcool	DOE (Orthogonal)	Virtual	ANN	GA	Virtual	Meta-model
Yin, Mao, Hua, Guo, & Shu (2011)	Warpage	Tmold, Tmelt, Ppack, Dpack, Dcool	DOE (Orthogonal)	Virtual	ANN	(Output Prediction)	Virtual	Meta-model
Zhao, Cheng, Ruan, & Li (2015)	Warpage, Shrinkage, Sink	Dinj, Tmelt, Dpack, Ppack, Tcool, Dcool	DOE (Latin Hypercube)	Virtual	Kriging Surrogate	EI based opt	Virtual	Meta-model

3.2.1 Assessment of the Studies from Data Collection Aspect

Understanding the parameter space for optimization requires data collection. The source of data in parameter setting can be grouped as; (1) past records, (2) interviews, and (3) design of experiments. Past records are easy to reach and become life saver in terms of time management. However, the validity, completeness and correctness of the data are question marks. Among the papers, only Mok et al., (2001) used past records in their study. The other source of information, interview method, is used in expert system applications to collect information about the relationship between inputs and outputs (Jan & O'Brien, 1993; Kwong & Smith, 1998; Kwong et al., 1997; Li et al., 2009; Mok & Kwong, 2002; Mok et al., 2000; Shelesh-Nezhad, & Siores, 1997; Vagelatos et al., 2001).

The third type of data source is design of experiments (DOE). In parameter setting, it is the most popular way of data collection. DOE can be described as structured set of tests of a process. DOE methods can be classified as orthogonal designs and random designs. In orthogonal designs, the model parameters are assumed to be statistically independent, uncorrelated and can be varied independently. Fractional and full-factorial designs, central composite design, Box-Behnken designs and Taguchi designs are the methods under orthogonal designs. In random designs, model parameter values are assigned based on a random process. Latin hypercube design, mode pursuing sampling, rectangular sampling and infilling sampling are the random designs used in the literature. Analysis of variance (ANOVA) studies accompany the DOE to define the statistically significant parameters for further interpretations.

Although DOE methods reduce the effort needed to understand the parameter space by decreasing the number of experiments, they ignore the effect of interactions. However, the parameters in plastic injection are interacting with each other (Mok et al, 1999). Moreover, Taguchi design, which is preferred intensively in the literature, uses prefixed values of parameters as test levels. But the range of parameters is continuous, and the optimum point may not be matched with the levels chosen.

The data source of a parameter setting study can be a virtual environment like simulation programs (MoldFlow) or real molding trials. Especially during the design phase, simulation programs are used to define optimal process parameters, for cost estimations and defect resolution. Real molding trials are used in the studies where the mold under consideration is already manufactured.

3.2.2 Assessment of the Studies from Modeling and Optimization Aspect

From the model approximation aspect, the studies can be grouped under four classes; meta-model based optimization, Taguchi prediction, expert system applications and direct discrete optimization. In Table 3.2 the numbers of studies are given for each class.

Table 3.2 Studies according to the type of approximation and optimization

General Class	Sub Class	Number of	Ratio
Direct discrete	Gradient-Based	2	3%
Expert System application	-	8	11%
Meta-model based optimization	ANN	28	40%
	Gaussian Process Surrogate	1	1%
	Kriging Surrogate	6	9%
	RSM	5	7%
Taguchi prediction	-	20	29%
Total		70	100%

The meta-model based optimization method is an approach wherein objective functions are approximated into the explicit form of low order polynomials with acceptable accuracy (Dang, 2014). 57% of the studies in the literature review use meta-model based optimization. Common meta-modeling techniques are artificial neural networks (ANN), Kriging surrogate (KS), response surface methodology (RSM) and Gaussian process surrogate (GPS).

ANN is a powerful tool that can predict highly nonlinear responses via function approximation and 40% of the studies in the review use this technique. The most popular optimization technique with ANN is GA (Chen, Fu et al., 2009; Chen et al., 2008; Kurtaran et al., 2005; Ozcelik & Erzurumlu, 2006; Shen et al., 2007; Shi et al., 2003; Wang et al., 2014; Yin et al., 2011). Particle swarm optimization is also used with ANN approximation (Chen et al., 2014; Chen & Kurniawan, 2014; Spina, 2006; Xu et al., 2012). Alvarado Iniesta et al., (2013) used artificial bee colony together with ANN to optimize warpage, and Shi et al., (2013) used sequential quadratic programming for optimization.

Surrogate models are established to approximate the time-consuming computer simulation software (Zhao et al., 2015). Kriging surrogate technique is one of the meta-model based optimization which can be used for deterministic and highly nonlinear problems with moderate number of parameters (Dang, 2014). Gao & Wang (2008, 2009) and Zhao et al., (2015) tried to optimize the Kriging surrogate model via EI (expected improvement) based optimization. Chen, Zhuo et al. (2010) used PSO, Deng et al. (2010) used GA and Gao et al. (2008) used SQP to optimize warpage model.

RSM method is used to express the relationship between inputs and outputs in quadratic polynomial form. Generally central composite design based DOE is used to create the RSM model. Chen, Huang et al. (2010), Chuang et al. (2010), Mathivanan & Parthasarathy (2009) used RSM modeling for warpage, shrinkage and sink mark prediction based on given inputs. Chen et al. (2011) and Kurtaran & Erzurumlu (2006) combined GA to optimize their model that they created via RSM.

The Gaussian process surrogate model is another meta-model based optimization technique, which can interpolate and can be used for deterministic simulations for smoothness. Xia et al. (2011) used GPS to model the warpage behavior of the process and tried to find the optimized parameters that minimize warpage using EPI function.

Direct discrete optimization methods are rarely used since this method requires a complex integration between simulation tool and optimization code (Dang, 2014). Beside of that, gradient based optimization converges quickly if the problem is low nonlinear. Lam et al. (2006) used gradient-based optimization together with genetic algorithms to define shear stress and cooling time. Farshi et al. (2011) used sequential simplex method to optimize GPS model for warpage and shrinkage minimization.

The last method for parameter setting used in the literature is expert systems. Expert systems simulate the human reasoning process by applying specific knowledge and inferencing. A typical expert system has two main components, knowledge base and inference engine (Mok et al., 1999). Fact and heuristics about the domain is stored in the knowledge base and activation and manipulation is done via inference engine. In the scope of expert systems, Jan & O'Brien (1993) built a system that stores initial operating conditions based on part, resin and mold data and troubleshooting guide is coded into the system to cope with defects during trials. Kwong & Smith (1998) and Kwong et al. (1997) tried to integrate all the knowledge sources about PIM (design, planning, machine and mold selection and cost estimation) into a blackboard database and aimed to find the process parameters via case-based reasoning from the database based on the similarity of the cases. Mok et al. (2000) and Mok & Kwong (2002) used fuzzy logic embedded into case-based reasoning to define the similarity of the cases. These studies also used GA-ANN and ANN for case adaptation to define initial process parameters that optimize shear stress, cavity temperature and shrinkage. Shelesh-Nezhad & Siores (1997) also built an expert system that includes case-based reasoning to define the similarity of the cases based on resin type, part geometry and flow pattern. They also integrate a rule-based system to tune the parameters for defect resolution.

Since the parameter space is huge in PIM process, mapping of all possible relations and actions using traditional expert system is a tough task. Moreover, the effectiveness of the systems that use case-based reasoning depends on the richness of the database in terms of past cases. Due to these limitations pure expert systems are not preferred since 2000s. Traditional expert systems have been substituted with fuzzy reasoning. He, Zhang, Lee, Fuh, and Nee (1998) used fuzzy inferencing for “initial parameter setting”. In their study, seven types of injection defects, part flow and part thickness were used as inputs to define the adjustment amount of nine molding parameters. Three fuzzy sets for the severity of the inputs and six fuzzy sets for the amount of change of parameters were defined. They have generated fuzzy rules using both the samples that were produced before and the real molding trials. They employed neural networks to generalize the fuzzy rules. Vagelatos, Rigatos, and Zafestas (2001) defined fifteen types of defects with five fuzzy sets of severity and fourteen molding parameters with five fuzzy sets of change amount to resolve quality issues during mass production.

The number of the fuzzy rules that must be embedded into the inferencing system increases proportionally with the number of inputs and/or outputs and their levels. He et al. (1998) and Vagelatos et al. (2001) did not propose a method to decrease the number of rules without sacrificing the possible cases. Moreover, if the rules are generated from real molding trials, the number of the rules will be limited to the observations. Neural networks may fail to predict the fuzzy rules of the cases that are not observed. Without a systematic elimination of rules, it is too difficult to allege that a fuzzy inference system can cover all possible cases, thus, is totally ready to be used in real environment. However, in injection molding, there is a strong necessity to an expert system that will assist the limited number of setup experts by converting machine operators into changeover staff.

It is a very important finding that only three papers over 70 tried to handle the whole set of injection defects (He et al., 1998, Vagelatos et al., 2001 and Li et al., 2009). The attempts presented in the literature mostly focus on the optimization of one or several issues (especially warpage and shrinkage).

3.3 Why a Tailored Approach is Required for Changeovers?

During initial parameter setting studies, the conditions are "static", which means the level of temperature and humidity, and the performances of the mold and machine are relatively stable, and the trials are done with the resin from the same lot and trials are conducted on the same injection machine. Therefore, the required data can be collected for model approximation and optimization. Likewise, the virtual environment of simulation programs let the decision makers obtain data from the same pool for optimization of parameters virtually.

In the contrary, each changeover setting is a unique case because the conditions are not the same as in any of the previous changeovers. There are four basic "*noise factors*" that create this dynamic environment in changeovers:

- During the use of the mold in mass production, mold wear, fatigue and contamination occurs, the performance of the mold starts to decrease and requires compensation via process parameters until its next planned maintenance.
- PIM has a sensitive nature, and the molding performance changes based on the level of environmental temperature and humidity.
- Injection machines with the same capabilities may perform different from each other due to their different maintenance requirements
- The quality level of the resin may have deviations between lots.

Therefore, the optimal set shifts from the initial set in changeovers. Due to the noise factors, the direction and the amount of the shift are different for each changeover.

Another challenge in changeover parameter setting is the "time limit" to accomplish the task. Since the lean target is to reduce total changeover time under 10 minutes, the time that can be allocated to parameter setting is not more than several minutes. In Figure 3.2, the three parameter setting modes and their distinguishing properties are summarized.

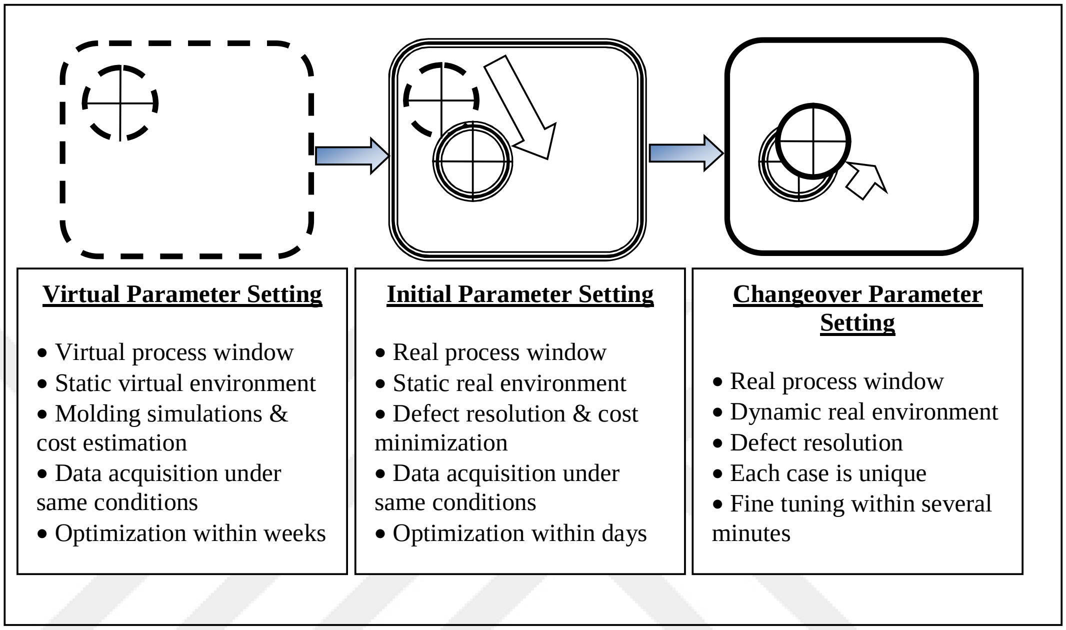


Figure 3.2 Properties of parameter setting modes

In changeover parameter setting, the uniqueness of the cases prevents collection of homogenous data for optimization. Moreover, the time limit impedes data collection to make analysis. Without a data set, both evolutionary and derivative-based optimization tools are useless. Changeover parameter setting is also too complex to model using traditional expert system applications, which cannot provide the amount of change as a function of defect severity (Mok & Kwong, 2002).

Contemporary expert system applications, e.g., fuzzy inference, can be applied, as presented in some of the studies. However, the rule set must be broad enough to cover all possible cases and narrow enough to be prepared and modified easily, which were not addressed in those papers. Since there is a strong necessity of such an expert system in plastic injection production, the proposed system should provide a complete solution and must be integrated into the whole changeover process. In the next chapter, a tailored approach is introduced for changeover operations in plastic injection.

CHAPTER FOUR
SMED AND FUZZINESS OF CHANGEOVER PARAMETER SETTING

4.1 Importance of Small Lot Production and SMED

One of the biggest challenges of the companies is to use the production resources efficiently to respond customer demand on time. It would be easier if the product ranges were narrow and demand were stable. However, mass customization is inevitable to survive in the market, which causes the need to have broader product ranges. As range gets wider, forecasting accuracy for these products gets lower and produce-to-stock strategy becomes unreasonable. The annual cost of carrying stock for most of the companies ranges from 20% to 36%, which composes of 10-15% cost of capital, 2-5% storage space, 4-6% obsolescence, 1-5% insurance, 1-2% material handling, and 2-3% taxes (Ross, 1996).

Under these circumstances, small lot production comes into play as an important element of lean manufacturing that provides

- Decrease in stock levels and related capital turnover.
- Free floor space via stock reduction.
- Increase in productivity and overall equipment efficiency.
- Increase in machine available time even if the number of changeovers increases.
- Increase in safety via simplified changeovers.
- Simplified housekeeping.
- Lower skill requirements via simplification.
- Reduction of the risk of obsolescence due to demand fluctuations.
- Simplified scheduling activities and increasing customer satisfaction.
- Decrease in quality problems arisen from changeover issues.

The biggest obstacle in lot size reduction is the time and cost of changeovers. For changeover time reduction, Dr. Shigeo Shingo introduced SMED (single minute exchange of dies) methodology (Shingo, 1985). The proposal of SMED is mostly based on methodological changes and design changes on the machinery and equipment to simplify the operations (Mileham, Culley, Owen, & McIntosh, 1999).

Shingo revealed that without the application of SMED only 5% of a changeover time is used for mounting the mold, while 50% of the time is spent for trial run and adjustments (Table 4.1). One of the most important reasons of the huge proportion of trial runs is the quality of the activities of remaining 50%, which are not improved and standardized before SMED.

Table 4.1 Steps in changeover (Shingo, 1985)

Steps in Changeover	Proportion of Setup Time Before SMED
Preparation, after-process adjustments, checking of materials and tools	30%
Mounting and removing blades, tools, and parts	5%
Measurements, settings, and calibrations	15%
Trial runs and adjustments	50%

This tree-step methodology starts with questioning all activities of a changeover to define whether they require stopping the machine or not. The activities that require stopping the machine are named internal activities and the others are called external activities. The proposals in this step are ensuring the readiness of people, molds, tools, and equipment in advance, controlling them via checklists, make them ready in front of the machine just before the changeover, and placing the replaced parts back to the storage area after starting the machine.

In step two, internal activities are converted to external activities mostly via design changes and/or modifications. Standardizing the mounting, demounting, dimensioning, centering, securing, expelling and gripping functions, using intermediary jigs and preparing conditions in advance (like pre-heating the injection molds) are the proposed improvements for internal activities.

In the last step of SMED, both external and internal activities are re-evaluated for further improvement. Since molding machines are heavy equipment, one person travels a lot during a changeover. A second operator, who will work in parallel, reduces the demounting and mounting time by half. Use of functional clamps, which provide one motion clamping/de-clamping, has a big advantage over use of nuts and bolts.

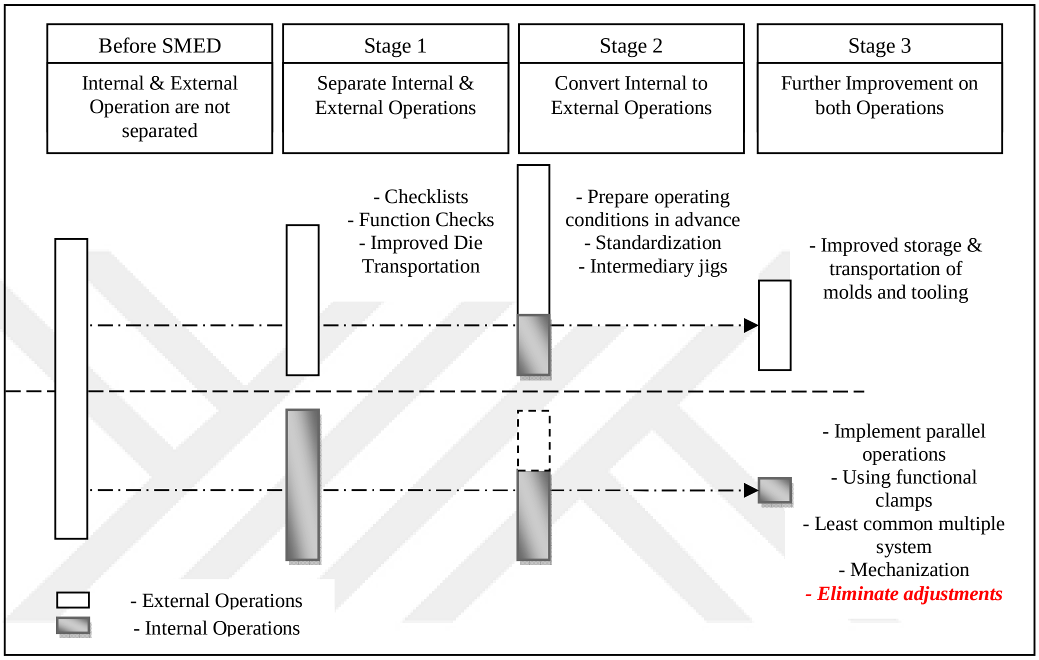
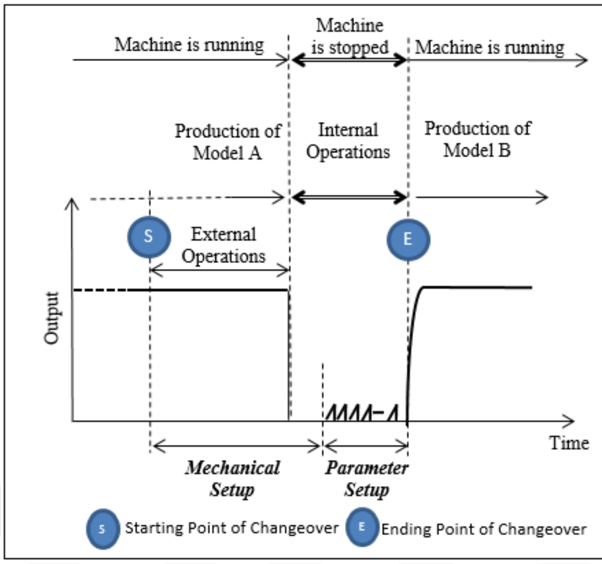


Figure 4.1 SMED conceptual stages and practical techniques (Shingo, 1985)

The changeover process in plastic injection can be analyzed under two sections; mechanical setup and parameter setup (Figure 4.2). Mechanical setup activities start with external operations and end with the first trial injection. Preparation, demounting and mounting the molds, and setting initial parameters are inside of this step and are able to be standardized via SMED.

On the other hand, parameter setup starts with the first trial shot and lasts until having the first quality approved product. This session requires high level of expertise and cannot be standardized. Currently, only setup experts can do this task mostly using trials and errors based on their expertise. Thus, the most critical part of the changeover is totally dependent on personal experience.



Mechanical Setup	Parameter Setup
* Starts with external operations ends with first trial shot.	* Starts with first trial shot ends with the first quality approved product.
* Can be improved (by SMED), standardized and documented.	* Session of trial-error, cannot be standardized.
* No high-level specialization is required.	* High level of expertise on plastic injection is required.
* Machine operators can do especially after SMED applications.	* Setup experts do the parameter setup.

Figure 4.2 Comparison of mechanical setup and parameter setup

SMED proposes three techniques for elimination of adjustments (which holds 50% of total changeover time before SMED) in step three. They are; (1) using a numerical scale and standardizing settings, (2) using standardized centering planes, and (3) using equipment which has multiple functions on it. However, none of these three suggestions is useful for plastic injection molding. Parameter setting in injection molding inevitably changes due to the noise factors. There is no issue of centering the molds onto the machine, and injection molds are not suitable to contain multiple functions on them. For special cases, multi-cavity molds may have dissimilar cavities but in one cycle all the cavities are used for production no matter what the demand ratio is. Closing unneeded cavities temporarily creates problems in injection balancing.

Dr. Shingo claimed that “SMED is a scientific approach that can be applied in any factory to any machine”, however, his claim has been criticized in academic area and also among practitioners because it has been observed that strictly obeying SMED rules in different processes or machines may lead to failures in implementation, and for those cases a tailored SMED approach is required (Guzmán & Salonitis, 2013).

Likewise, a tailored approach is also necessary for plastic injection molding since SMED proposals has no use in eliminating the trial runs and adjustments session in plastic injection mold changeover.

4.2 Understanding the Reasoning of Setup Experts in Changeovers

Changeover parameter setting process starts with recalling the initial parameter set from the memory of the machine. The type and severity of the defect(s) observed in the trial shots give clues about the molding parameter to be adjusted. If the amount of tuning of a parameter from its previous value is underestimated, the severity of the defect reduces but cannot be resolved completely. In the contrary, if there is an overestimation, one or several counter-defect(s) occur.

Briefly, the counter defect is an outcome observed on the product when the adjustment amount of a molding parameter for a defect resolution is more than that it should be. As an example, the short shot is an injection defect that occurs if the molten plastic cannot fill the mold cavity properly. Increasing injection pressure is one of the actions to resolve this defect. However, excessive injection pressure may cause flash, which is another defect that can be described as the squeezed plastic out of the cavities. So, flash and short shot are the counter-defects. In Figure 4.3, the first trial is an example of overestimation and the second one represents an underestimation case.

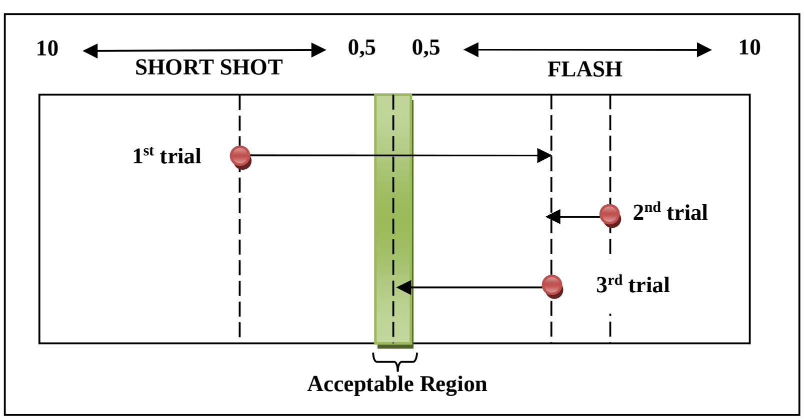


Figure 4.3 Defect resolution process

In the same example, excessively increased injection pressure may also prevent the air inside the cavity from escaping through the ventilation holes and overheats the trapped air that results in burn marks on the product surface. In the cases that there is more than one type of defects that require adjusting different molding parameters, only one parameter is adjusted at a time, that belongs to the defect which has the highest importance. Concurrent adjustment of different parameters makes the current problem hard to understand and creates confusion about the action to be taken.

Experts define the level of inputs and outputs in linguistic forms and connect them with rules. For example, “if there is slight short shot, then increase the injection pressure slightly”. This rule-based reasoning encircles the study space. Even if there is an underestimation or overestimation of the adjustment amount of parameters, the result observed on the product fires the corresponding rule that keeps the decision maker on the path.

Tackling with a problem without an objective function and mostly based on expertise requires dealing with uncertainty, imprecision, partial truth and approximation to reach practical, robust and low cost solution. The techniques that provide such a solution is named as soft computing. In this dissertation two of the popular soft computing techniques; fuzzy inferencing system (FIS) and artificial neural networks (ANN) are employed for the changeover parameter setting problem.

4.3 Overview of Fuzzy Logic

4.3.1 Fuzzy Sets and Membership Functions

The fuzzy set theory was firstly introduced by Lotfi Zadeh (Zadeh, 1965). Unlike classical two-valued Boolean sets, his approach opens the door to defining the set as it is perceived in real life. Zadeh explained how to define the grayness of a color (that is between black and white) mathematically. With the help of fuzzy sets, the logic of human thought can be mimicked since the linguistic variables become usable with the characterization by ambiguity and multiplicity of meaning (Kashyap & Datta, 2015). Zadeh (1965) listed the essential characteristics of fuzzy logic as;

- Exact reasoning is viewed as a limiting case of approximate reasoning.
- Everything is a matter of degree.
- Any logical system can be fuzzified.
- Knowledge is interpreted as a collection of elastic or, equivalently, a fuzzy constraint on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.

In classical set theory, a set S is defined as crisp and for an element $x \in U$, where U is the universe of discourse; we say either $x \in S$ or $x \notin S$. However, in fuzzy theory, S becomes a fuzzy set where x is defined by a membership function showing its membership degree to S by $\mu_S: U \rightarrow [0, 1]$. The pair of this definition in the fuzzy set $(x, \mu_S(x))$ is called as a singleton. If $\mu_S(x) = 0$ then x is called "not included" in the fuzzy set S, if $\mu_S(x) = 1$ then x is called "fully included". These two points are the extremes of the fuzzy set which also represents the crisp set.

Both the degree of truth in fuzzy logic and the probabilities range between 0 and 1. However, fuzzy logic uses the degree as a mathematical model of vagueness while probability is a mathematical model of ignorance. For example, the water inside a bottle is cold or hot with 50% probability. If it is said to be cold, 50% probability of being hot is ignored. Based on Figure 4.4, 26 ºC is 100% hot. However, in fuzzy logic, 26 ºC is (a%) cold and (b%) hot, which is linguistically warm. Thus, fuzzy logic is used to express the temperature of the water in vague form via the degree of membership.

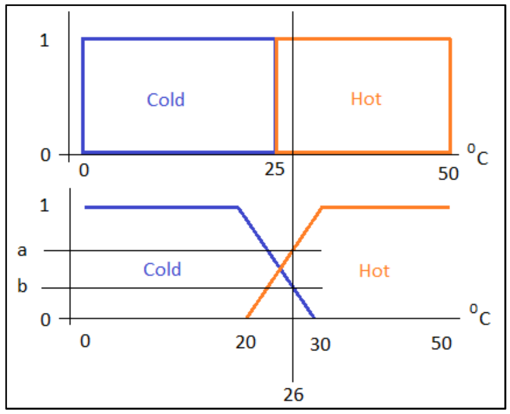
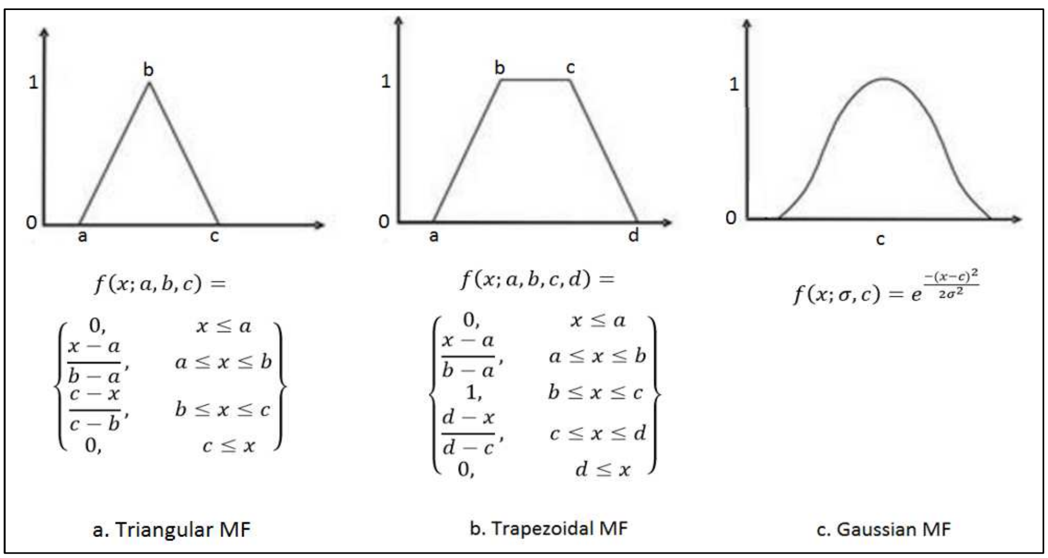


Figure 4.4 The use of fuzzy membership functions

There are several types of membership functions which are mainly derived from piece-wise linear functions, Gaussian distribution function, sigmoid curve and quadratic-cubic polynomial curves. Linear functions are used suitable for simplicity. On the other hand, Gaussian functions have the advantage of being smooth and non-zero at all points. Studies have shown that linear membership functions can provide similar solutions with complex non-linear functions (Delgado, Herrera, Verdegay, & Vila, 1993). Sigmoid and polynomial curves can be used to assess the tuning on the results. In Figure 4.5 the mostly used three membership functions are given with their mathematical representations.



$$f(x;a,b,c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

$$f(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

Figure 4.5 Popular membership functions a) triangular MF b) trapezoidal MF c) Gaussian MF

4.3.2 Fuzzy Operators

The logical operators of crisp sets are re-defined in fuzzy logic. Conventional "and" operator (intersection) is substituted by "min", conventional "or" operator (union) is substituted by "max" and complement operator as in the crisp sets provide the same function for different membership degrees. Graphical representations of "and", "or" and "not" operators are given in Figure 4.6.

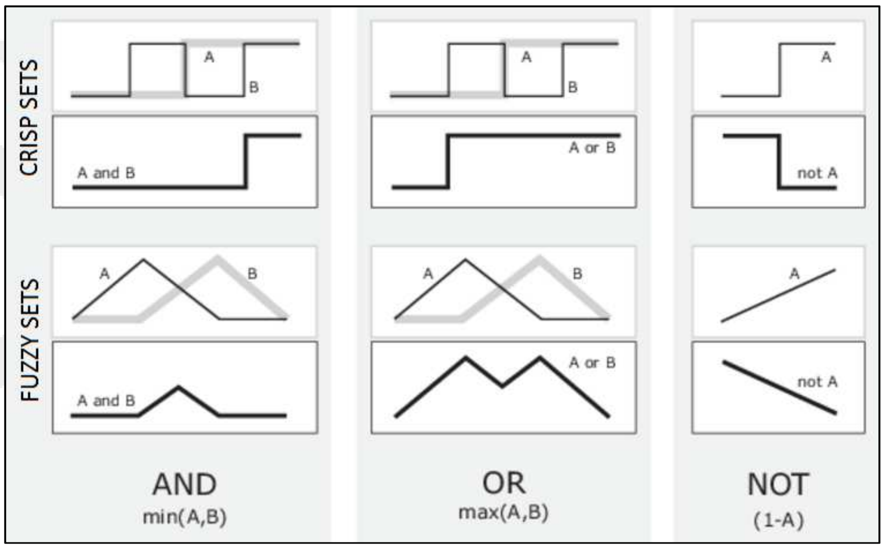


Figure 4.6 Comparison of operators in crisp sets and fuzzy sets (Matlab tutorials, 2017)

The intersection operator as a function T (.,.), which is a part of general class of aggregation operators (also named as t-norms) satisfies the following

- Boundary: $T(0,0) = 0$, $T(a,1) = T(1,a) = a$
- Monotonicity: $T(a,b) \leq T(c,d)$ if a ≤ c and b ≤ d
- Commutativity: $T(a,b) = T(b,a)$
- Associativity: $T(a, T(b,c)) = T(T(a,b),c)$
- T is a continuous function
- Idempotent: $T(a,a) = a$

In fuzzy sets, intersection of two sets is shown in Equation 4.1.

$$\mu_{A \cap B}(x) = min\,(\mu_A(x), \mu_B(x)), \forall\, x \in X \qquad (4.1)$$

The union operator as a function *S* (.,.) is referred to as *T-conorms* or *S-norms* which satisfies the following

- Boundary: $S\,(1,1) = 1$, $S\,(a,0) = S\,(0,a) = a$
- Monotonicity: $S\,(a,b) \le S\,(c,d)$ if $a \le c$ and $b \le d$
- Commutativity: $S\,(a,b) = S\,(b,a)$
- Associativity: $S\,(a, S\,(b,c)) = S\,(S\,(a,b),c)$
- *S* is a continuous function
- Idempotent: $S(a,a) = a$

Union of two sets is shown in Equation 4.2.

$$\mu_{A \cup B}(x) = max\,(\mu_A(x), \mu_B(x)), \forall\, x \in X \qquad (4.2)$$

A truth table in fuzzy logic for union and intersection is shown in Table 4.2.

Table 4.2 Truth table for union and intersection

A	*B*	*T (A,B)*	*S (A,B)*
0	0	0	0
0	1	0	1
1	0	0	1
1	1	1	1

4.3.3 Fuzzy Rules

Fuzzy sets and fuzzy operators are connected via fuzzy rules in an inference system. The fuzzy if-then rule assumes the form “If *x* is *A* then *y* is *B*”, where *A* and *B* are linguistic values defined by fuzzy sets. The “if” part of the rule is called as *antecedent* or *premise* and the “then” part of the rule is called as *consequent* or *conclusion.*

A fuzzy rule may have multiple antecedents and/or multiple consequents e.g., if x_1 is A_1 and x_2 is A_2 then y_1 is B_1 and y_2 is B_2.

4.4 Fuzzy Inference System

A fuzzy inference system (FIS) is used to formulate the mapping from a given input to an output using fuzzy logic. Unlike other soft computing techniques like neural networks, FIS does not require complex models derived from training data but allows building the system based on a rule set provided by the experts. The generic architecture of FIS is shown in Figure 4.7.

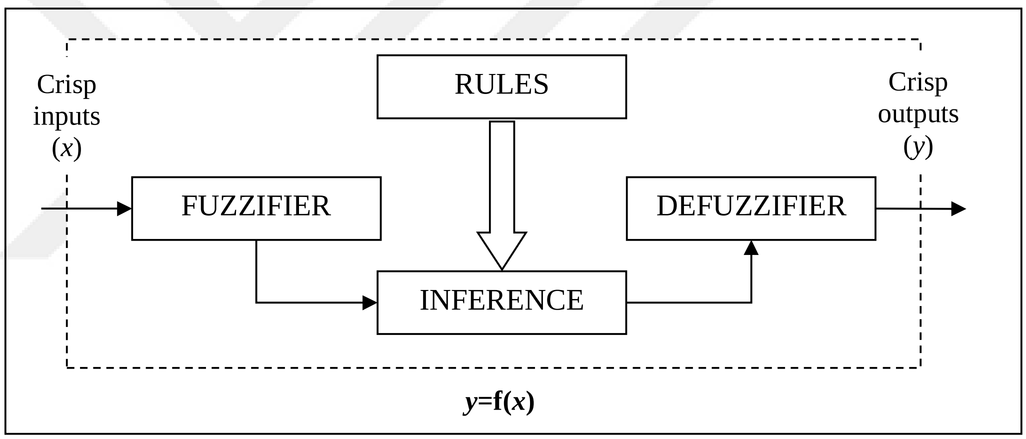


Figure 4.7 The generic architecture of FIS

4.4.4 Mamdani-Type Inference

Mamdani-type inference is the most popular fuzzy inference technique which has five main steps. The first step is ***"fuzzification"***, wherein crisp inputs are fuzzified by membership functions. In Figure 4.8, the crisp input *x1* corresponds to the membership function A1 and A2 with the degrees of 0.5 and 0.2, respectively.

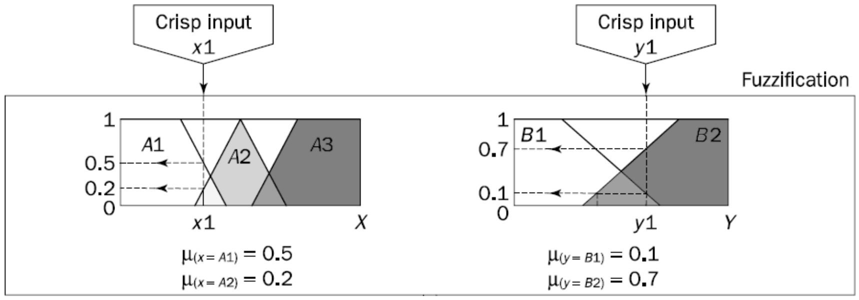


Figure 4.8 Fuzzification (Michael, 2005)

The second step is the ***"application of fuzzy operators"*** used if the antecedent of a given rule has more than one part (Figure 4.9). Multiple values of membership functions (MF) entering into the fuzzy operator are converted into a single output. To evaluate the conjunction of the rule antecedents, "and" operator is used via intersection operation of "min" (Equation 4.1) or "prod" (Equation 4.3).

$$\mu_{A \cap B}(x) = prod(\mu_A(x), \mu_B(x)) = \mu_A(x) * \mu_B(x)) \qquad (4.3)$$

In order to evaluate the disjunction, "or" operator is used via union operation of "max" (Equation 4.2) or "probor" (Equation 4.4).

$$\mu_{A \cup B}(x) = probor(\mu_A(x), \mu_B(x)) = \mu_A(x) + \mu_B(x) - \mu_A(x) * \mu_B(x) \qquad (4.4)$$

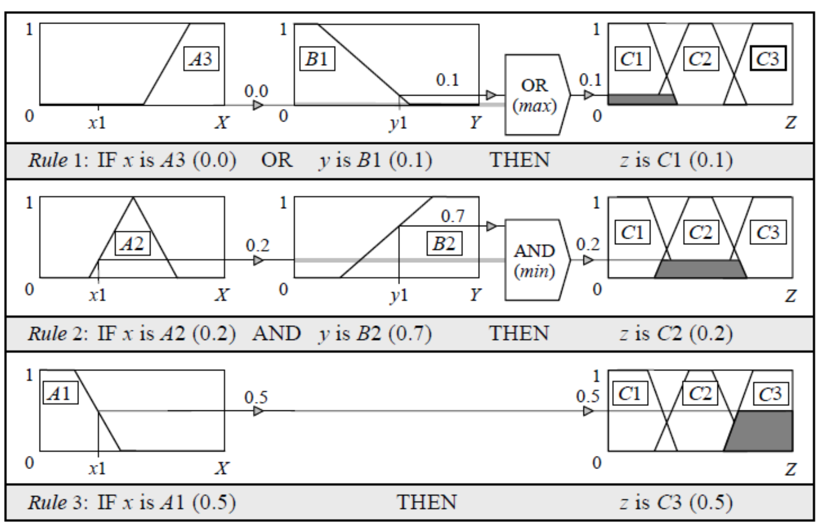


Figure 4.9 Application of fuzzy operators (Michael, 2005)

The third step is ***"application of implication method"*** to deduct a consequence from the antecedent(s). The result of fuzzy operator is re-shaped using implication method for each rule. The most popular method for implication is named as "clipping", wherein the consequent membership function is cut at the level of the antecedent truth (Figure 4.10a). Although during clipping some of the information is lost due the sliced membership function, this method is less complex and computationally efficient. In order to prevent information loss in clipping, "scaling" method offers the adjustment of the original membership function of the rule consequent by multiplying all membership degrees by the truth value of the rule antecedent (Figure 4.10b).

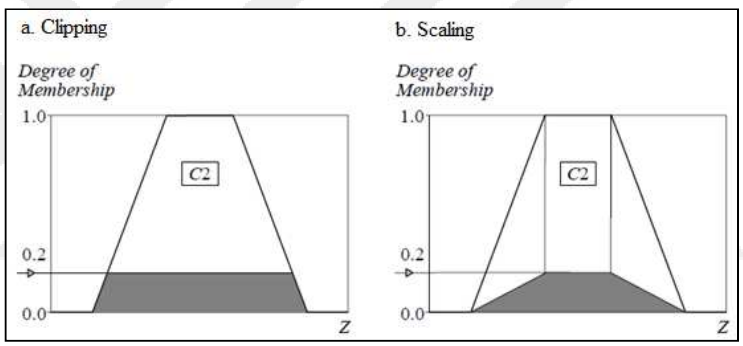


Figure 4.10 a) Clipping b) scaling of membership functions (Michael, 2005)

The fourth step ***"aggregation"*** is the process of combining the results of implication of each rule to define the final decision (Figure 4.11).

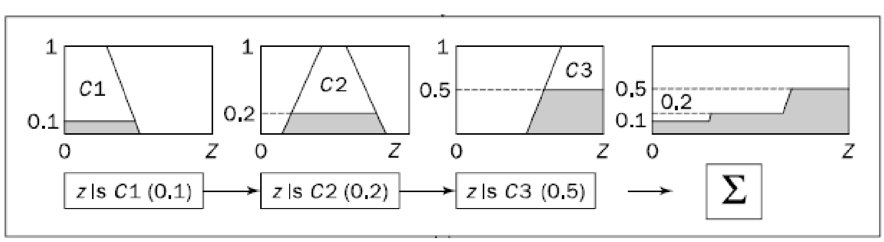


Figure 4.11 Fuzzy aggregation (Michael, 2005)

The last step "***defuzzification"*** is the final step wherein the aggregated fuzzy set is used to find the crisp output (Figure 4.12). Centroid of the area under the output set is the commonly used defuzzification method. Other methods use bisector of the area, and average, largest or smallest of maximum value of the output set. The complete process of Mamdani-type inference is shown in Figure 4.13.

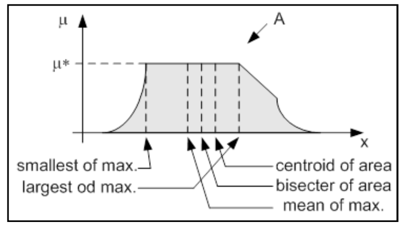


Figure 4.12 Defuzzification (Michael, 2005)

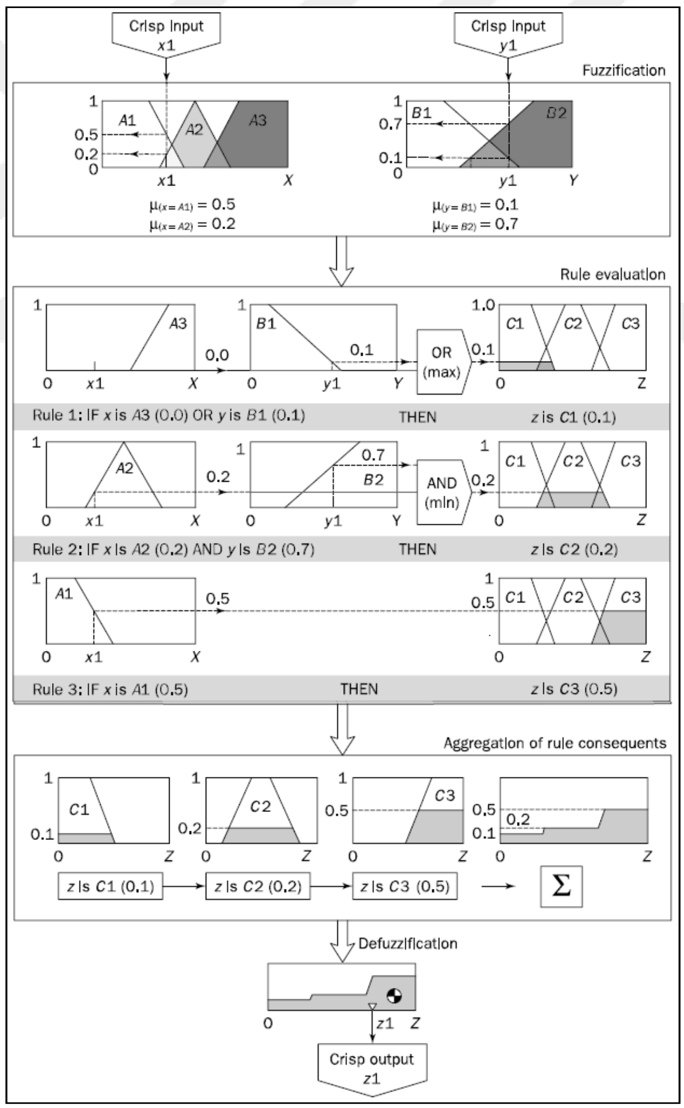


Figure 4.13 The complete process of Mamdani-type inference (Michael, 2005)

4.4.5 Sugeno-Type Fuzzy Inference

The necessity of finding the centroid of a two-dimensional area that is re-shaped continuously by varying functions in defuzzification step of Mamdani process creates inefficiency in computation. To overcome this inefficiency, Sugeno process uses a single spike as the membership function of the rule consequent. In this type of inference, the output of each fuzzy rule is a constant. The complete process of Sugeno-type inference is shown in Figure 4.14.

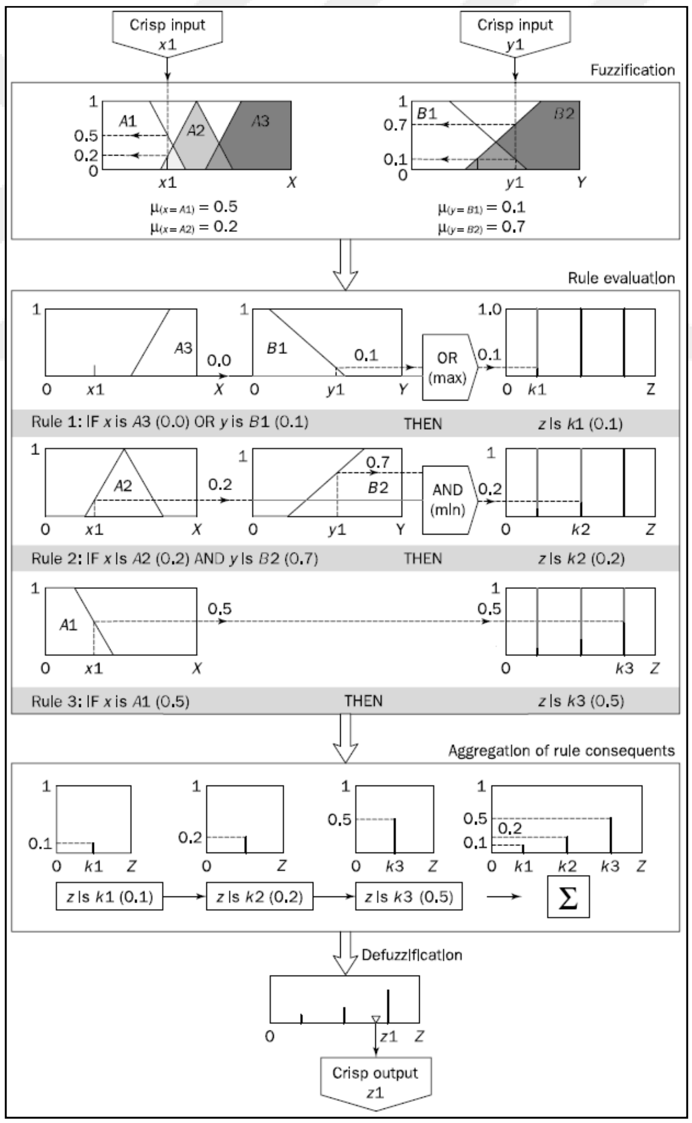


Figure 4.14 The complete process of Sugeno-type inference (Michael, 2005)

The Mamdani method has a wide acceptance in capturing of expert knowledge because of its ability to describe the expertise in more intuitive and more human-like manner. The Sugeno method is more efficient in computation and preferred in optimization and adaptive techniques like controlling systems. In this dissertation, the Mamdani method is used for knowledge capturing in changeover parameter setting.

CHAPTER FIVE

FUZZY INFERENCE SYSTEM FOR CHANGEOVER PARAMETER SETTING

5.1 Systematic Elimination for Fuzzy Inference Application

As explained in Chapter 2, there are many root causes of an injection defect, which can be assigned to five main groups: design issues, resin selection, machine selection, maintenance and management of process parameters. In Table 5.1, one possible root cause for each category is exemplified for nine types of injection defects commonly observed when ABS (acrylonitrile butadiene styrene) type resin is used.

Based on the root cause, the actions to be taken differ. In order to narrow the content of the proposed fuzzy inference system, it is assumed that a structured mold validation process is followed so that there is no major design issue, and resin and machine selection is compatible with the intended manufacturability and cost. It is also assumed that required housekeeping is carried out and the periodic maintenance of the machine, mold and equipment is properly followed up. These assumptions are also prerequisites for mass production. In defining the fuzzy rules, the experts are asked to define the actions for the defects under these assumptions.

In the cases that there is more than one defect, the experts take one action at a time to resolve the most critical defect. Therefore, the questionnaire contains the cases of “one type of defect in a trial” and “two types of defects in a trial”.

In order to systematically eliminate the possible cases thus eliminating the corresponding fuzzy rules, a table is prepared together with the experts for the defect couples that cannot be observed at the same time. For example, if a short shot is observed, it means the cavity of the mold cannot be filled properly and it is not possible to observe flash (squeezed melt) unless there is an exceptional issue.

Therefore, the rules regarding “flash-short shot” couple can be removed from the questionnaire.

Table 5.1 Root causes of injection defects observed in use of ABS type resin

Defect	Short Description	Design Issue	Resin Selection	Machine Selection	Maintenance / Housekeeping	Parameter Management
Short Shot	Incomplete filling	Sharp corners	High viscosity	Insufficient shot volume	Non-return valve leaking	Low temperature
Flash	Squeezed plastic	Too deep venting	High flow rate	Insufficient clamping force	Unclean mold surface	High pressure
Burn Marks	Overheated surface	Wrong gate positioning	High flow rate	Narrow nozzle	Contamination in venting holes	High injection speed
Charring	Splash-like appearance	Poor runner design	High flow rate	Narrow nozzle	Moisture in resin	High temperature
Ejector Marks	Depression marks	Small ejector pin surface	-	-	Ejection system malfunction	High backpressure
Jetting	Wavy folds on surface	Narrow gate	High flow rate	Wrong screw selection	Contamination in gate	High injection speed
Weld Lines	Knitted melt streams	Sharp corners	High viscosity	Low shot volume capacity	Injection system malfunction	Low injection speed
Sink Mark	Depression marks	Uneven part thickness	-	Low shot volume capacity	Back pressure malfunction	Low back pressure
Matt Surface	Gloss difference	Uneven part thickness	High viscosity	Low inj. pressure capacity	Unsteady cooling	Low injection pressure

If the defect(s) cannot be resolved via parameter fine tuning, that means the root cause may be a design issue, or resin, machine selection or maintenance issue. In practice, in such cases, setup experts escalate the problem to shift supervisors and the production plan is revised. Likewise, in the cases that the proposals of the fuzzy inference system are incapable of solving the problem, machine operators will escalate the issue to setup experts to validate that the problem requires troubleshooting rather than parameter setting.

5.2 Implementation of the Fuzzy Inference System in Changeovers

The proposed fuzzy inference system is implemented in a plant manufacturing wiring device products (wall outlets and switches). Plastic parts of these products are produced in plastic injection unit that has 20 injection machines with 350 active molds. There are two main product classes for injection; cosmetic parts and inner body plastics. Cosmetic parts constitute around 70% of the total injection workload (Figure 5.1a) and 80% of the total raw material consumption (Figure 5.1b). There are seven types of raw materials, and ABS is the one with the highest ratio of usage (60%, Figure 5.1c). 55% of the total number of molds in the mold shop is used for ABS cosmetic parts (Figure 5.1d). From these figures "all cosmetic parts made of ABS, regardless of their geometry" is chosen as the scope of the study. The project team has three setup experts, production manager, production supervisor, mold shop supervisor and two machine operators.

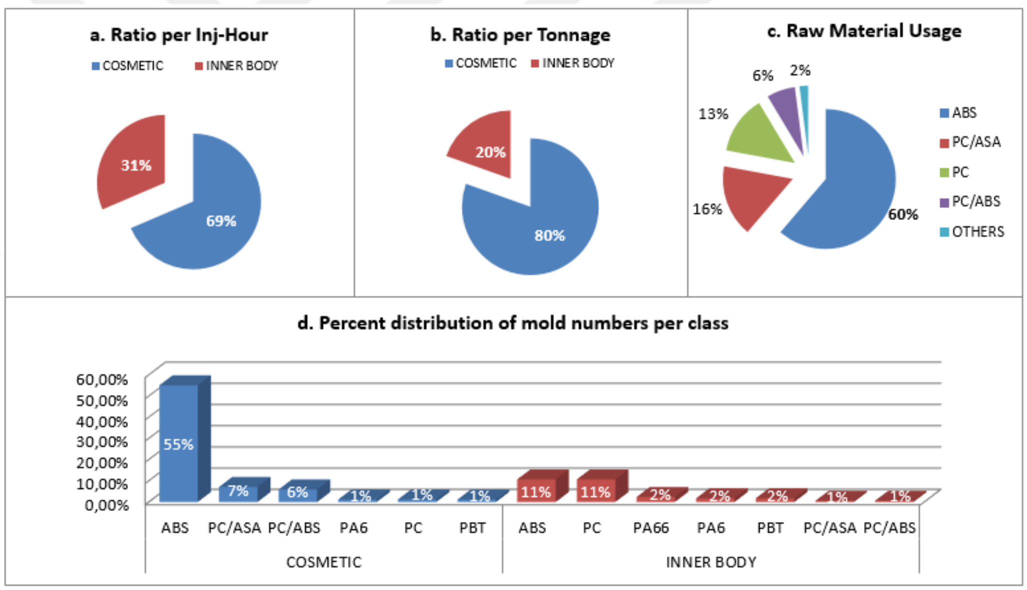


Figure 5.1 General information for scope definition **a)** Ratio per injection-hour **b)** Ratio per tonnage **c)** Raw material usage **d)** Percent distribution of mold numbers per class

Nine types of defects (the same as in the previous section), which are encountered in manufacturing of ABS-made cosmetic parts, are reported to be resolved by five process parameters during a changeover. The severities of the defects are defined in four levels as "ignorable, slight, medium and serious" with an interval of [0, 10]. A rectangular membership function is used for "ignorable" level and a triangular membership function is used for the remaining severity levels. Membership function parameters for inputs (severity of defects) are given in Table 5.2.

Table 5.2 Fuzzy membership function parameters for defect severity

Defect Severity	Ignore	Slight	Medium	Serious
Flash	[0 0 0.5 0.5]	[0.5 0.5 3.5]	[3.5 3.5 10]	[3.5 10 10]
Short Shot	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Burn Mark	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Charring Streaks	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Ejector Mark	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Jetting	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Weld Lines	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Sink Mark	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]
Matt Surface	[0 0 0.5 0.5]	[0.5 0.5 5]	[1 5 9]	[5 10 10]

The tuning amount of process parameters are defined in six levels as "negative small, negative medium, negative high, positive small, positive medium and positive high" with an interval of [-15, 15] unit for injection pressure and [-10, 10] unit for remaining parameters. A triangular membership function is used also for defining the tuning amount. Membership parameters of outputs (process parameter tuning amount) are given in Table 5.3.

Table 5.3 Fuzzy membership function parameters for process parameters

Parameter Tuning Level	Neg High	Neg Medium	Neg Small	Pos Small	Pos Medium	Pos High
Nozzle Temp. (°C)	[-10 -10 -5]	[-7 -5 -3]	[-5 0 0]	[0 0 5]	[3 5 7]	[5 10 10]
Mold Temp. (°C)	[-10 -10 -5]	[-7 -5 -3]	[-5 0 0]	[0 0 5]	[3 5 7]	[5 10 10]
Inj. Speed (mm/sec)	[-10 -10 -5]	[-7 -5 -3]	[-5 0 0]	[0 0 5]	[3 5 7]	[5 10 10]
Hold Press. (bar)	[-10 -10 -5]	[-7 -5 -3]	[-5 0 0]	[0 0 5]	[3 5 7]	[5 10 10]
Inj. Press. (bar)	[-15 -15 -7.5]	[-11 -9 -4]	[-7.5 0 0]	[0 0 7.5]	[4 9 11]	[7.5 15 15]

Mamdani type FIS is preferred in this study due to its widespread acceptance and the ability to be used for nonlinear output functions. In order to decrease the number of rules without losing the domain knowledge, the table of possible defect couples (PC) and counter defect couples (CD) is created with the experts (Table 5.4). The rules regarding the couples that cannot be observed at the same time are removed from the case list. The counter defects keep the decision maker inside the feasible parameter space. The reason is that, FIS does not have generalization capability by itself. Therefore, all of the combinations at different severity levels for single and remaining double defects are added into the fuzzy rule set. Thus, the inference system encircles the search space with 180 fuzzy rules given in Table 5.5 to keep the machine operator on track during changeover parameter setting. The "and" operator is used to build the rules regarding defect couples, e.g., if flash "and" burn then. The "min" method for implication and "max" method for aggregation is chosen by default for the Mamdani type. For defuzzification, the widely accepted "centroid" method is used.

Table 5.4 Properties of defect couples (CD: Counter Defects, PC: Possible Couple)

Properties of Defect Couples	Flash	Short Shot	Burn Mark	Char. Streaks	Ejector Mark	Jetting	Weld Line	Sink Mark	Matt Surface
Flash		CD	PC	PC	PC			CD	PC
Short Shot	CD		CD	CD	CD	PC			
Burn Mark	PC	CD		PC	PC	CD	CD	CD	CD
Charring Streaks	PC	CD	PC		PC	CD		PC	PC
Ejector Mark	PC	CD	PC	PC				CD	PC
Jetting		PC	CD	CD			PC	PC	PC
Weld Line			CD			PC		PC	PC
Sink Mark	CD		CD	PC	CD	PC	PC		PC
Matt Surface	PC		CD	PC	PC	PC	PC	PC	

Table 5.5 Fuzzy rules for parameter setting of ABS made injection products

No	Rule	No	Rule
1	If Flash is Slight then InjSpeed is NegSmall	**91**	If Charring is Slight and Ejector is Slight then InjSpeed is NegSmall
2	If Flash is Medium then InjPress is NegSmall	**92**	If Charring is Slight and Ejector is Medium then InjSpeed is NegSmall
3	If Flash is Serious then InjPress is NegMed	**93**	If Charring is Slight and Ejector is Serious then InjSpeed is NegSmall
4	If ShortShot is Slight then InjPress is PosSmall	**94**	If Charring is Medium and Ejector is Slight then InjSpeed is NegMed
5	If ShortShot is Medium then InjPress is PosMed	**95**	If Charring is Medium and Ejector is Medium then InjSpeed is NegMed
6	If ShortShot is Serious then InjPress is PosHigh	**96**	If Charring is Medium and Ejector is Serious then InjSpeed is NegMed
7	If Burn is Slight then NozzleTemp is NegSmall	**97**	If Charring is Serious and Ejector is Slight then InjSpeed is NegHigh
8	If Burn is Medium then NozzleTemp is NegMed	**98**	If Charring is Serious and Ejector is Medium then InjSpeed is NegHigh
9	If Burn is Serious then NozzleTemp is NegHigh	**99**	If Charring is Serious and Ejector is Serious then InjSpeed is NegHigh
10	If Charring is Slight then InjSpeed is NegSmall	**100**	If Charring is Slight and Sink is Slight then InjSpeed is NegSmall
11	If Charring is Medium then InjSpeed is NegMed	**101**	If Charring is Slight and Sink is Medium then InjSpeed is NegSmall
12	If Charring is Serious then InjSpeed is NegHigh	**102**	If Charring is Slight and Sink is Serious then InjSpeed is NegSmall
13	If Ejector is Slight then InjPress is NegSmall	**103**	If Charring is Medium and Sink is Slight then InjSpeed is NegMed
14	If Ejector is Medium then InjPress is NegMed	**104**	If Charring is Medium and Sink is Medium then InjSpeed is NegMed
15	If Ejector is Serious then InjPress is NegHigh	**105**	If Charring is Medium and Sink is Serious then InjSpeed is NegMed
16	If Jetting is Slight then NozzleTemp is PosSmall	**106**	If Charring is Serious and Sink is Slight then InjSpeed is NegHigh
17	If Jetting is Medium then NozzleTemp is PosMed	**107**	If Charring is Serious and Sink is Medium then InjSpeed is NegHigh
18	If Jetting is Serious then NozzleTemp is PosHigh	**108**	If Charring is Serious and Sink is Serious then InjSpeed is NegHigh
19	If WeldLine is Slight then MoldTemp is PosSmall	**109**	If Charring is Slight and MattSurf is Slight then InjSpeed is NegSmall
20	If WeldLine is Medium then MoldTemp is PosMed	**110**	If Charring is Slight and MattSurf is Medium then InjSpeed is NegSmall
21	If WeldLine is Serious then MoldTemp is PosHigh	**111**	If Charring is Slight and MattSurf is Serious then InjSpeed is NegSmall
22	If Sink is then BackPress is PosSmall	**112**	If Charring is Medium and MattSurf is Slight then InjSpeed is NegMed
23	If Sink is BackPress is PosMed	**113**	If Charring is Medium and MattSurf is Medium then InjSpeed is NegMed
24	If Sink is Serious then BackPress is PosHigh	**114**	If Charring is Medium and MattSurf is Serious then InjSpeed is NegMed
25	If MattSurf is Slight then MoldTemp is PosSmall	**115**	If Charring is Serious and MattSurf is Slight then InjSpeed is NegHigh
26	If MattSurf is Medium then MoldTemp is PosMed	**116**	If Charring is Serious and MattSurf is Medium then InjSpeed is NegHigh
27	If MattSurf is Serious then MoldTemp is PosHigh	**117**	If Charring is Serious and MattSurf is Serious then InjSpeed is NegHigh
28	If Flash is Slight and Burn is Slight then NozzleTemp is NegSmall	**118**	If Ejector is Slight and MattSurf is Slight then InjPress is NegSmall
29	If Flash is Slight and Burn is Medium then NozzleTemp is NegMed	**119**	If Ejector is Slight and MattSurf is Medium then InjPress is NegSmall
30	If Flash is Slight and Burn is Serious then NozzleTemp is NegHigh	**120**	If Ejector is Slight and MattSurf is Serious then InjPress is NegSmall
31	If Flash is Medium and Burn is Slight then InjPress is NegSmall	**121**	If Ejector is Medium and MattSurf is Slight then InjPress is NegMed
32	If Flash is Medium and Burn is Medium then InjPress is NegSmall	**122**	If Ejector is Medium and MattSurf is Medium then InjPress is NegMed
33	If Flash is Medium and Burn is Serious then InjPress is NegSmall	**123**	If Ejector is Medium and MattSurf is Serious then InjPress is NegMed
34	If Flash is Serious and Burn is Slight then InjPress is NegMed	**124**	If Ejector is Serious and MattSurf is Slight then InjPress is NegHigh
35	If Flash is Serious and Burn is Medium then InjPress is NegMed	**125**	If Ejector is Serious and MattSurf is Medium then InjPress is NegHigh
36	If Flash is Serious and Burn is Serious then InjPress is NegMed	**126**	If Ejector is Serious and MattSurf is Serious then InjPress is NegHigh

Table 5.5 continues

No	Rule	No	Rule
37	If Flash is Slight and Charring is Slight then InjSpeed is NegSmall	**127**	If Jetting is Slight and WeldLine is Slight then MoldTemp is PosSmall
38	If Flash is Slight and Charring is Medium then InjSpeed is NegMed	**128**	If Jetting is Slight and WeldLine is Medium then NozzleTemp is PosSmall
39	If Flash is Slight and Charring is Serious then InjSpeed is NegHigh	**129**	If Jetting is Slight and WeldLine is Serious then NozzleTemp is PosMed
40	If Flash is Medium and Charring is Slight then InjPress is NegSmall	**130**	If Jetting is Medium and WeldLine is Slight then NozzleTemp is PosMed
41	If Flash is Medium and Charring is Medium then InjPress is NegSmall	**131**	If Jetting is Medium and WeldLine is Medium then NozzleTemp is PosMed
42	If Flash is Medium and Charring is Serious then InjPress is NegMed	**132**	If Jetting is Medium and WeldLine is Serious then NozzleTemp is PosMed
43	If Flash is Serious and Charring is Slight then InjPress is NegMed	**133**	If Jetting is Serious and WeldLine is Slight then NozzleTemp is PosHigh
44	If Flash is Serious and Charring is Medium then InjPress is NegMed	**134**	If Jetting is Serious and WeldLine is Medium then NozzleTemp is PosHigh
45	If Flash is Serious and Charring is Serious then InjPress is NegMed	**135**	If Jetting is Serious and WeldLine is Serious then NozzleTemp is PosHigh
46	If Flash is Slight and Ejector is Slight then InjPress is NegSmall	**136**	If Jetting is Slight and Sink is Slight then NozzleTemp is PosSmall
47	If Flash is Slight and Ejector is Medium then InjPress is NegSmall	**137**	If Jetting is Slight and Sink is Medium then NozzleTemp is PosSmall
48	If Flash is Slight and Ejector is Serious then InjPress is NegMed	**138**	If Jetting is Slight and Sink is Serious then NozzleTemp is PosSmall
49	If Flash is Medium and Ejector is Slight then InjPress is NegSmall	**139**	If Jetting is Medium and Sink is Slight then NozzleTemp is PosMed
50	If Flash is Medium and Ejector is Medium then InjPress is NegSmall	**140**	If Jetting is Medium and Sink is Medium then NozzleTemp is PosMed
51	If Flash is Medium and Ejector is Serious then InjPress is NegHigh	**141**	If Jetting is Medium and Sink is Serious then NozzleTemp is PosMed
52	If Flash is Serious and Ejector is Slight then InjPress is NegMed	**142**	If Jetting is Serious and Sink is Slight then NozzleTemp is PosHigh
53	If Flash is Serious and Ejector is Medium then InjPress is NegMed	**143**	If Jetting is Serious and Sink is Medium then NozzleTemp is PosHigh
54	If Flash is Serious and Ejector is Serious then InjPress is NegHigh	**144**	If Jetting is Serious and Sink is Serious then NozzleTemp is PosHigh
55	If Flash is Slight and MattSurf is Slight then InjPress is NegSmall	**145**	If Jetting is Slight and MattSurf is Slight then NozzleTemp is PosSmall
56	If Flash is Slight and MattSurf is Medium then InjPress is NegSmall	**146**	If Jetting is Slight and MattSurf is Medium then NozzleTemp is PosSmall
57	If Flash is Slight and MattSurf is Serious then InjPress is NegSmall	**147**	If Jetting is Slight and MattSurf is Serious then NozzleTemp is PosSmall
58	If Flash is Medium and MattSurf is Slight then InjPress is NegSmall	**148**	If Jetting is Medium and MattSurf is Slight then NozzleTemp is PosMed
59	If Flash is Medium and MattSurf is Medium then InjPress is NegSmall	**149**	If Jetting is Medium and MattSurf is Medium then NozzleTemp is PosMed
60	If Flash is Medium and MattSurf is Serious then InjPress is NegSmall	**150**	If Jetting is Medium and MattSurf is Serious then NozzleTemp is PosMed
61	If Flash is Serious and MattSurf is Slight then InjPress is NegMed	**151**	If Jetting is Serious and MattSurf is Slight then NozzleTemp is PosHigh
62	If Flash is Serious and MattSurf is Medium then InjPress is NegMed	**152**	If Jetting is Serious and MattSurf is Medium then NozzleTemp is PosHigh
63	If Flash is Serious and MattSurf is Serious then InjPress is NegMed	**153**	If Jetting is Serious and MattSurf is Serious then NozzleTemp is PosHigh
64	If ShortShot is Slight and Jetting is Slight then InjPress is PosSmall	**154**	If WeldLine is Slight and Sink is Slight then MoldTemp is PosSmall
65	If ShortShot is Slight and Jetting is Medium then InjPress is PosSmall	**155**	If WeldLine is Slight and Sink is Medium then MoldTemp is PosSmall
66	If ShortShot is Slight and Jetting is Serious then InjPress is PosSmall	**156**	If WeldLine is Slight and Sink is Serious then MoldTemp is PosSmall
67	If ShortShot is Medium and Jetting is Slight then InjPress is PosMed	**157**	If WeldLine is Medium and Sink is Slight then MoldTemp is PosMed
68	If ShortShot is Medium and Jetting is Medium then InjPress is PosMed	**158**	If WeldLine is Medium and Sink is Medium then MoldTemp is PosMed
69	If ShortShot is Medium and Jetting is Serious then InjPress is PosMed	**159**	If WeldLine is Medium and Sink is Serious then MoldTemp is PosMed
70	If ShortShot is Serious and Jetting is Slight then InjPress is PosHigh	**160**	If WeldLine is Serious and Sink is Slight then MoldTemp is PosHigh
71	If ShortShot is Serious and Jetting is Medium then InjPress is PosHigh	**161**	If WeldLine is Serious and Sink is Medium then MoldTemp is PosHigh
72	If ShortShot is Serious and Jetting is Serious then InjPress is PosHigh	**162**	If WeldLine is Serious and Sink is Serious then MoldTemp is PosHigh
73	If Burn is Slight and Charring is Slight then NozzleTemp is NegSmall	**163**	If WeldLine is Slight and MattSurf is Slight then MoldTemp is PosSmall
74	If Burn is Slight and Charring is Medium then NozzleTemp is NegSmall	**164**	If WeldLine is Slight and MattSurf is Medium then MoldTemp is PosSmall

Table 5.5 continues

No	Rule	No	Rule
75	If Burn is Slight and Charring is Serious then NozzleTemp is NegSmall	**165**	If WeldLine is Slight and MattSurf is Serious then MoldTemp is PosSmall
76	If Burn is Medium and Charring is Slight then NozzleTemp is NegMed	**166**	If WeldLine is Medium and MattSurf is Slight then MoldTemp is PosMed
77	If Burn is Medium and Charring is Medium then NozzleTemp is NegMed	**167**	If WeldLine is Medium and MattSurf is Medium then MoldTemp is PosMed
78	If Burn is Medium and Charring is Serious then NozzleTemp is NegMed	**168**	If WeldLine is Medium and MattSurf is Serious then MoldTemp is PosMed
79	If Burn is Serious and Charring is Slight then NozzleTemp is NegHigh	**169**	If WeldLine is Serious and MattSurf is Slight then MoldTemp is PosHigh
80	If Burn is Serious and Charring is Medium then NozzleTemp is NegHigh	**170**	If WeldLine is Serious and MattSurf is Medium then MoldTemp is PosHigh
81	If Burn is Serious and Charring is Serious then NozzleTemp is NegHigh	**171**	If WeldLine is Serious and MattSurf is Serious then MoldTemp is PosHigh
82	If Burn is Slight and Ejector is Slight then NozzleTemp is NegSmall	**172**	If Sink is Slight and MattSurf is Slight then BackPress is PosSmall
83	If Burn is Slight and Ejector is Medium then NozzleTemp is NegSmall	**173**	If Sink is Slight and MattSurf is Medium then BackPress is PosSmall
84	If Burn is Slight and Ejector is Serious then NozzleTemp is NegSmall	**174**	If Sink is Slight and MattSurf is Serious then BackPress is PosSmall
85	If Burn is Medium and Ejector is Slight then NozzleTemp is NegMed	**175**	If Sink is Medium and MattSurf is Slight then BackPress is PosMed
86	If Burn is Medium and Ejector is Medium then NozzleTemp is NegMed	**176**	If Sink is Medium and MattSurf is Medium then BackPress is PosMed
87	If Burn is Medium and Ejector is Serious then NozzleTemp is NegMed	**177**	If Sink is Medium and MattSurf is Serious then BackPress is PosMed
88	If Burn is Serious and Ejector is Slight then NozzleTemp is NegHigh	**178**	If Sink is Serious and MattSurf is Slight then BackPress is PosHigh
89	If Burn is Serious and Ejector is Medium then NozzleTemp is NegHigh	**179**	If Sink is Serious and MattSurf is Medium then BackPress is PosHigh
90	If Burn is Serious and Ejector is Serious then NozzleTemp is NegHigh	**180**	If Sink is Serious and MattSurf is Serious then BackPress is PosHigh

For the fuzzy inference application, “qtFuzzyLite-4.0” software is used. This software can be easily installed and used in real production plants. In Figure 5.2, the case of facing “short shot and jetting at the same injection trial” is simulated in this software. Rule number 67, 68, 70 and 71 are fired and the system proposes to increase injection pressure by approximately 11 bars.

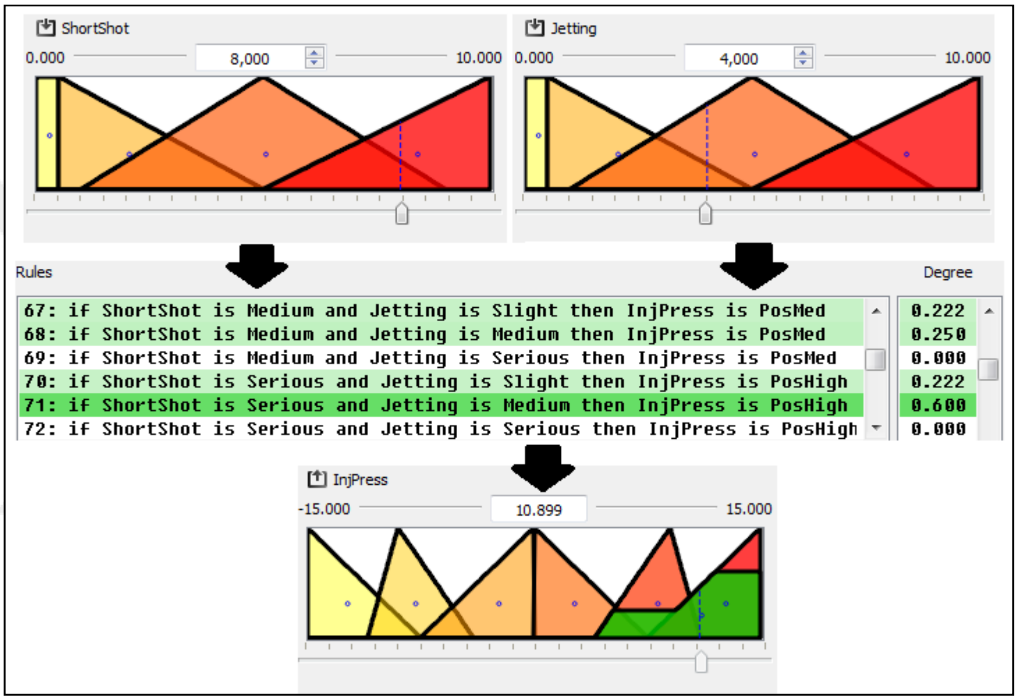


Figure 5.2 Double defect simulation in qtfuzzylite

Before using the FIS in real molding trials, a fitness test is applied. In FIS, each fuzzy rule represents a possible case. For each of the 180 cases, the amount of tuning defined by the expert and the amount of tuning computed by the proposed fuzzy inference system are depicted in Figure 5.3 and compared using Pearson’s R (see Table 5.6). The results confirm that the desired fit is achieved.

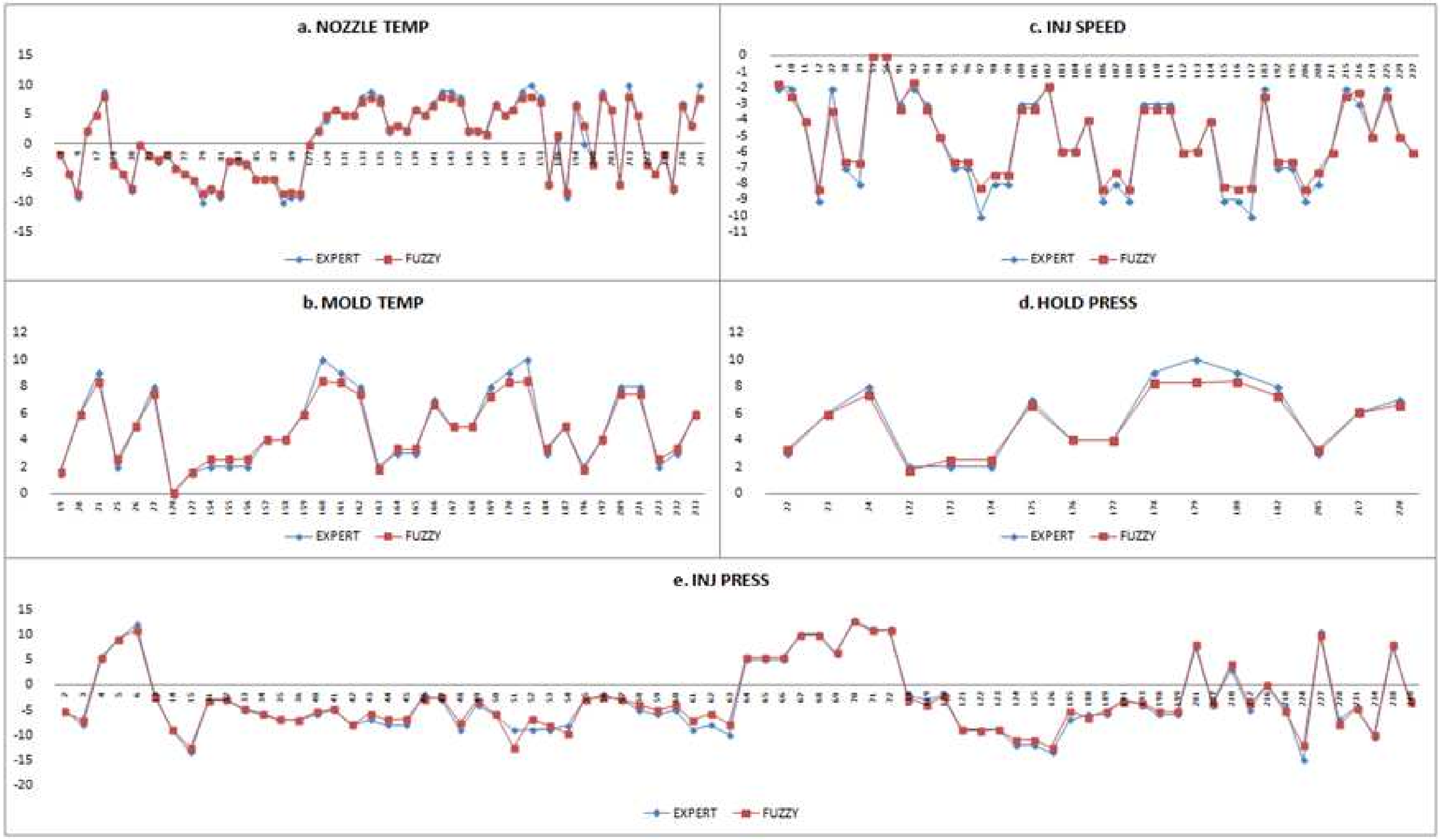


Figure 5.3 Expert vs fuzzy responses for each case **a)** Nozzle temperature, **b)** Mold temperature, **c)** Injection speed, **d)** Hold pressure, **e)** Injection pressure

Table 5.6 Fitness statistics between the responses of expert and FIS

Corr. (Expert vs. Fuzzy)	Pearson's R	R^2
Δ (Nozzle Temp. °C)	0.9948	98.97%
Δ (Mold Temp. °C)	0.9932	98.65%
Δ (Inj. Speed mm/sec)	0.9871	97.43%
Δ (Hold Press. bar)	0.9925	98.51%
Δ (Inj. Press. bar)	0.9907	98.15%

5.3 Results of Real Molding Trials Using FIS

The fuzzy inference system is tested on ABS-made parts with different geometries. Trials are carried out after recalling the initial parameter settings from the database for each part. The results show that the proposed system can mimic the experts successfully. The results and actions for five different changeover sessions are given in Table 5.7.

Table 5.7 Implementation of FIS in five changeover (C/O) sessions

C/O No	Trial No	Defect Type 1	Severity of Defect 1 (0-10)	Defect Type 2	Severity of Defect 2 (0-10)	Proposal of FIS	Result
1	1	Weld Line	5	-	-	Increase mold temperature by 5 °C	Slight Burn Mark
	2	Burn Mark	2	-	-	Decrease nozzle temperature by 3 °C	OK
2	1	Sink Mark	3	-	-	Increase hold pressure by 3.5 bar	OK
3	1	Burn Mark	6	Charring Streaks	2	Decrease nozzle temperature by 6 °C	Slight Weld Line
	2	Weld Line	1	-	-	Increase mold temperature by 1.5 °C	OK
4	1	Jetting	4	-	-	Increase nozzle temperature by 4 °C	OK
5	1	Short Shot	6	-	-	Increase injection pressure by 9 bar	Slight Sink Mark
	2	Sink Mark	2	-	-	Increase hold pressure by 2.5 bar	OK

In the last changeover session, a short shot is observed at the end of the first trial. Severity of the short shot is graded 6 over 10 and the grading is entered into the FIS. The proposal of FIS is to increase the injection pressure by 9 bars in order to fill the cavity. After the implementation of the proposal, a slight sink mark is observed on the part graded by 2 over 10. For resolution of slight sink mark, FIS proposes to increase hold pressure by 2.5 bars and the defect-free product is reached. Product visuals for each step of this session are given in Figure 5.4.

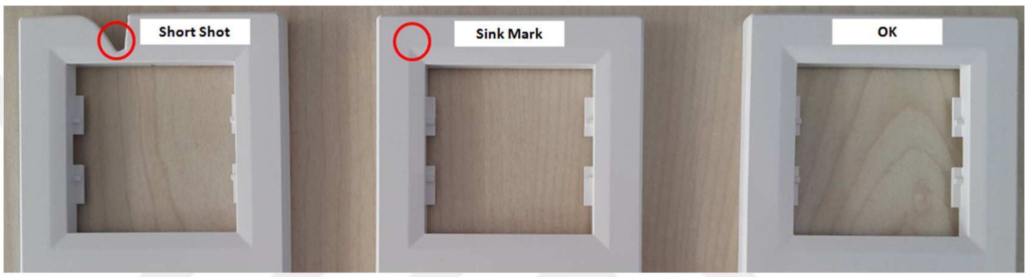


Figure 5.4 Visuals of the results of FIS steps for the fifth changeover session (Personal archive, 2017)

Real molding trials reveal that the proposed fuzzy inference system can generate correct solutions with several trials as experts do.

In this chapter, a fuzzy inference system is applied successfully to capture the domain expertise in changeover parameter setting. In the production plants, there is a strong need for such kind of application since there had been no study specific to changeover parameter setting that generates a solution for all possible injection defects. In the next chapter, the same problem is solved using multi-layer neural networks (MLNN) to make comparison between FIS and MLNN in terms of performance and applicability.

CHAPTER SIX
ARTIFICIAL NEURAL NETWORKS FOR CHANGEOVER PARAMETER SETTING

6.1 Overview of Artificial Neural Networks

Artificial neural networks are composed of simple processing elements called "neurons" that operate in parallel and communicate with each other. The main advantage of neural networks is the ability to use the unknown information hidden in the data. Although there are many types of neural networks, the basic principles are similar (Svozil, Kvasnicka, Pospichal, 1997). Basically, the learning process in neural networks relies on adjustment of input weights based on the comparison of calculated outputs and targeted outputs (Figure 6.1).

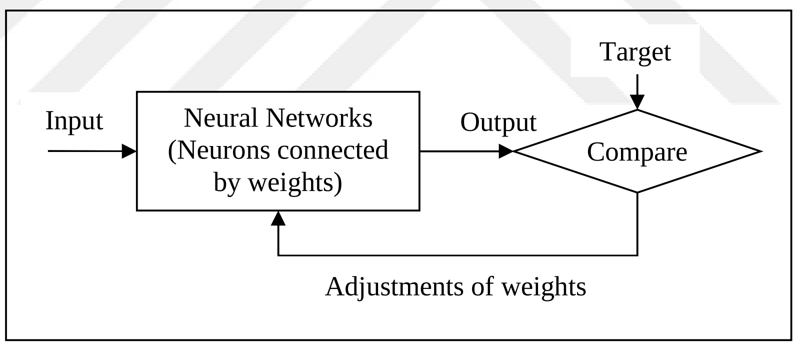


Figure 6.1 The basic learning process in neural networks

6.1.1 Single Layer Neural Networks (SLNN)

In a single layer neural network as is Figure 6.2, inputs (a_1, a_2,…, a_n) are multiplied by their own associated weights (w_1,w_2,…,w_n) and these weighted values are summed to form a pre-activation function (z). The bias (b) with input value +1 is added to the pre-activation function. A non-linear activation function $g(z)$ is used to transform the pre-activation value to an output value (a_{out}).

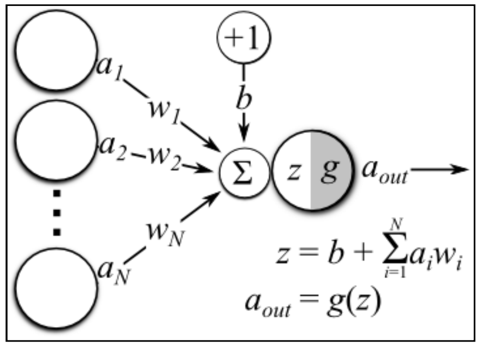


Figure 6.2 Single layer neural network (Theclevermachine, 2007)

The activation function is used to limit the output signal to a finite value. The widely used three activation functions are given in Figure 6.3. The key property of the activation functions is that they are all smooth and differentiable.

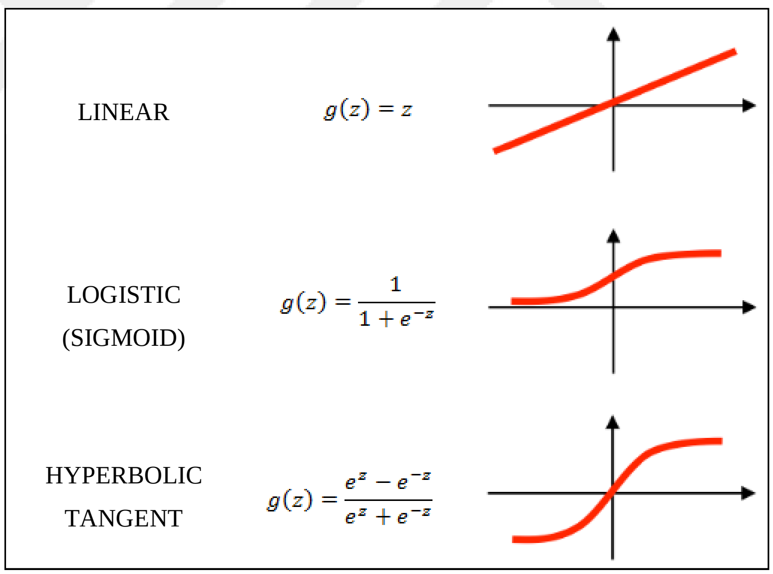


Figure 6.3 Main activation functions

6.1.2 Multi-Layer Neural Networks (MLNN)

Multi-layer neural networks are formed by adding single layer networks between inputs and output. These intermediary single layers constitute the “hidden layer”. The reason of calling intermediary layers as hidden is because of the fact that the inputs and outputs are not processed directly by this layer. In Figure 6.4, a two-layer neural network is depicted. Although bias inputs are used in MLNN, for simplicity of the representation, biases are not shown in the figure.

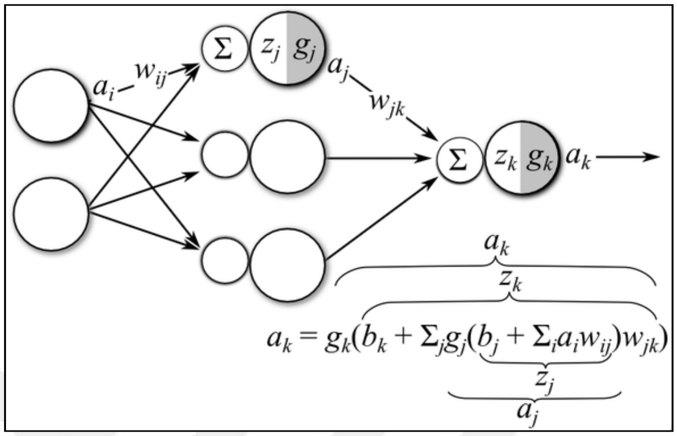


Figure 6.4 Multi-layer neural networks (Theclevermachine, 2007)

The notation in Figure 6.4 is as follows

a_i: *i*th input

w_{ij}: weight between *i*th input and *j*th neuron in the hidden layer

b_j: bias for the *j*th neuron in the hidden layer

z_j: summation function of *j*th neuron in the hidden layer

g_j: activation function of *j*th neuron in the hidden layer

a_j: output of the *j*th neuron in the hidden layer and input to the output neuron

w_{jk}: weight between *j*th neuron in the hidden layer and output neuron

b_k: bias for the output neuron

z_k: summation function of the output neuron

g_k: activation function of the output neuron

a_k: output value of the net

t_k: target value of the net

The output of the two-layer neural network is computed with the same logic as in single-layer. As the additional step, the outputs from each neuron in the hidden layer is multiplied by their associated weights and summed to form the pre-activation function of the output neuron ($z(k)$). Again via using the activation function ($g(k)$), the output value is computed. For non-linear regression problems, non-linear activation function in the hidden layer and linear activation function in the output layer is preferred.

6.1.3 Training Neural Networks

The performance of a neural network is measured based on the error statistics. The most popular error functions (also referred as loss functions or cost functions) use squared difference between the target output and the calculated output. The aim of training the network is to adjust the weights to minimize the error function. Different values of weights in each layer result in an error value which eventually forms a surface in parameter space. Formulation of SSE (sum of square error) is given in Equation 6.1.

$$E = \frac{1}{2}(output - target)^2 \tag{6.1}$$

The output value is calculated as in Equation 6.2 by a single layer network with logistic sigmoid activation function.

$$a_{out} = g_{logistic}(a_0 w_1) \tag{6.2}$$

If the range for weights (w_1) is set as [-10, 10] to train this network for identity function for value 1 (the input value is 1 and expected output is 1), the results of error^2 for each weight forms a 2D error graph (Figure 6.5).

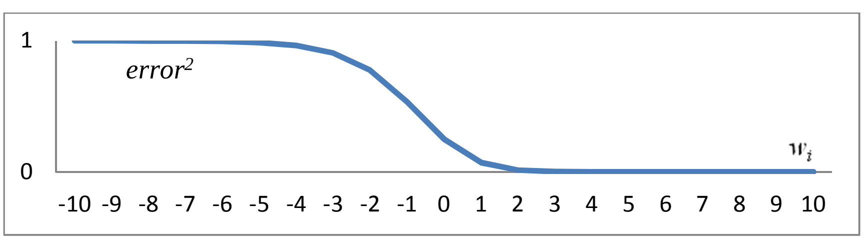


Figure 6.5 Error^2 graph for single-layer neural network

If the same training is applied to two-layer network, then the output would be calculated as in Equation 6.3.

$$a_{out} = g_{logistic}(g_{logistic}(a_o w_1) w_2) \tag{6.3}$$

Again by setting the range of weights as [-10, 10] for both first layer and the second layer, error^2 would form a 3D non-linear surface as in Figure 6.6.

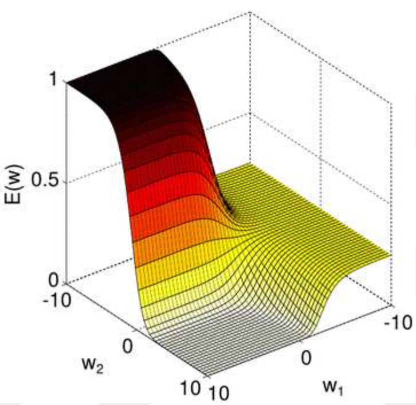


Figure 6.6 Error^2 graph for two-layer neural network (Theclevermachine, 2007)

As the number of layers increase, the error surface gets more complex. The weight set that minimizes the network error function is computed using the gradient descent algorithms. This algorithm iteratively calculates the derivative of the error function with respect to each of the model parameters to define the direction in parameter space that decreases the height of the error surface until no better solution is reached.

6.1.4 Backpropagation

Backpropagation is the process of determining the degree of impact of each network parameters (weights) on mis-prediction of the output value and adjusting them based on their impacts to minimize the network error.

As the result of backpropagation, previous values of weights in the second layer and in the first layer are modified as in Equation 6.4 and Equation 6.5, respectively:

$$w_{jk}(t) = w_{jk}(t-1) - \eta\left(\frac{\partial E}{\partial w_{jk}}\right) \tag{6.4}$$

$$w_{ij}(t) = w_{ij}(t-1) - \eta\left(\frac{\partial E}{\partial w_{ij}}\right) \tag{6.5}$$

where η is the learning rate and t is the iteration (epoch) number.

6.1.4.1 Gradients for Weights of Neurons and Biases in Output Layers

The amount of weight correction $\left(\frac{\partial E}{\partial w_{jk}}\right)$ is calculated using gradient of error corresponding to each weight with the steps as in Equation 6.6.

$$\frac{\partial E}{\partial w_{jk}} = \frac{1}{2}\sum\nolimits_{k\in K}(a_k - t_k)^2 = (a_k - t_k)\frac{\partial}{\partial w_{jk}}(a_k - t_k) \tag{6.6}$$

Here, t_k is a target output value, hence its derivative is zero and $a_k = g(z_k)$.

$$\frac{\partial E}{\partial w_{jk}} = (a_k - t_k)\frac{\partial}{\partial w_{jk}}g_k(z_k) = (a_k - t_k)g_k'(z_k)\frac{\partial}{\partial w_{jk}}z_k \tag{6.7}$$

$z_k = b_k + \sum_j g_j(z_j)w_{jk}$. Thus, its partial derivative is $\frac{\partial z_k}{\partial w_{jk}} = g_j(z_j) = a_j$. Then,

$$\frac{\partial E}{\partial w_{jk}} = (a_k - t_k)g_k'(z_k)a_j \tag{6.8}$$

Thus, the adjustment amount of a weight is the multiplication of $(a_k - t_k)g_k'(z_k)$ and the output value of the preceding layer (a_j). Here, $(a_k - t_k)g_k'(z_k)$ is also named as the “error signal” and shown as (δ_k). In the same manner, the correction of output layer bias is computed as in Equation 6.9.

$$\frac{\partial E}{\partial b_k} = (a_k - t_k)g_k'(z_k)1 = \delta_k \tag{6.9}$$

6.1.4.2 Gradients for Weights of Neurons and Biases in Hidden Layers

The amount of weight correction $\left(\frac{\partial E}{\partial w_{ij}}\right)$ is calculated using gradient of error corresponding to each weight with the steps as shown below.

$$\frac{\partial E}{\partial w_{ij}} = \frac{1}{2}\sum\nolimits_{k\in K}(a_k - t_k)^2 = \sum\nolimits_{k\in K}(a_k - t_k)\frac{\partial}{\partial w_{ij}}a_k \tag{6.10}$$

Since $a_k = g_k(z_k)$, the following holds.

$$\frac{\partial E}{\partial w_{ij}} = \sum\nolimits_{k\in K}(a_k - t_k)\frac{\partial}{\partial w_{ij}}g_k(z_k) = \sum\nolimits_{k\in K}(a_k - t_k)g_k'(z_k)\frac{\partial}{\partial w_{ij}}z_k \tag{6.11}$$

In order to compute the partial derivative of z_k for w_{ij};

$$\begin{aligned} z_k = b_k + \sum\nolimits_j a_j w_{jk} = b_k + \sum\nolimits_j g_j(z_j)w_{jk} = b_k \\ + \sum\nolimits_j g_j(b_i + \sum\nolimits_i z_i w_{ij})w_{jk} \end{aligned} \tag{6.12}$$

Therefore,

$$\frac{\partial z_k}{\partial w_{ij}} = \frac{\partial z_k}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}} = \frac{\partial}{\partial a_j}a_j w_{jk}\frac{\partial a_j}{\partial w_{ij}} = w_{jk}\frac{\partial a_j}{\partial w_{ij}} = w_{jk}\frac{\partial g_j(z_j)}{\partial w_{ij}} \tag{6.13}$$

$$= w_{jk}g_j'(z_j)\frac{\partial z_j}{\partial w_{ij}} = w_{jk}g_j'(z_j)\frac{\partial}{\partial w_{ij}}(b_i + \sum\nolimits_i a_i w_{ij}) = w_{jk}\, g_j'(z_j)a_i \tag{6.14}$$

By replacing $\frac{\partial z_k}{\partial w_{ij}}$ in Equation 6.14;

$$\frac{\partial E}{\partial w_{ij}} = \sum\nolimits_{k \in K} (a_k - t_k) g'_k(z_k)\, w_{jk} g'_j(z_j) a_i \tag{6.15}$$

$$= g'_j(z_j) a_i \sum\nolimits_{k \in K} (a_k - t_k) g'_k(z_k)\, w_{jk} \tag{6.16}$$

Thus, the adjustment amount of the weights in the hidden layer is computed as in Equation 6.17.

$$\frac{\partial E}{\partial w_{ij}} = a_i g'_j(z_j) \sum\nolimits_{k \in K} \delta_k w_{jk} \tag{6.17}$$

If the error signal of the hidden layer is shown as $\delta_j = g'_j(z_j) \sum_{k \in K} \delta_k w_{jk}$, then the final representation of adjustment amount can be denoted as follows.

$$\frac{\partial E}{\partial w_{ij}} = \delta_j a_i \tag{6.18}$$

The bias of the hidden layer is given in Equation 6.19.

$$\frac{\partial E}{\partial b_i} = g'_j(z_j) \sum\nolimits_{k \in K} \delta_k w_{jk} = \delta_j \tag{6.19}$$

The complete feed-forward back-propagate process is shown in Figure 6.7.

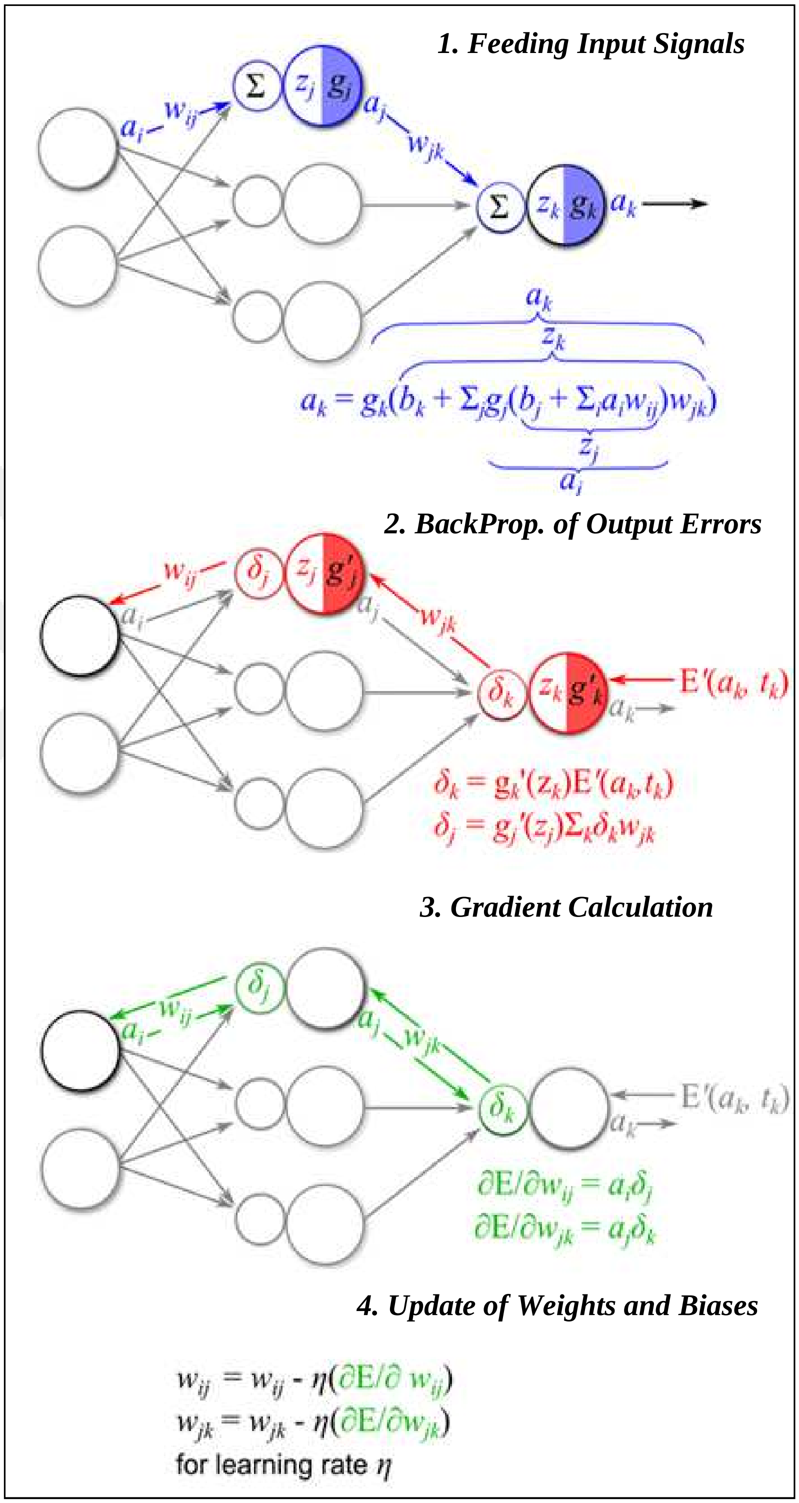


Figure 6.7 Feed forward back propagate mechanism (Theclevermachine, 2007)

6.1.5 Training Algorithms

There are many variations of the training algorithms in neural networks, which can be grouped under three main classes. In this section, only brief explanation is presented for the mostly used ones.

The first one (traingd), "gradient descent algorithms", as described in the previous section, update weights and biases in the direction of the negative gradient of the performance function. In gradient descent algorithms, learning rate defines the step size for learning. If the step size is set too high, then the search function will jump from one point to another and fail to reach a solution. If the step size is set too small, then the computation time will increase. In the modified version of this technique (traingdm), a momentum factor is used to incorporate the result of the previous change in order to prevent the network from getting stuck in to a shallow local minimum.

The second type of the training algorithms is "conjugate gradient algorithms". These algorithms provide faster convergence than in the gradient descent algorithms by performing the search along the conjugate directions. In the scaled conjugate version (trainscg), the step size scaling mechanism is used instead of line search that provides faster convergence with more iteration which requires less computation.

The third type is "quasi-Newton algorithms", which outperforms previous two types in terms of both quality and speed of the solution (Sharma & Venugopalan, 2014). The basic Newton algorithms use second partial derivatives (Hessian matrix) at the current values of weights and biases. However, since the computation of Hessian matrix takes time for MLNN, some other algorithms were developed using the approximate of Hessian matrix. One of the most popular quasi-Newton algorithms, Levenberg-Marquardt (trainlm), uses a Hessian approximation given in Equation 6.20.

$$H \approx J^T J + \mu I \tag{6.20}$$

where J is the Jacobian matrix (first partial derivatives), I is the identity matrix and μ is the combination coefficient and always positive. In trainlm the weights are updated as in Equation 6.21.

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \tag{6.21}$$

Here, if μ is zero, then the equation represents the Newton's method, and when μ is large, the equation becomes gradient descent with a small step size. Since Newton's method is faster and more accurate near a local minimum, μ is decreased after each successful step to reach the minimum point quickly. Only if a tentative step increases the performance function, then μ is increased so the performance function is always reduced iteratively.

Bayesian regularization (trainbr) is another quasi-Newton method which has high generalization capability. In trainbr the loss function is defined as in Equation 6.22.

$$F = \beta E_D + \alpha E_W \tag{6.22}$$

where $E_D$is the sum of squares of network error and E_W is the sum of all network weights. For $\alpha \ll \beta$the network minimizes the loss function without really trying to keep the weights low. For $\alpha \gg \beta$ the network minimize the weights and allows some more error. Thus a large α prevents the network from overfitting and provides better generalization at the cost of larger training error. The optimization in trainbr finds the optimum set for α and β that provides high generalization with still small error.

6.2 Implementation of MLNN for Parameter Setting in Changeovers

The same problem in the previous chapter is solved using MLNN to make comparison between the two soft computing techniques in terms of performance and applicability to production floor. The input-output pairs prepared for performance measurement of fuzzy inference system is used and training data set for the neural network. Additional 61 cases and corresponding expert responses are added for testing and validation purpose. The NN tool of Matlab R2013a is used.

The input data is normalized using, the min-max function. The network has one hidden layer that uses logsig function for activation. The linear activation function is used for outputs. In the trial runs, trainlm and trainbr algorithms are used. The best result is achieved with a network structure of 9-11-5 using trainbr (Figure 6.8). The oscillation of the neural network responses around zero line is filtered by adding a control formula into the background of the user-interface.

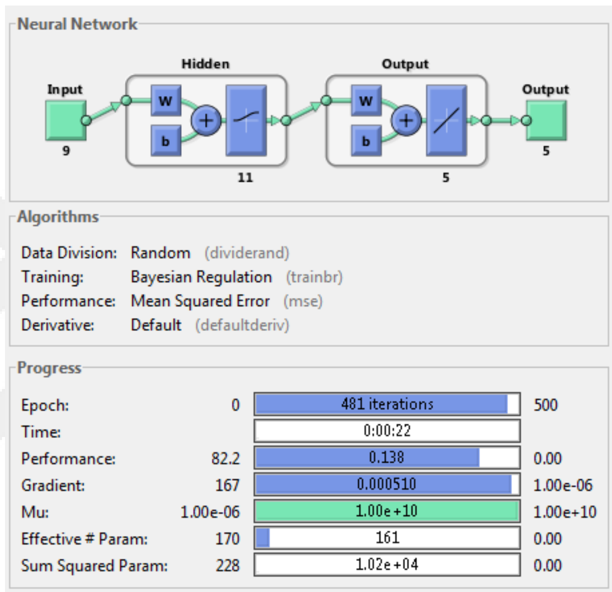


Figure 6.8 Network structure and training statistics

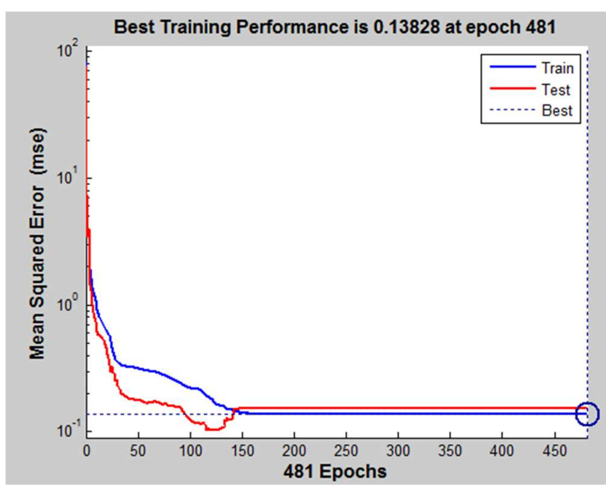


Figure 6.9 Best training performance

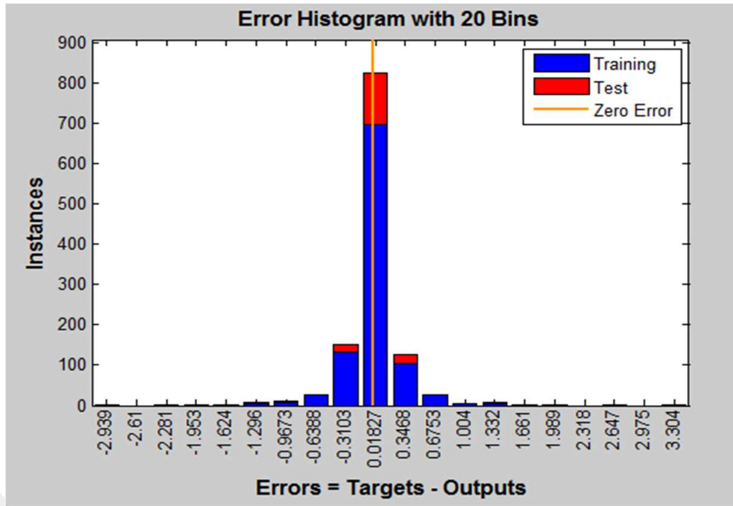


Figure 6.10 Error histogram

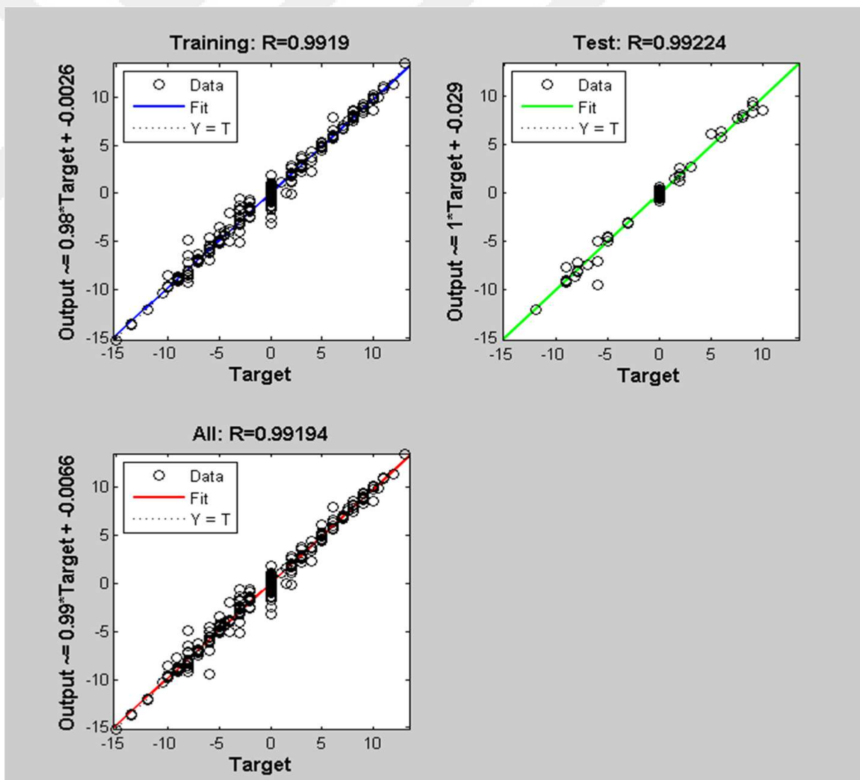


Figure 6.11 R values for training, testing and all

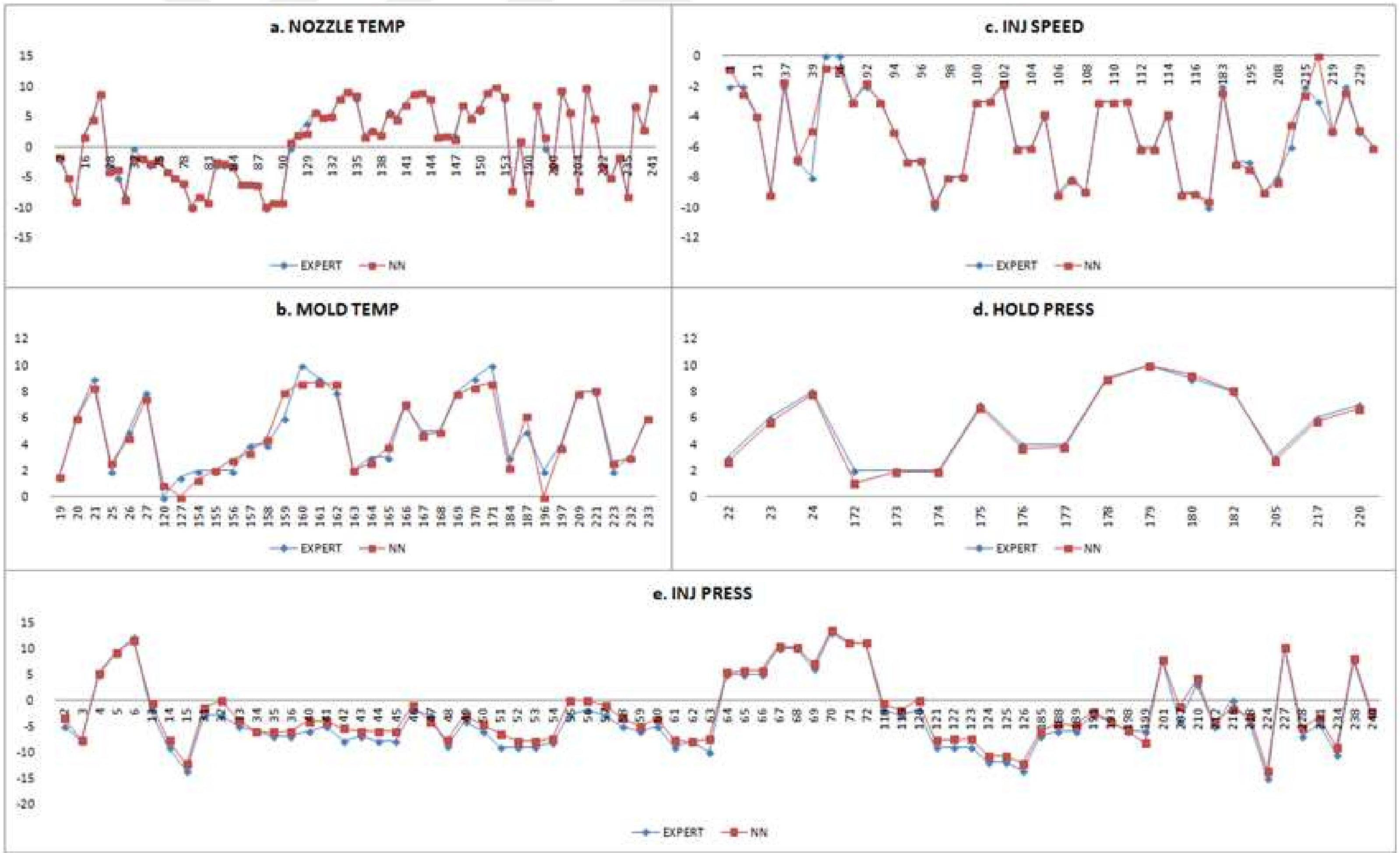


Figure 6.12 Expert vs NN responses for each case **a)** Nozzle temperature, **b)** Mold temperature, **c)** Injection speed, **d)** Hold pressure, **e)** Injection pressure

No overfitting is observed in the training performance graph (Figure 6.9). The error histogram shows that the network errors are accumulated around zero in a very narrow range (Figure 6.10). High R value (relationship between output and target values) for both training and test results proves that the network has a good generalization (Figure 6.11). Pearson's R and R^2 statistics for each output are given in Table 6.1, which are quite satisfactory.

Table 6.1 Fitness statistics between the responses of expert and neural network

OUTPUT	PEARSON'S R	R^2
	EXPERT vs MFNN	EXPERT vs MFNN
Δ (Nozzle Temp. °C)	0.9967	99.35%
Δ (Mold Temp. °C)	0.9617	92.48%
Δ (Inj. Speed mm/sec)	0.9667	93.45%
Δ (Hold Press. bar)	0.9975	99.49%
Δ (Inj. Press. bar)	0.9912	98.26%

There are several cases that MLNN generated alternative solutions. In case 127 and 196 when the part has very slight jetting and weld line with severity 1 and 2 over 10 correspondingly, the expert response is to increase the mold temperature by 2 °C but MLNN responses are to increase the nozzle temperature by 1 °C and 2 °C correspondingly. Similarly, in case 216, the flash with severity 3 over 10 is resolved by the experts by decreasing the injection speed by 3 mm/sec, while MLNN suggests decreasing the injection pressure by 2 bars. These proposals are accepted by the experts as an alternative solution that may require an additional adjustment.

Table 6.2 Weights and biases in the hidden layer

net,iw{1,1}	*input 1*	*input 2*	*input 3*	*input 4*	*input 5*	*input 6*	*input 7*	*input 8*	*input 9*	net,b{1}
neuron 1	-4.93	7.62	-0.27	0.39	0.08	-1.92	-0.09	-0.01	-0.13	3.09
neuron 2	0.00	0.53	0.08	0.11	0.05	14.34	-3.26	-0.80	0.05	14.34
neuron 3	-19.05	1.13	-4.84	-9.96	2.55	1.13	1.13	1.13	-4.75	-1.13
neuron 4	1.10	1.70	4.34	11.20	-0.20	14.12	-3.19	-0.75	0.04	31.52
neuron 5	12.30	1.45	-7.65	-1.61	0.57	-0.22	0.23	0.24	0.13	5.76
neuron 6	3.36	2.60	20.54	-2.42	0.22	-0.90	0.02	0.08	0.07	26.26
neuron 7	4.78	-0.32	1.66	-0.17	0.01	-10.90	-7.45	1.43	0.07	-13.04
neuron 8	1.65	0.00	6.75	12.19	-0.80	-0.09	-0.10	-0.07	0.02	19.77
neuron 9	4.69	-3.21	1.70	-0.13	-0.01	-5.00	-0.61	-0.72	0.12	-5.32
neuron 10	-9.22	-2.13	-4.06	-5.72	-12.39	-10.71	-2.60	-7.96	0.98	-57.32
neuron 11	2.22	-0.56	8.08	14.39	-0.93	-0.20	-0.19	-0.13	0.05	22.20

Table 6.3 Weights and biases in the output layer

LW{2,1}	*Neu. 1*	*Neu. 2*	*Neu. 3*	*Neu. 4*	*Neu. 5*	*Neu. 6*	*Neu. 7*	*Neu. 8*	*Neu. 9*	*Neu. 10*	*Neu. 11*	net,b{2}
output1	-1.19	0.32	0.02	-0.20	0.25	-0.20	-0.12	-0.31	-1.19	0.47	0.32	1.14
output2	-0.05	-2.10	-0.01	0.29	-0.05	-0.03	-0.36	0.29	0.36	11.79	-0.30	0.83
output3	-0.50	0.29	-0.20	-0.34	-0.51	2.19	0.07	0.16	-0.22	0.74	-0.64	0.08
output4	-0.05	17.36	0.02	-17.54	-0.04	0.07	3.02	1.33	-3.05	-0.80	-0.07	-1.50
output5	0.10	0.21	0.37	-0.21	-0.04	0.03	0.03	6.77	-0.07	0.51	-4.71	-2.44

One of the advantages of neural networks is that the weights and biases of the trained network can be used to build a mathematical model of the system. By using the weights and biases in the hidden layer (Table 6.2) and in the output layer (Table 6.3), the mathematical model is prepared in Microsoft Excel with a simple user-interface for machine operators to enter the defect severity and to get the proposal of the neural network (Figure 6.13). For mistaken defect entries, a defect combination control is embedded (Figure 6.14).

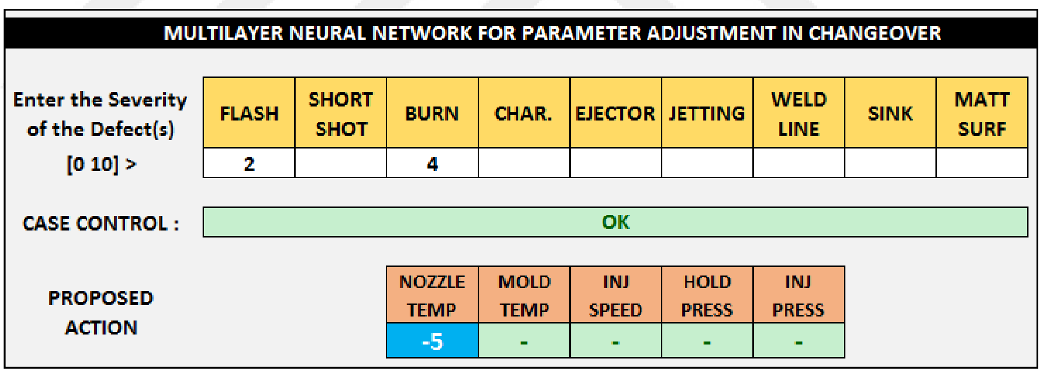


Figure 6.13 User interface for parameter adjustment

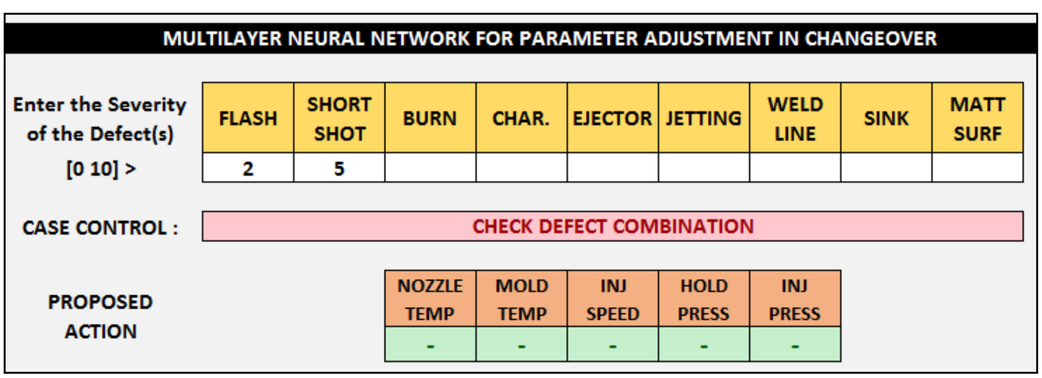


Figure 6.14 Warning message of the user interface about the defect entry

6.3 Performances of FIS and MLNN in the Same Figures

The results confirm that both FIS and MLNN can generate satisfactory resolution proposals for defects during a changeover. Combined performance statistics are given in Table 6.4 and plot diagrams are given in Figure 6.15.

The rules in FIS make the relationships in the system easy to understand. Especially with the interactive fuzzy software, the inference mechanism becomes visible so FIS can be named as a “white box”. New rules can be added or some of them can be removed easily. Individual rules can be optimized. However, FIS does not have generalization capability and requires tuning on membership functions and ranges. On the other hand, MLNN is a very powerful tool to map nonlinear relationships between inputs and outputs with a generalization capability. The user-interface built for MLNN outputs provides the interactivity. But, adding a new rule requires re-training the net.

Table 6.4 Comparative performances of FIS and MLNN

OUTPUT	PEARSON'S R		R^2	
	EXPERT vs FIS	EXPERT vs MLNN	EXPERT vs FIS	EXPERT vs MLNN
Δ (Nozzle Temp. °C)	0.9948	99.67%	0.9897	99.35%
Δ (Mold Temp. °C)	0.9932	96.17%	0.9865	92.48%
Δ (Inj. Speed mm/sec)	0.9871	96.67%	0.9743	93.45%
Δ (Hold Press. bar)	0.9925	99.75%	0.9851	99.49%
Δ (Inj. Press. bar)	0.9907	99.12%	0.9815	98.26%

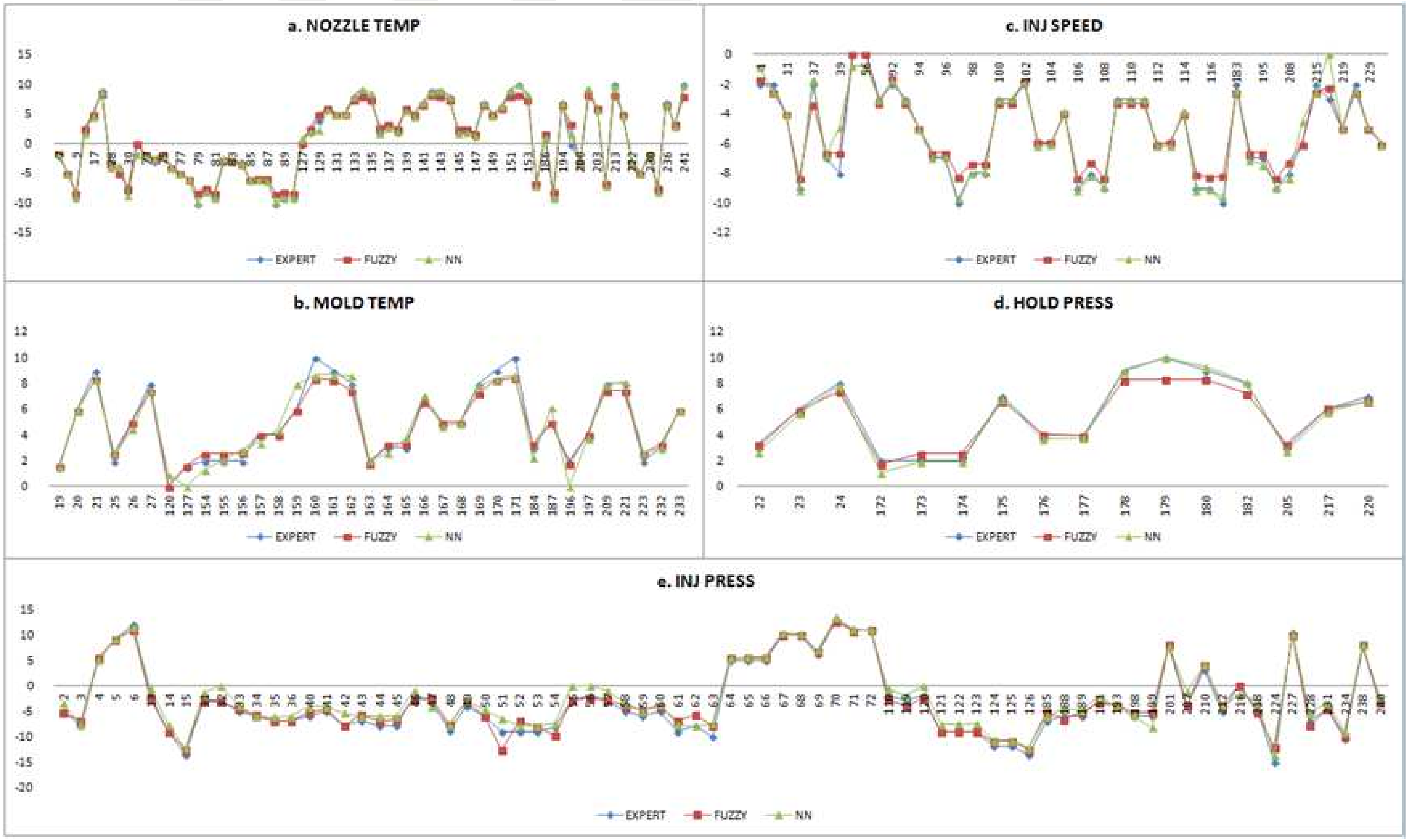


Figure 6.15 Comparison of expert, fuzzy and NN responses **a)** Nozzle temperature, **b)** Mold temperature, **c)** Injection speed, **d)** Hold pressure, **e)** Injection pressure

CHAPTER SEVEN
CONCLUSION

7.1 Summary of the Dissertation

It is a reality that companies have difficulties in finding experts on plastic injection molding so changeovers are still unpleasant tasks. High workload on setup experts affects lot size planning, and expected benefits of SMED cannot be realized due to expert scarcity. Because of the uncontrollable factors (environmental humidity and temperature changes, gradual wear on mold surfaces and machine parts, quality deviations of the resin), changeover parameter setting in plastic injection is a dynamic problem that cannot be solved via optimization algorithms that require data from a static study space. So, there is a strong need for an expert system to capture the highest level of domain expertise to let it be used by machine operators to increase the number of staff who can make changeover parameter setting.

During a parameter setting, the defects on the parts are used as inputs to define the actions on the process parameters. However, there are many root causes of an injection defect that make it difficult to build an expert system covering all the actions. Yet, in changeovers, the experts are expected to fine tune the process parameters to resolve the quality issues within several minutes. Therefore, quality problems related to design issues, machine or resin selection and maintenance requirements are out of the scope of changeover parameter setting. In this manner, the experts are asked for their actions of resolving the defects under the assumption of there is no issue on design, machine or resin selection and maintenance.

As the severity of the defects and the amount of change of process parameters are defined with linguistic terms, fuzzy inference system is used. Membership functions of inputs and outputs are chosen and 180 fuzzy rules are defined together with three injection experts. Fitness tests are applied to see the correlation between the responses of Mamdani-type fuzzy inference system and experts’ responses to the 180 questions representing each of 180 cases. After reaching the desirable fit, real molding trials are conducted to ensure the readiness of the system. A dozen of trials prove that the fuzzy inference system provides satisfactory responses.

The dataset of 180 cases is used to build a multilayer neural network to compare the performance and applicability of fuzzy inference systems and artificial neural networks. Current 180 cases are used as training dataset and additional 61 cases are added as test dataset. Bayesian regulation is used in a one hidden layer network with 11 neurons. It is observed that neural networks can also generate satisfactory responses in changeover parameter setting.

7.2 Discussions & Future Research Directions

During the validation process, it is observed that assessing the severity of the defect is an important point to reach the solution with fewer trials. Overestimating the severity triggers the counter-defect, and underestimating improves the result but falls short to resolve the current problem totally. Although in both of the cases an additional trial would be needed, the boundary of the rules in the expert system leads the operator to manipulate the correct parameter with a level inferred based on the last result. In other words, soft reasoning and human reasoning are combined to get the result with fewer trials.

In the future studies, the defect types and severities can be detected using cameras and neural networks to overcome the interpretation differences. The autonomous changeover of parts and tools would support full automation and Industry 4.0 initiatives.

The use of proposed expert system in current organizations motivates the machine operators to understand how to generate solutions for various quality problems. Total quality awareness inside the plant is expected to increase as those machine operators also keep their eyes on mass production. Interactive fuzzy tools and neural network user interface presented in the thesis can also be used as training tools for new comers.

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