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Application of Iterative Learning Control to MoldFlow Simulations of a Thermoplastic Injection Molding Process

by

Che-Lun Mai

A Thesis

Presented to the Graduate and Research Committee

of Lehigh University

in Candidacy for the Degree of

Master of Science

in

Mechanical Engineering and Mechanics

Lehigh University

September, 2011

This thesis is accepted and approved in partial fulfillment of the requirements for the Master of Science.

Date

Thesis Advisor

Chairperson of Department

Acknowledgments

First of all, I would like to give my honor and appreciation to my advisor Dr. Chew. With his wisdom, help, knowledge and advice, this thesis has now successfully written. It is my honor to work with you. I appreciated for everything Dr. Chew has taught. Thank you very much.

Many thanks to Dr. Coulter, Dr. Angstadt and the manufacturing group. Thanks Dr. Coulter and Dr. Angstadt for the help and advice. Thanks for being generous to me. Thanks to Tyler Skiba, Punlop Teeraparpwong and Qi Lee. Thank you-all for always so kind to me and giving me your extra time helping me with the injection molding and MoldFlow and all kinds of techniques.

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Special thanks to my girlfriend Erin Wu. She has been the most important person to me and plays the most important role in my life. I appreciated to your kindness, generous and thoughtfulness. Thank you for always support me and love me. Thank you for all your sacrifices. Thank you for keeping walking with me for the past six and half years.

I would like to thank my family. Thanks to my mom and dad, thanks for all your support, I am heartily grateful to your help and love. And many thanks to my grandparents, thanks to all your support and love. Also, thanks to my uncle and aunt, my sister and cousins, thank you-all for your support and love.

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Nomenclature

$\theta^{(i+1)}$ next iteration input valve opening angle θ

$\theta^{(i)}$ previous iteration input valve opening angle θ

G learning gain

X_d desired weld line position

X weld line position from previous iteration

e error

Abstract

This study uses iterative learning control (ILC) in conjunction with simulations using MoldFlow. The objective is to apply iterative learning control theory as a predictive model of a thermoplastic injection molding process.

Iterative learning control shifts the weld line to some specified desirable location using MoldFlow as a simulator. The deviation between the simulated to the desired weld line location is feedback to modify the input for the next iteration.

To ensure that the MoldFlow simulator results are comparable to the actual experimental models, a simple procedure of parametric curve-fit is used to compensate for the inherent modeling inaccuracies in the MoldFlow simulator. With ILC and MoldFlow, it is then possible to located weld line in same desirable locations with the direct iterative uses of an injection molding machine, thereby resulting in significant saving in time and materials.

CHAPTER 1:

Introduction

1.1 Objective

Injection molding is a very important mass production thermoplastic process. Over the years, many have tried to improve the injection molding process and many articles have focused on various different control respects.

Iterative learning control is an intelligent control method that utilizes error information from a prior iteration to modify the next input so to improve the system. Most modern systems have sensors at the outputs to perform this error calculation. However, injection molding process is still far away from being an automatic control process; the quality control is almost always performed by way of human inspection. Since the error of an output relative to some desired output is actually being determined by an operator, the latter sensors as the iterative learning controller in the process. He/she exams the output and determines the error and in conjunction with the previous input determines the new input for the next iteration. In so doing, ILC provides a systematic approach to improving the quality of an injection molded part.

The use of MoldFlow as a simulator to simulate the injection molding process serves as a prediction tool. The most recent version of MoldFlow software, the AutoDesk MoldFlow Insight 2011, facilitates simulation and analysis of the injection molding process so that the resulting molded parts more accurate when compared to that from an actual injection molding machine. With its new 3-dimensional capability, it is also possible to simulate a micro-structure injection mold very rapidly.

In this thesis, 3D MoldFlow simulations will be performed, and used as predictive model for iterative learning control. By so doing the operator can perform a simulation before doing it on the actual machine, so that all the input conditions are determined quickly to result in a quality product. With the high accuracy MoldFlow 3D simulations, one can save a lot plastics, and energy, and begin the whole injection molding process at a better starting point.

1.2 Content of this Thesis

In Chapter 2 a discussion of previous investigations related to the control of injection molding process is provided. Chapter 3 presents the experimental setup while Chapter 4 explains the theory behind iterative learning control. Chapter 5 describes the MoldFlow simulation model setup and Chapter 6 provides the MoldFlow results using iterative learning control. In this chapter, two cases will be discussed with two different learning gains to illustrate the power of iterative learning control. Chapter 7 compares the MoldFlow simulation with Experimental results. Chapter 8 presents the conclusion and suggestions for future work. An appendix is also provided that discusses the simulation model test, solid work model, and relationship profile between the valve in MoldFlow and in the Experiment.

CHAPTER 2:

Previous Investigations

2.1 Experimental Studies with Iterative Learning Controller

2.1.1 Li, Wang and Liu [1]

The cavity pressure is the most important factor that can affect the quality of the final part, resulting in flash and under-injection if the packing pressure is too high or too low. Since filling and packing are important phases that can determine quality in terms of weight and dimension, therefore the specification of the velocity to pressure control transfer point is also a very important aspect for product quality. Cavity pressure changes very fast and is nonlinear with time. Therefore, this paper focuses on controlling the cavity pressure, in order to control the quality of the final part.

In 2010, Li et al. applied an iterative learning controller with standard linear feedback control and iterative learning feed-forward control to a hydraulic injection molding system. And in order to prevent leaning high frequency components they use zero-phase filtering method. The control arithmetic can track the cavity pressure profile accurately so that the cavity pressure is very close to its control set point.

2.1.2 Wang, Zhou and Gao [2]

In 2007, Wang et al. presents iterative learning model predictive control for multi-phase batch processes. The transition from filling to packing-holding has a huge impact for the final part quality. The approach and the timing for transferring the control system from velocity control to pressure control are crucial. The objective in this paper is to perform a smoother transient when switching from the velocity to pressure control.

Wang et al. have used a 2-dimensional Fornasini-Marchesini system with Iterative Learning Control controller to smoothen the filling to packing phase. Since the transfer time to switch from velocity control to pressure control is critical, and since there is uncertainty in determining filling time of the cavity, Wang et al. used the application of a switching-prediction-model and switching-cost function near the switching step.

With the iterative learning model predictive control, the proposed scheme is effective resulting in a smoother transition.

2.1.3 Zheng and Alleyne [3]

The objective is to perform a smoother transition when switching from velocity control to pressure control. The transition from filling to packing-holding has a huge impact for the final part quality. Transferring the control system from velocity control to pressure control is crucial.

In 2003, Zheng et al. built a control system and applied an iterative learning controller with position learning feed-forward control and pressure learning feed-forward control with PID feedback to smoothen the fill-to-pack transition. A hydraulic system with proportional control for both flow valve and pressure relief valve incorporating a latent tracking approach and a reference-conditioning algorithm combines two ILC controllers together and results a smooth transition.

2.1.4 Yao, Gao and Allgower [4]

In 2008, Yao et al. presents the barrel temperature control during operation transition in injection molding. There are two issues in industry which is being seriously concerned. One is to shorten the start-up period without barrel temperature overshoots, and the other is the consistency of the final part quality.

In this paper, the objective is to prevent large temperature variations between the idle state and the operational state during the transient. The authors used a hydraulic system with proportional control on both the flow valve and the pressure relief valve with barrel temperature control.

The result shows that the feedforward controller combined with an adaptive generalized predictive feedback controller, the barrel temperatures can be maintained close to the set point both during the operation, the idle, and in between. The start-up time is also shortened.

2.2 Simulation Studies with Commercial Software Tool

2.2.1 Dairanieh, Haufe, Wolf and Mennig [5]

In 1996, Dairanieh et al. presents a computer simulation of weld lines in injection molded part. The appearance and the mechanical properties of the weld line is undesirable for the final part, in particular, it is the weakness that occurs at weld line. Unfortunately, it is not always possible to eliminate the weld line from the final part. The objective of this paper is to use a model prediction tool to predict the final part to save time and resources by performing trial and error experiments to relocate weld lines.

This paper has used an old version of Moldflow simulation software to simulate the weld lines in injection molded polymer part. The simulation result is correct in material viscosity, density, and weld line severity. MoldFlow accurately predicted the weld line.

2.2.2 Tsai, Ou, Huang, Cheng, Shen, Chang, Wu, Chen and Guan [6]

In 2008, Tsai et al. used MoldFlow to simulate the light guiding plate on micro injection molding using a 3D numerical simulation with control volume finite element method. The objective of this paper is to discuss the simulation result with several process situations of injection pressure, temperature, shear rate, and velocity distribution.

The MoldFlow was very accurate in simulating the 3D model and providing data of filling stages, injection pressure, pressure history, temperature distribution, shear rate distribution, and velocity distribution.

2.2.3 Shen, Chang, Shen, Hsu and Wu [7]

In 2008, Shen et al. presents the analysis of the microstructure of microlens arrays on micro-injection molding by using MoldFlow. In order to simulate the microlens arrays, a 3D numerical simulation with control volume finite element method was used.

The objective of this paper is to simulate with different process properties in order to test the performance of the MoldFlow simulation.

The simulation results shows that MoldFlow is capable of 3D simulation of the filling stages, temperature distribution, meld front, and velocity distribution of the injection process.

2.2.4 Chen, Chen and Chen [12]

In 2006, M. Y. Chen, Y. C. Chen and S. C. Chen applied fuzzy theory to the control of weld lines in plastic injection moldings. The weld line affects both the appearance and the strength of the products. This study tried to use computer-aid engineering package software called C-Mold to simulate the molded part and to apply fuzzy logic to control the position of the weld line.

This investigation partitions the part into four regions with different thicknesses. The inputs of this study are the gate position as well as the thickness of each region's thickness. The output is the weld line position.

Results show that the fuzzy logic was successful in controlling the weld line within four cycles, much faster than the conventional trial and error approach. By the accurately simulating the process using a CAE software, the control study saves a lot plastics and places the experimental work at a better starting point resulting in time savings.

2.3 Iterative Learning Control

2.3.1 Chew and Phan [9, 10]

In 1994, M. Chew and M Phan used iterative learning control applying to mechanisms. They reduced residual vibrations in high-speed electromechanical bonding machines as a cam follower system.

This cam follower system is a single degree of freedom system with a flexible link. Iterative learning control obtains the input from the previous iteration's input and error, and it adjusted the current input with error calculated from the current output. Every iteration is a complete new cycle with exactly same initial processing conditions and parameters.

By iteratively changing the input of the angle of rotation of the DC motor, the vibrations were reduced by iterative learning control within cycles.

Chapter 3:

Experimental Setup

3.1 Injection Molding Machine

This thesis used Nissei 22mm Injection Molding Machine with NC9000G controller. Figure 3.1 shows the Nissei 22mm Injection Molding Machine Model PS40E5ASE with NC9000G controller. Machine specs are listed in Appendix D. NC9000G controller has several input functions such as injection speed, barrel temperatures, nozzle temperature, injection time, cooling and packing time, max packing pressure and shot size.

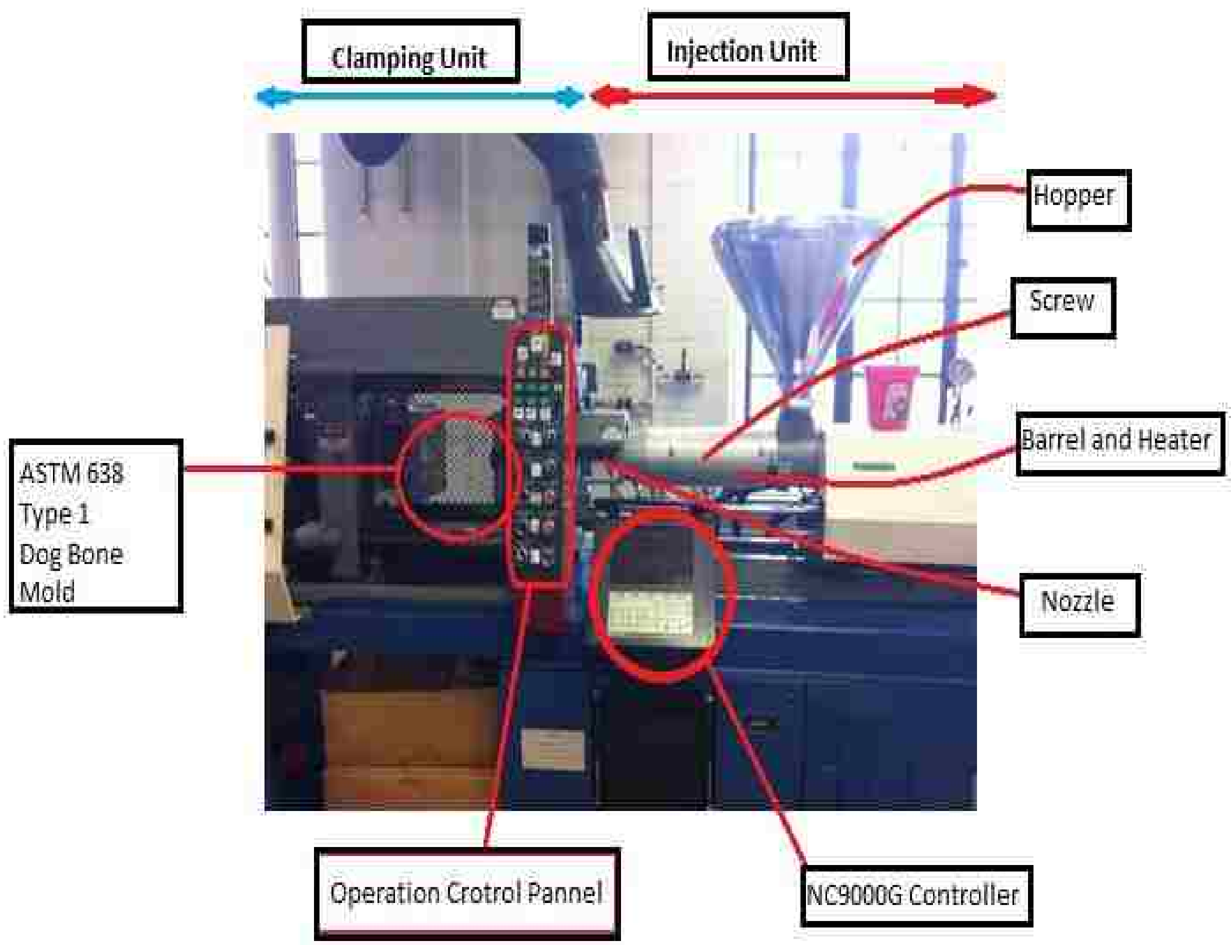

Figure 3.1: Nissei 22mm Injection Molding Machine

There are several inputs variables and parameters used in the experiment, the injection speed, velocity to pressure control transfer point (% volume filled), mold temperature, barrel temperature (front, middle, rear), nozzle temperature, injection time, cooler temperature, cooling and packing time, max packing pressure, shot size, plastic resin, and two valve openings.

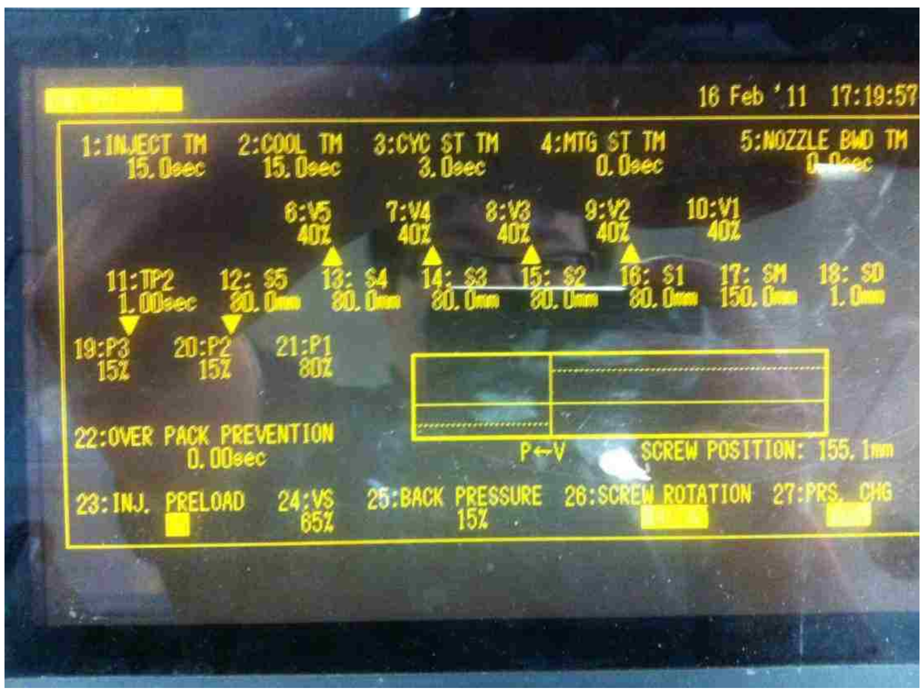

Figure 3.2: NC9000G Controller A

Figure 3.2 shows the NC9000G controller control panel. In this section, there are settings for the injection time, cooling time, cycle time, screw velocity, shot size, packing pressure, and maximum packing pressure.

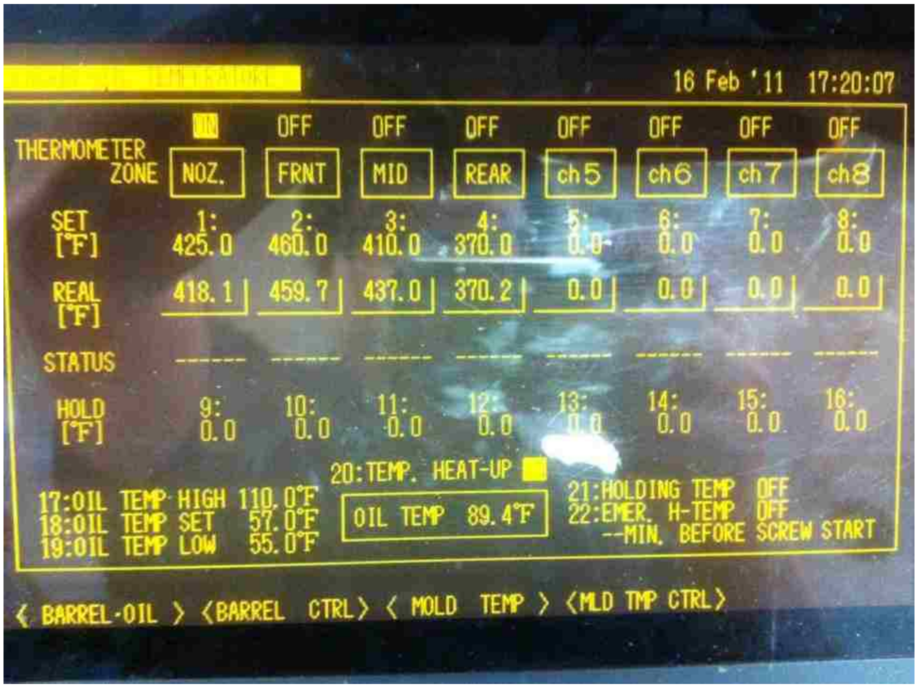

Figure 3.3: NC9000G Controller B

In Figure 3.3, there are settings for nozzle temperature, front barrel temperature, middle barrel temperature, rear barrel temperature and mold temperature. It also shows the real temperatures in the barrel in real time.

Temperature settings are recommended by the plastic resin provider. By carrying out several testing molding processes, parameters such as injection time, cooling time, velocity, packing pressure and shot size are determined based on the molded part. Using these parameters, the molded part should have the correct shape, is clear and properly molded. That is why these parameters will be used in this investigation.

The NC9000G controller has setup with these parameters when performing the experimental work:

Injection speed	40% (20 cm^3/s)
Max clamping force	40 ton
V/P transfer	95% volume filled
Mold temperature	60 ℃
Barrel Temperature (front, middle, rear)	460, 410, 370 ℃
Nozzle Temperature	425 ℃
Injection Time	15 sec
Cooling and Time	15 sec
Max Packing Pressure	256 MPa
Packing Pressure	15% (38.4 MPa)
Shot Size: S5	80mm
SM	150mm

Table 3.1: NC9000G Controller Input Parameters

With all these parameters, the experiment can keep the starting point consistent for iterations. Every iteration starts from the same condition but with different input based on previous iteration errors. Two valve openings will be the input variables for the iterations.

3.2 Plastic Resin

Polystyrene, shown in Figure 3.8, is used in this experiment because of its clear color and the ease to locate the weld line. Polystyrene is a petroleum based vinyl polymer made from the styrene monomer, which is colorless, rigid, transparent thermoplastic. Polystyrene resin shape is rectangular solid granule with about 10 mm^3 volume. The polystyrene used in this thesis is made by Dow Chemical Company; the product code is 5903442, and the product name is PS DOW 685 D W CL STYRON.

Figure 3.4: Polystyrene Resin

3.3 Mold

Figures 3.9 and 3.10 are the ASTM 638 Type I Dog Bone Mold which has been chosen to use in this investigation. The availability of a valve system permits a power of iterative learning control of the weld line. These two valves are perfect for performing control to the weld line position. The purple lanes indicate the runner system.

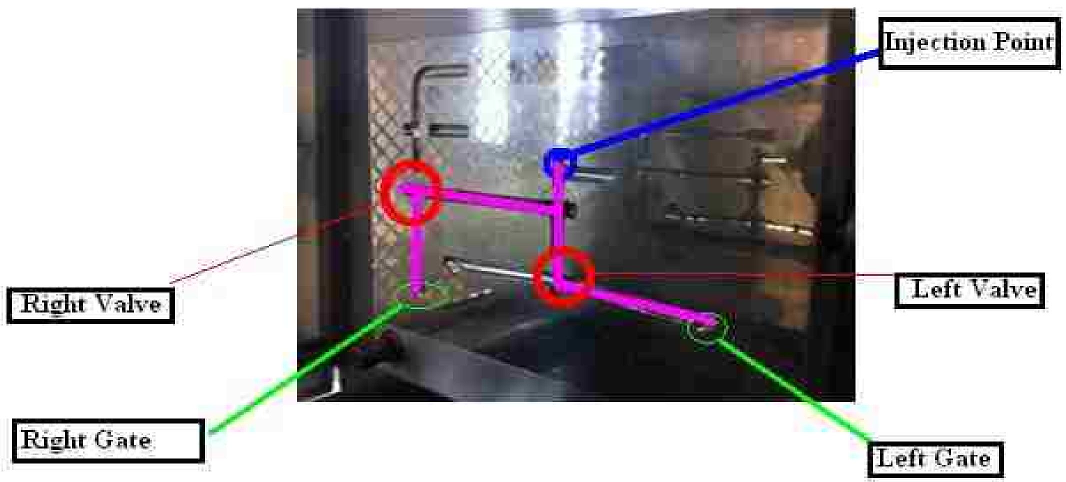

Figure 3.5: ASTM 638 Type I Dog Bone Mold A

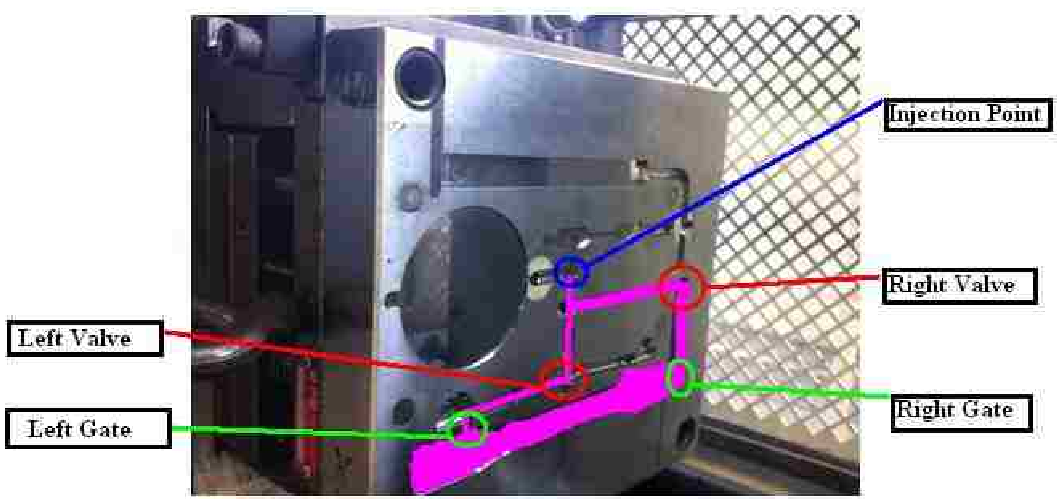

Figure 3.6: ASTM 638 Type I Dog Bone Mold B

3.4 Injection Molding Process

The process of injection molding is divided into 6 major steps as shown below:

1. Mold Clamping
2. Plastic Injection
3. Plastic Dwelling
4. Part Cooling
5. Mold Opening
6. Part Ejecting

Injection molding machine is divided into 2 units, injection and clamping. Injection unit includes a material hopper, a heating unit, and a screw-type plunger or injection ram. Clamping unit holding the molds in which the components are molded.

This process need to heat the plastic materials in order to melt it down. The screw rotates the melt plastic materials, metering from the hopper to the front. Wait until it accumulated the needed amount of melt plastic materials, the injection process gets started. Plastics are fed from the hopper into a heated barrel, and then mixed. After that, the screw forced the plastic into a mold, which is usually a metal mold either aluminum or steel, where is lower temperature than the input, so that the material start cool down and then solidify to form a part.

Chapter 4:

Iterative Learning Control Theory

4.1 Iterative Learning Control Theory

In 1994, M. Chew and M. Phan [9,10] used learning control theory to apply to several mechanisms. They have reduced residual vibrations in high-speed electromechanical bonding machines. This cam-follower system is a single degree-of-freedom system with a flexible link. Iterative learning control determines the new input from the input of previous iteration along with the output error calculated with an approximately determined learning gain. Every iteration is a complete new cycle with exactly same initial processing conditions and parameters. By iteratively changing the input, the vibrations were reduced by iterative learning control.

M.Chew and M. Phan have brought the idea of applying iterative learning control into several different applications. The idea of the iterative learning control is simple but it is very powerful. The beauty of the iteration learning control is just like the daily life. Just like the old saying goes: “Once bitten, twice shy.” or “Shame on you if you fool me once, shame on me if you fool me twice.” Maybe not just twice while doing iterative learning control, but we all learn from previous experiences.

The current thesis investigation uses iterative learning control with MoldFlow as a simulator to control the weld line position. The iterative learning control obtains the input which is the valve opening degree from the previous iteration’s input and output error which is the distance between the desired location and the actual location along with the learning gain G. Every iteration is a complete new cycle with exactly same initial processing conditions and parameters.

In this thesis, this iteration equation has been used.

$$\theta^{(i+1)} = \theta^{(i)} + G * (X_d - X) \tag{4-1}$$

Where

$\theta^{(i+1)}$ is the next iteration input θ

$\theta^{(i)}$ is the previous iteration input θ

G is the learning gain, the unit is $(\frac{\deg}{mm})$

X_d is the desired weld line target position

X is the actual weld line position from previous iteration

$X_d - X$ is the error in this iteration.

The operator is the controller who examines the output and returns the error along with a new input to improve on the performance of the process or in of the part for the next iteration. Before reaching the desired weld line target position, every iteration will have an error, which is the distance between the desired weld line position and the actual weld line position. By using this Equation 4-1 above, with the error calculated, the new input for next iteration can be obtained.

Using MoldFlow 3D simulation along with the built prediction model, one can save a lot plastics, and energy, and start the whole injection molding process at a better starting point.

Chapter 5:

Moldflow Simulation Setup

5.1 MoldFlow Model Setup

Begin by constructing a SolidWorks 3D Model and then importing the part model from SolidWorks to MoldFlow. Then set up the runner system exactly same as is in the ASTM 638 Type I Dog Bone Mold. In this MoldFlow simulation models, are shown in Figures 5.1, 5.2 and 5.3. In Figure 5.1, it shows the original MoldFlow simulation model setup. There are one injection point, two injection gates and two valves.

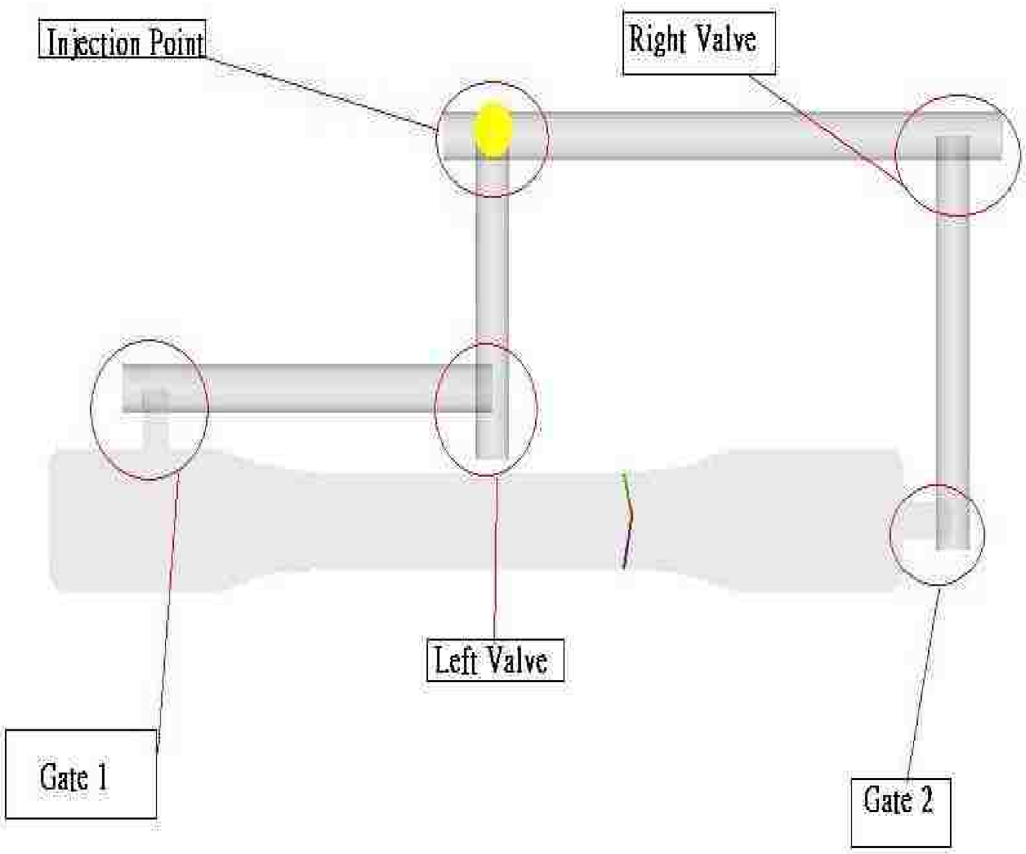

Figure 5.1 MoldFlow Model

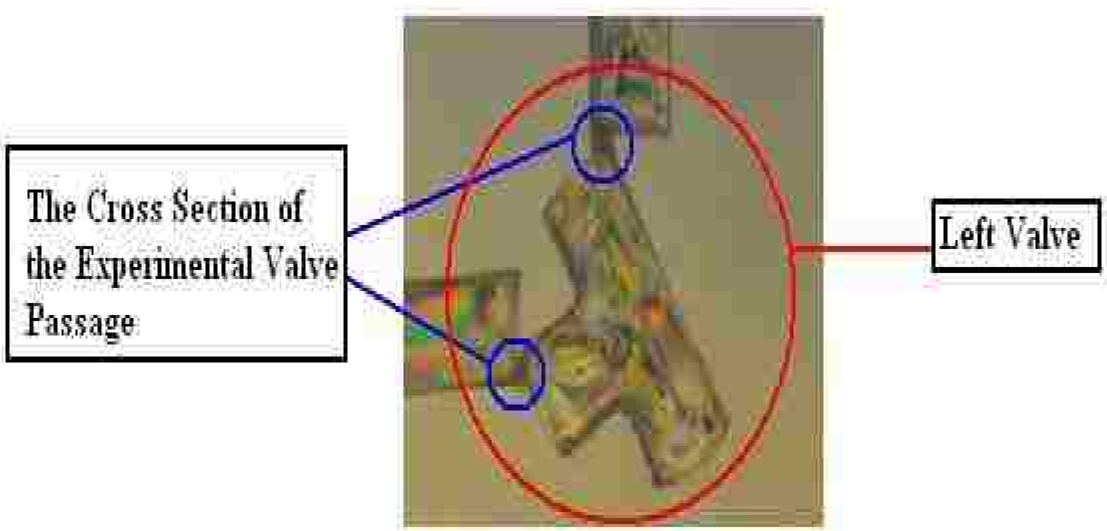

Figure 5.2: ASTM 638 Type I Dog Bone Valve

When the ASTM 638 Type I Dog Bone Mold valve turns, there will be a narrowed runner passage, and this special runner is modeling that cross section. In Figure 5.2, it shows the cross section of the experimental valve passage with blue circle, the red circle indicates the valve system.

Based on the valve system in Figure 5.2, a valve system in MoldFlow simulation is molded. In Figure 5.3 and 5.4, the red circle is modeled valve system, which performs the same functionality as the valve system in the ASTM 638 Type I Dog Bone Mold in Figure 5.2. The blue circles indicate the special runner which uses to model the cross section of the experimental valve passage.

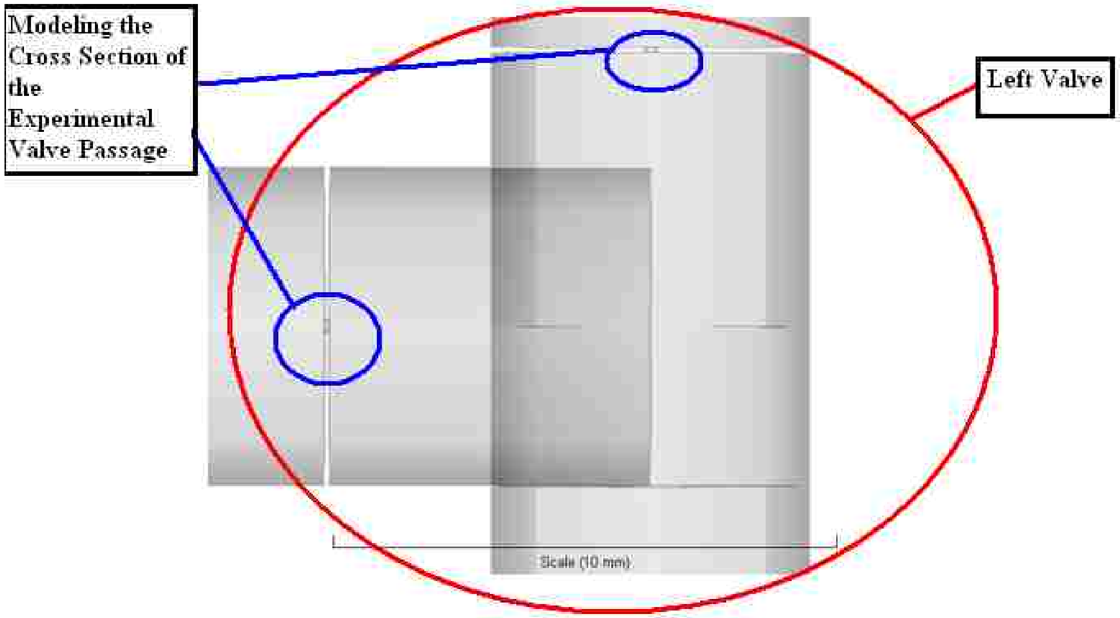

Figure 5.3: MoldFlow Left Valve

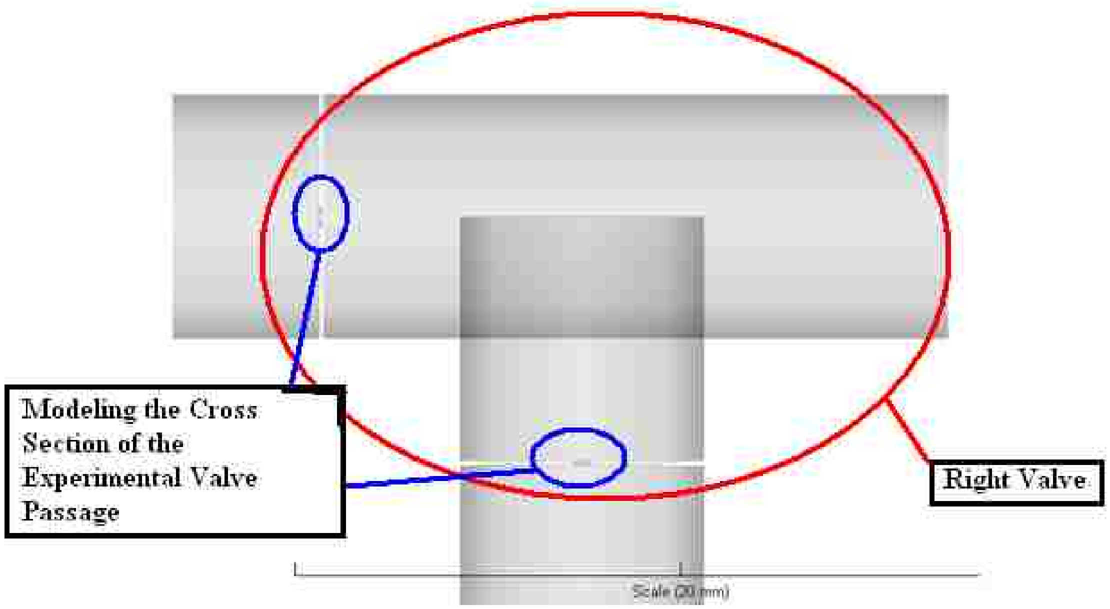

Figure 5.4: MoldFlow Right Valve

5.2 MoldFlow Simulation Parameters Setup

Following experimental setup, same parameters have been used to perform the MoldFlow simulation, shown in Table 5.1, with all these parameters, the simulation can keep the starting point consistent for iterations. Every iteration starts from the same condition but with different input based on previous iteration errors. Two valve openings will be the input variables for the iterations.

Injection speed	40% (20 cm^3/s)
Max clamping force	40 ton
V/P transfer	95% volume filled
Mold temperature	60 ℃
Barrel Temperature (front, middle, rear)	460, 410, 370 ℃
Nozzle Temperature	425 ℃
Injection Time	15 sec
Cooling and Time	15 sec
Max Packing Pressure	256 MPa
Packing Pressure	15% (38.4 MPa)
Shot Size: S1	80mm
S2	150mm

Table 5.1: MoldFlow Simulation Parameters

Chapter 6:

MoldFlow Results Using Iterative Learning Control

6.1 Iterative Learning Control in MoldFlow(ILCM) – Case 1 with Learning Gain G = -0.125 (degree/mm)

Begin with determine the Learning Gain G. Assuming the next iteration will be left valve opening at 30^0, and the desired weld line position is 100mm. Also, assuming the previous iteration was left valve opening at 35^0, and using the date from Experimental Case 1 in Appendix B to determine the previous iteration. From Appendix B, when the left valve opining is at 35^o, the weld line position is at 60mm. By using all these numbers above, and putting into Equation 4.1, the Learning Gain G will be -0.125(deg/mm).

Set 100mm from left border of the dog bone is the desired target for the weld line position, and set the learning gain G = -0.125(degree/mm) for the iteration, and set the starting point as left valve opening is 35^o and right valve opening is 0^o.

First iteration has shown in Figure 6.1with left valve opening 35^o and right valve opening 0^o, where the weld line is located at 60 mm, so the error is 40mm from the desired target position.

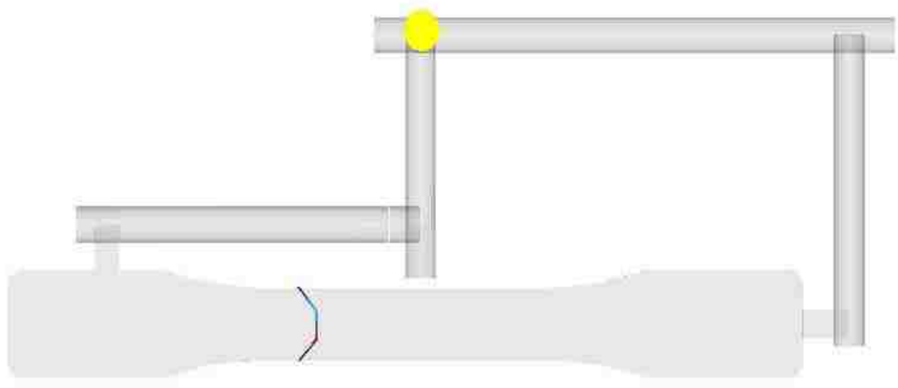

Figure 6.1: ILCM 1.1(Left Valve Opening: 35^o, Right Valve Opening: 0^o)

From the first iteration output, the error is 40mm, and the previous input is left valve opening is 35^o and right valve opening is 0^o. By calculating with Equation 4-1, the second iteration input will be left valve opening 30^o and right valve opening -5^o, where the weld line position is located at 94 mm, so the error is 6 mm from the desired target position.

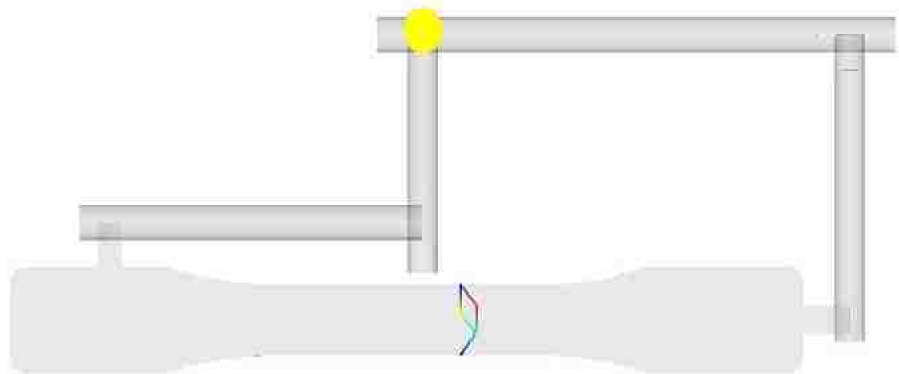

Figure 6.2: ILCM 1.2(Left Valve Opening: 30^o, Right Valve Opening: -5^o)

From the second iteration output, the error is 6mm, and the previous input is left valve opening is 30^o and right valve opening is -5^o. By calculating with Equation 4-1, the third iteration input will be left valve opening 29.25^o and right valve opening -5.75^o, where the weld line position is located at 97 mm, so the error is 3 mm from the desired target position.

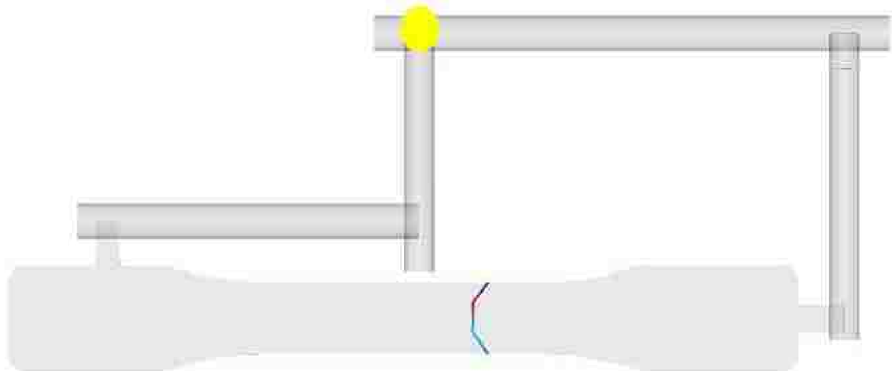

Figure 6.3: ILCM 1.3 (Left Valve Opening: 29.25^{o} Right Valve Opening: -5.75^{o})

From the third iteration output, the error is 3mm, and the previous input is left valve opening is 29.25^{o} and right valve opening is -5.75^{o} .By calculating with Equation 4-1, the forth iteration input will be left valve opening 28.875^{o} and right valve opening -6.125^{o}, where the weld line position is located at 97 mm, so the error is still 3 mm from the desired target position. Since it stays at the same error for two iterations already, a gain scheduling needed to be performed. So the next iteration the learning gain will times 2 in order to make the iteration learns faster.

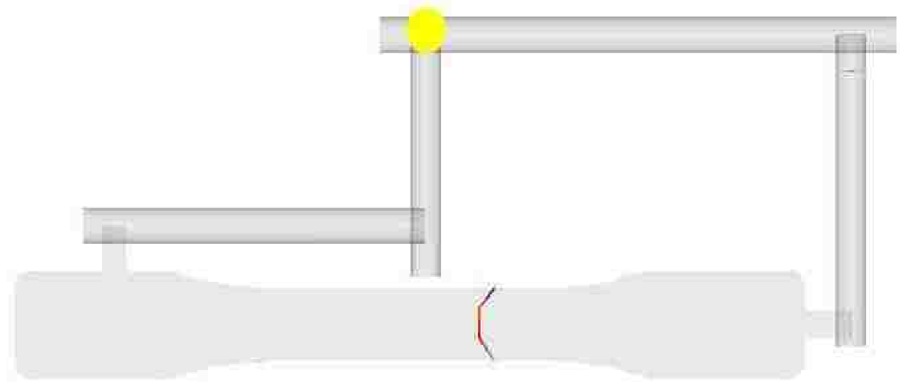

Figure 6.4: ILCM 1.4(Left Valve Opening: 28.875^{o}, Right Valve Opening: -6.125^{o})

From the forth iteration output, the error is still 3mm, and the previous input is left valve opening is 28.875^{o} and right valve opening is -6.125^{o} . By calculating with Equation 4-1, along with 2 times learning gain, the fifth iteration input will be left valve opening 28.125^{o} and right valve opening -6.875^{o}, where the weld line position is still located at 97 mm, so the error is still 3 mm again from the desired target position. Since it stays at the same error again for three iterations already, a bigger learning gain is needed to be performed. So the next iteration the learning gain will times 4 in order to make the iteration learns faster.

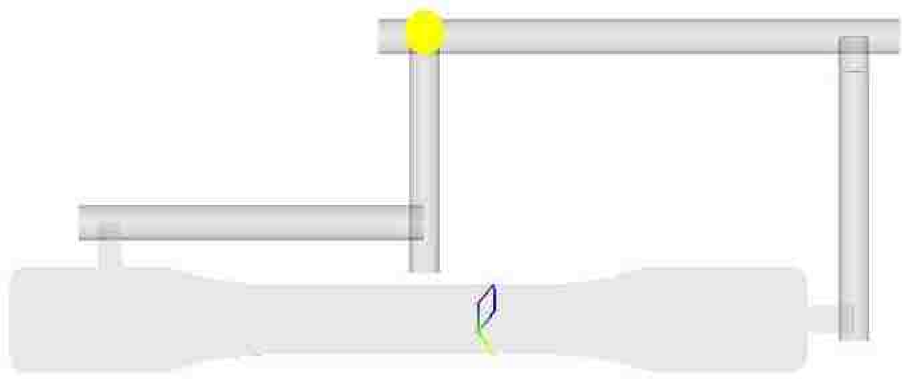

Figure 6.5: ILCM 1.5(Left Valve Opening: 28.125^o, Right Valve Opening: -6.875^o)

From the fifth iteration output, the error is still 3mm again, and the previous input is left valve opening is 28.125^o and right valve opening is -6.875^o .By calculating with Equation 4-1, along with 4 times the initial learning gain, the sixth iteration input will be left valve opening 26.625^o and right valve opening -7.625^o, where the weld line position is located at 100 mm, so the iteration has achieve the desired target weld line position. With iterative learning control and the learning gain scheduling, this simulation reaches desired target in six iterations.

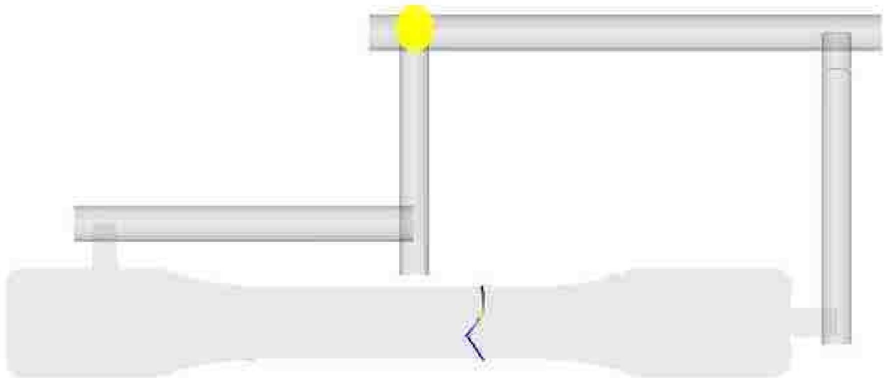

FIgure 6.6: ILCM 1.6 (Target Achieved)

(Left Valve Opening: 26.625^{o}, Right Valve Opening: -7.625^{o})

In Case 1, with the learning gain G = -0.125, the learning gain might be too small since it used the learning gain scheduling up to 4 times the original gain, the next case will perform the iterative learning control with a bigger learning gain.

6.2 Iterative Learning Control in MoldFlow(ILCM) – Case 2 with Learning Gain G = -0.3 (degree/mm)

Begin with determine the Learning Gain G. Because in Case 1 the learning gain seems like too small to bounce around. In order to test if the iteration will bounce around, the doubled learning gain will be chosen. Assuming the next iteration will be left valve opening at 23^0, and the desired weld line position is 100mm. Also, assuming the previous iteration was left valve opening at 35^0, and using the date from Experimental Case 1 in Appendix B to determine the previous iteration. From Appendix B, when the left valve opining is at 35^o, the weld line position is at 60mm. By using all these numbers above, and putting into Equation 4.1, the Learning Gain G will be -0.3(deg/mm).

Set 100mm from left border of the dog bone is the target for the weld line position, and set the learning gain G = -0.3(degree/mm) for the iteration, and set the starting point as left valve opening is 35^o and right valve opening is 0^o.

First iteration has shown in Figure 6.1with left valve opening 35^o and right valve opening 0^o, where the weld line is located at 60 mm, so the error is 40mm from the desired target position.

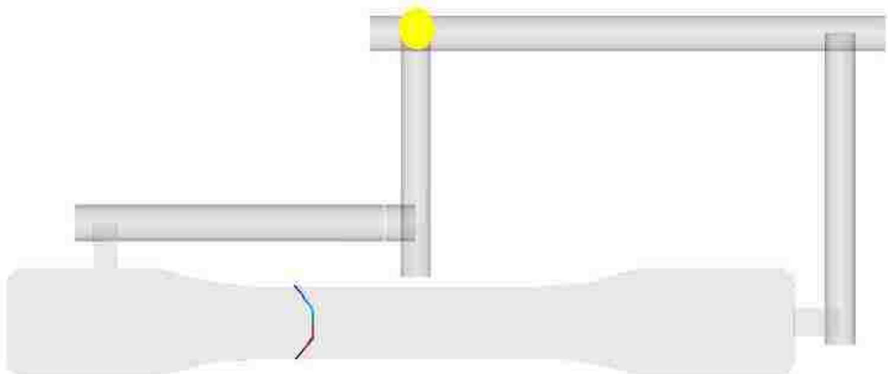

Figure 6.7: ILCM 2.1(Left Valve Opening: 35^o, Right Valve Opening: 0^o)

From the first iteration output, the error is 40mm, and the previous input is left valve opening is 35^o and right valve opening is 0^o. By calculating with Equation 4-1, the second iteration input will be left valve opening 23^o and right valve opening -12^o, where the weld line position is located at 107 mm, so the error is -7 mm from the desired target position.

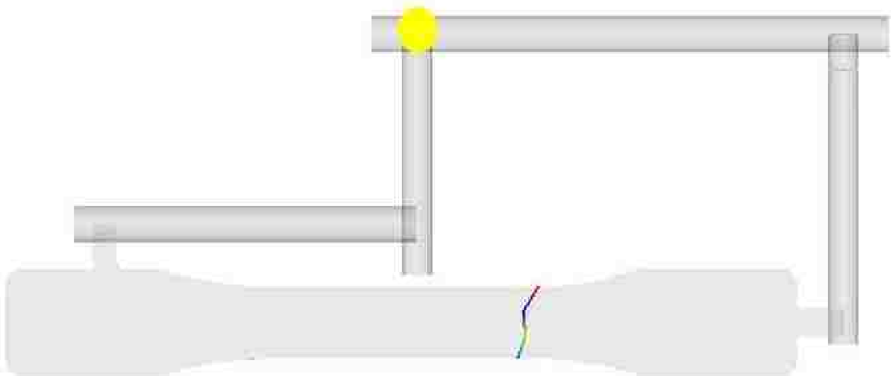

Figure 6.8: ILCM 2.2(Left Valve Opening: 23^o, Right Valve Opening: -12^o)

From the second iteration output, the error is -7mm, which means the weld line bounced over the target position at this point, which had never show in previous case earlier this chapter. The previous input is left valve opening is 23^o and right valve opening is -12^o. By calculating with Equation 4-1, the third iteration input will be left valve opening 25.1^o and right valve opening -9.9^o, where the weld line position is located at 106 mm, so the error is -6 mm from the desired target position.

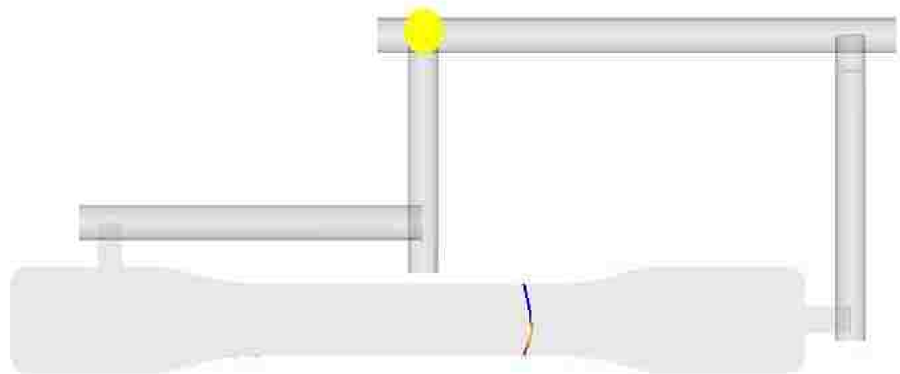

Figure 6.9: ILCM 2.3(Left Valve Opening: 25.1^{o}, Right Valve Opening: -9.9^{o})

From the third iteration output, the error is -6mm, and the previous input is left valve opening is 25.1^{o} and right valve opening is -9.9^{o} . By calculating with Equation 4-1, the forth iteration input will be left valve opening 26.9^{o} and right valve opening -8.1^{o}, where the weld line position is located at 103 mm, so the error is -3 mm from the desired target position.

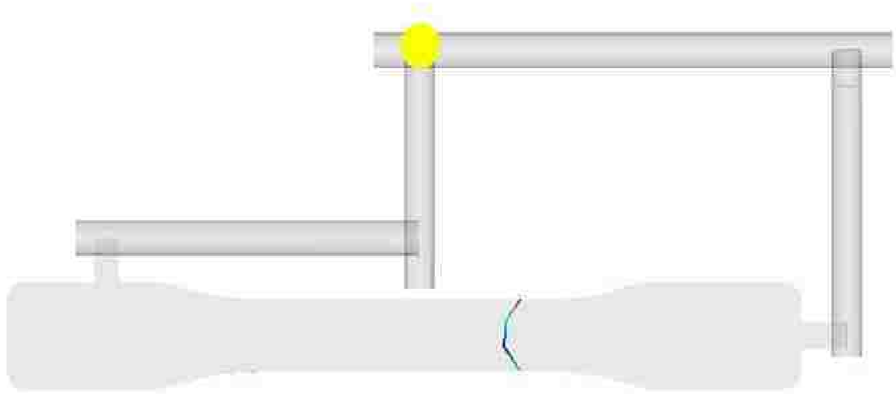

Figure 6.10: ILCM 2.4(Left Valve Opening: 26.9^{o}, Right Valve Opening: -8.1^{o})

From the fourth iteration output, the error is -3mm, and the previous input is left valve opening is 26.9^{o} and right valve opening is -8.1^{o}. By calculating with Equation 4-1, the fifth iteration input will be left valve opening 27.8^{o} and right valve opening -7.2^{o}, where the weld line position is still located at 100 mm, so the iteration has achieve the desired target weld line position without the learning gain scheduling. This simulation reaches desired target in five iterations.

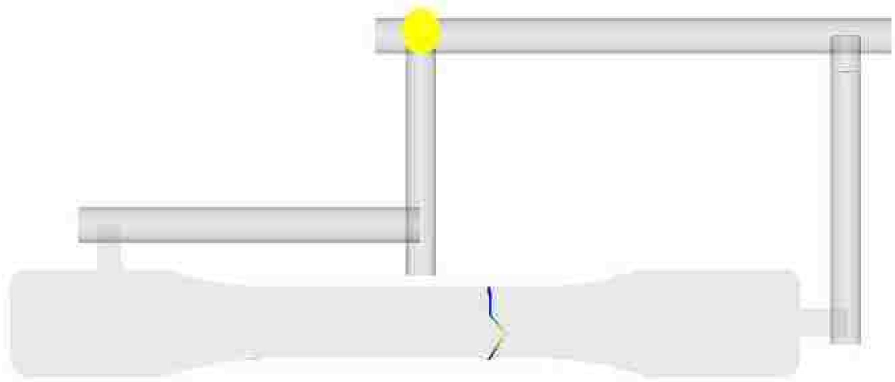

Figure 6.11: ILCM 2.5(Left Valve Opening: 27.8^{o}, Right Valve Opening: -7.2^{o})

In Case 2, with a bigger learning gain g = -0.3, iterative learning control reaches the desired target weld line position in five iterations without performing learning gain scheduling.

Chapter 7:

Analysis and Comparison of MoldFlow Simulation Results and Experimental Results

7.1 Analysis and Comparison of MoldFlow Simulation Results

In both Case 1 and Case 2 MoldFlow simulations, the initial conditions are unchanged except for the learning gain. In Case 1, with the learning gain G = -0.125, it takes six times iterations to reach the desired target weld line position. The weld line traverses from left to right as the iterations increase. The learning gain is increased up to 4 times the original learning gain.

In Case 2, a larger learning gain G = -0.3 is used and the weld line reaches its desired target position in five iterations without changing the learning gain. In this case, the weld line bounced around the desired target and still reaches the target in five iterations.

Iterative learning control theory using MoldFlow as the prediction model, shows that it is possible and is efficient to systematically move the weld line position to some desired position. This approach allows savings in plastics, energy, and time.

Figure 7.1 shows the error chart for iteration Case 1 and Case 2. When the Iteration Case 1 reaches the target by decreasing the error toward to the desired position, the Iteration Case 2 bounces around to reach the desired position. In Figure 7.2, it shows the learning gain scheduling plot, which indicates that the Iteration Case 2 uses the same learning gain to reach the target while the Iteration Case 1 needs to use up to 4 times the original learning gain. However, both cases reach the desired position in only 5 to 6 iterations. This is an excellent approach.

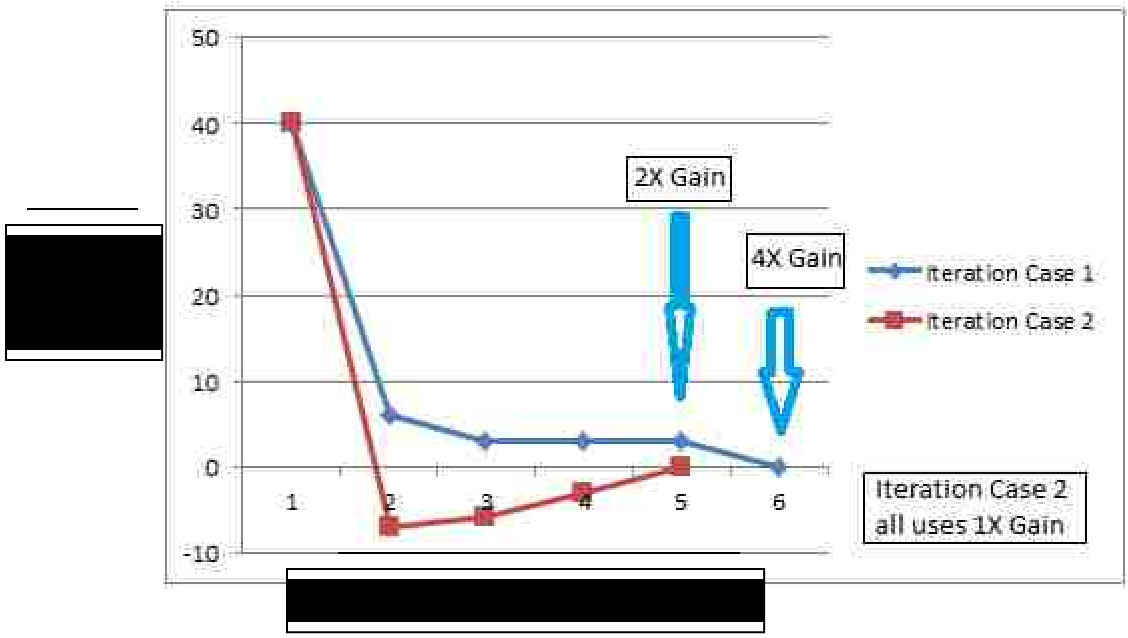

Figure 7.1: Errors Chart in Case 1 and Case 2

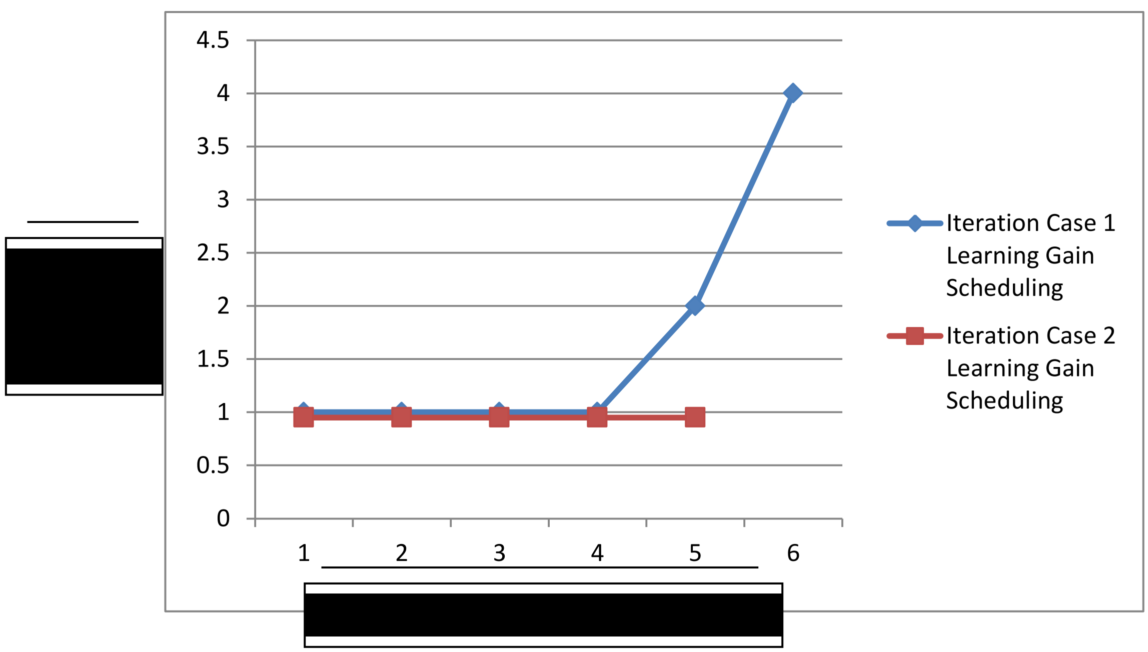

Figure 7.2: Learning Gain Scheduling

7.2 Analysis and Comparison of MoldFlow simulation Results and Experimental Results

After the MoldFlow prediction model has constructed, with the application of iterative learning control, an excellent starting point for the inputs to an injection molding machine is obtained. Comparing the actual injection molded part (Fig. 7.3) with Case 1 MoldFlow simulation result (Fig. 7.4), the weld line matches exactly. Similarly for Case 2 the experimental result (Fig. 7.5) and MoldFlow simulation result (Fig. 7.6) matches exactly as well.

The application of iterative learning control theory with MoldFlow simulation predictive model, results in an efficient and effective approaches to the specification of inputs to the injection molding machine to position the weld line at some desired location. The result is that there is a reduction in time and resources to waive at a desirable part, without the use of trial and error methods.

The Case 1 actual injection molded part, shown in Figure 7.3, where the weld line is located at 100mm, so does the Case 1 MoldFlow simulation result, shown in Figure 7.4, the weld line matches exactly at 100 mm. Similarly for Case 2 the experimental result, shown in Figure 7.5, the weld line is located at 100mm, so does the Case 2 MoldFlow simulation result, shown in Figure 7.6, the weld line matches exactly as well.

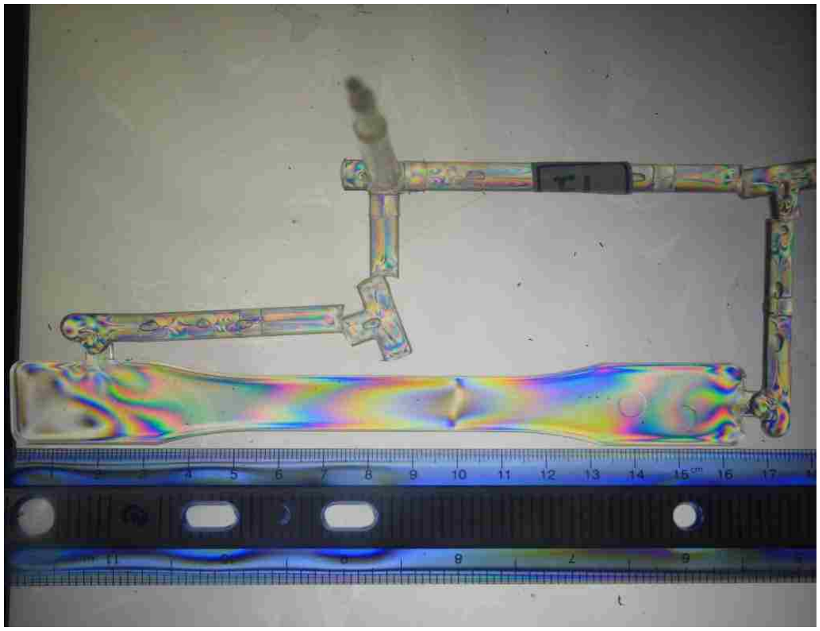

Figure 7.3: Experiment Final Part Case 1

(Left Valve Opening: 27.8^{o}, Right Valve Opening: -7.2^{o})

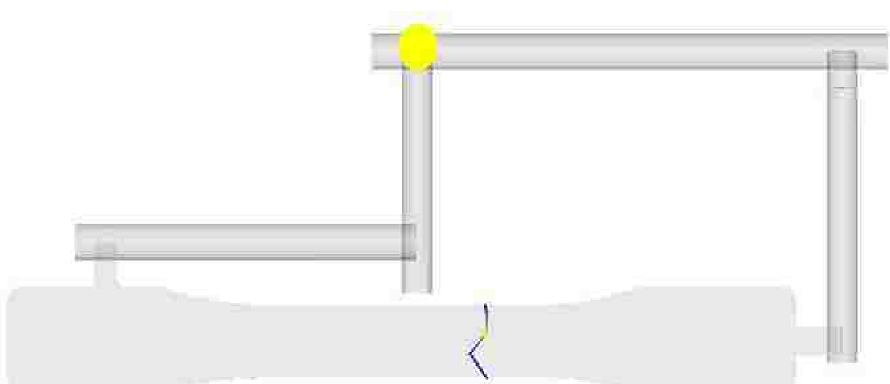

Figure 7.4: MoldFlow Final Part Case 1

(Left Valve Opening: 26.625^{o}, Right Valve Opening: -7.625^{o})

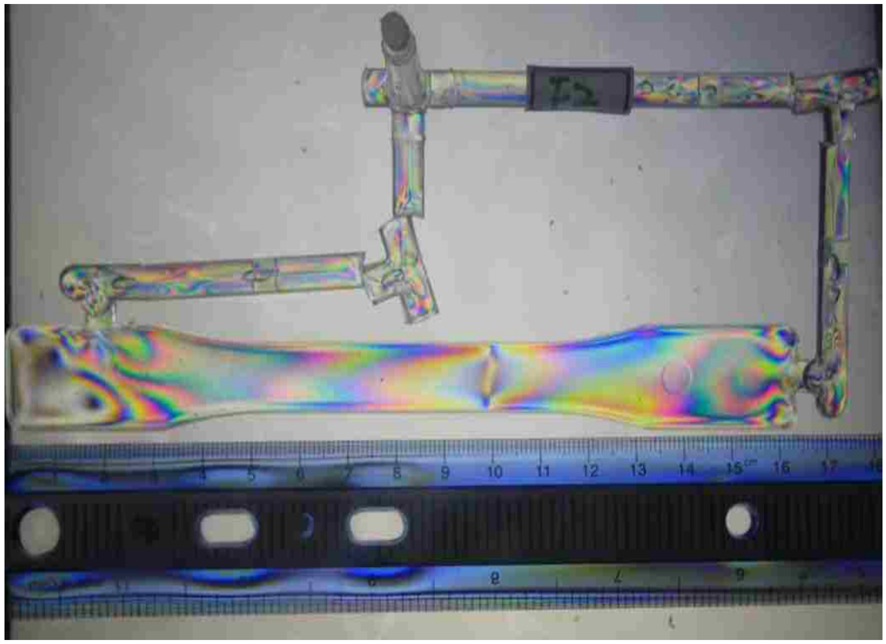

Figure 7.5: Experiment Final Part Case 2

(Left Valve Opening: 27.8^o, Right Valve Opening: -7.2^o)

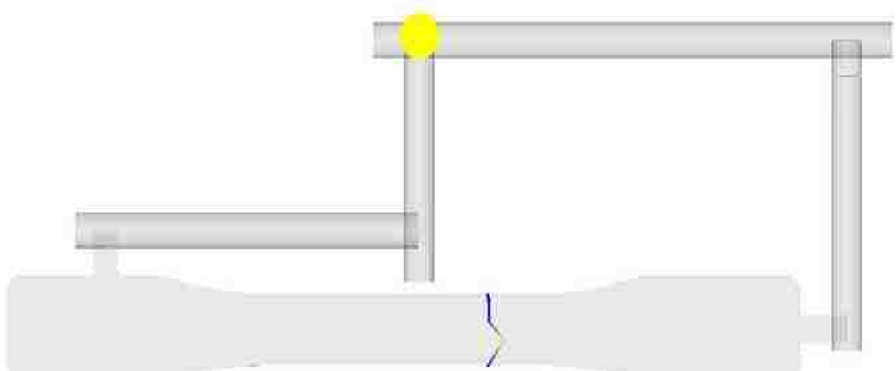

Figure 7.6: MoldFlow Final Part Case 2

(Left Valve Opening: 27.8^o, Right Valve Opening: -7.2^o)

Chapter 8:

Conclusion and Suggestions for Future Work

8.1 Conclusions

This investigation has successfully utilized iterative learning control to move the weld line position to a desirable target position within 5 to 6 iterations. Such a systematic approach is more efficient and effective than the use of trial-and-error methods.

A MoldFlow predictive model has been successfully constructed. The MoldFlow prediction model has been tested and been shown to be accurate when compared to experimental data using an injection molding machine with this model it is then possible to perform simulations without the use of the actual injection molding machine thereby saving plastic, energy, and time.

A comparison between the final parts from an injection molding machine to the simulations from MoldFlow, the weld lines are matched exactly. In chapter 7, Figures 7.3, 7.4, 7.5 and 7.6 shows the weld lines are matched exactly at the target position at 100mm.

8.2 Suggestions for Future Work

In the future, considering using iterative learning control to learn other inputs to the system is expected. Apply adaptive control to the velocity and pressure schedule is another ideal work. Building a more complicated geometry is another plan for the future work, so does changing the polystyrene to other types of resins as well. Improving on the valve modeling in MoldFlow is another progress to make.

References

[1] Li, C., Wang, F., Niu, D., Liu, Y., "Cavity Pressure Control by Iterative Learning Control with Zero-Phase Filtering in Injection Molding," *IEEE Chinese Control and Decision Conference*, 2010.

[2] Wang, Y., Zhou, D., Gao, F., "Iterative Learning Model Predictive Control for Multi-Phase Batch Processes," *Journal of Processes Control*, Vol. 18, 2008, pp. 543-557.

[3] Zheng, D., Alleyne, A., "Modeling and Control of an Electro-Hydraulic Injection Molding Machine with Smoothed Fill-to-Pack Transition," *Journal of Manufacturing Science and Engineering*, Vol.125, February, 2003, pp. 154-163.

[4] Yao, K., Gao, F., Allgower, F., "Barrel Temperature Control During Operation Transition in Injection Molding," *Control Engineering Practice*, Vol. 16, 2008, pp. 1259-1264.

[5] Dairanieh, I. S., Haufe, A., Wolf, H. J., Mennig, G., "Computer Simulation of Weld Lines in Injection Molded Poly," *Polymer Engineering and Science*, Vol. 36, August, 1996, No. 15, pp. 2050-2057.

[6] Tsai, M. H., Ou, K. L., Huang, C.F., Cheng, H. C., Shen, Y. K., Chang, C. Y., Wu, C.H., Chen, J. H., Guan, P. J., "Study on Micro Injection Molding of Light Guiding Plate by Numerical Simulation," *International Communications in Heat and Mass Transfer*,

Vol. 35, 2008, pp. 1097-1100.

[7] Shen, Y. K., Chang, C. Y., Shen, Y. S., Hsu, S. C., Wu, M. W., "Analysis for Microstructure of Microlens Arrays on Micro Injection Molding by Numerical Simulation," *International Communications in Heat and Mass Transfer*, Vol. 35, 2008, pp. 723-727.

[8] Rahman, W. A. W. A., Sin, L. T., Rahmat, A. R., "Injection Molding Simulation Analysis of Natural Fiber Composite Window Frame," *Journal of Matericals Processing Technology*, Vol. 197, 2008, pp. 22-30.

[9] Chew, M., Phan, M., "Application of Learning Control Theory to Mechanisms: Part 1 – Inverse Kinematics and Parametric Error Compensation," *Machine Elements and Machine Dynamics, Trans. Of ASME*, Vol. 71, 1994, pp. 25-32.

[10] Chew, M., Phan, M., "Application of Learning Control Theory to Mechanisms: Part 2 – Reduction of Residual Vibrations in High-Speed Electromechanical Bonding Machines," *Machine Elements and Machine Dynamics*, *Trans. Of ASME*, Vol. 71, 1994, pp. 33-39.

[11]Chew, M., Longman, R. W., Phan, M., "Intelligent Mechanisms," International Design Engineering Technical Conferences and 28th Biennial Mechanisms & Robotics Conference. *Proceedings of IDETC 2004, Of ASME*, Salt Lake City, Utah USA, 2004.

[12] Chen, M. Y., Chen, Y. C., Chen, S. C., "Fuzzy Control on Manufacturing Welding Systems: To Apply Fuzzy Theory in the Control of Weld Line of Plastic Injection-Molding," Advanced Fuzzy Logic Technologies in Industrial Applications, Springer London, ISBN 978-1-84628-469-4, 2006, pp. 315-324.

Appendix A: Relationship between Valves in MoldFlow and the Valves in Experiment

Since there has no current valve system in MoldFlow, this study is going to make a valve in MoldFlow runner system to imitate the valve in experimental mold. The Cut Area of the Valve Opening is approximately an Ellipse Shape when it turns, but in MoldFlow the Runner is a circle. A x B x π = r^2 x π.

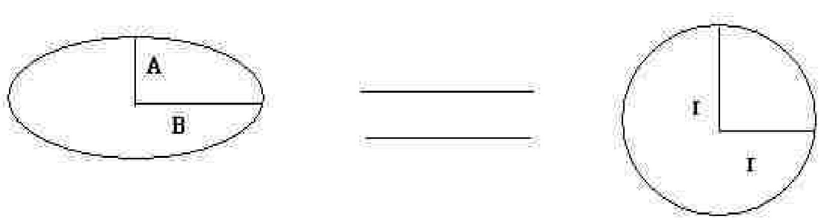

Figure Appendix A1: Runner Area Ellipse vs. Circle

By examine experiment Case 1 with left valve opening at -35 degree and right valve opening at 0 degree. The weld line should be at 60mm. If measuring the size of the cut area by caliper, the radius A is 1.35mm, radius B is 0.5mm. Then the r^2 is 0.675mm, r = 0.822 mm.

However, by using 0.822 mm as the runner size, the simulation result will not give you the weld line at 60mm. So, there has a constant K as a relationship ratio between the imitated valve in MoldFlow and the valve in experiment.

By trying several sizes, finally, the 0.259 mm diameter valve in MoldFlow can get the weld line exactly at 60mm. Hence, $A*B*\pi*K = r^2*\pi$, K = 0.0248.

By calculation above from the experiment part transfer into MoldFlow, the relationship between valve opening in experiment testing cases and the valve size in MoldFlow:

0^o = 6.35 mm

10^o = 0.964mm

15^o = 0.934mm

30^o = 0.496mm

32.5^o = 0.373mm

35^o = 0.259mm

And all these data matches the test in Appendix B. With these data, it can be project into a diameter profile for all various theta which is shown in Table Appendix A1.

In Table Appendix A1, the X-coordinate, theta is the valve opening (in degrees) used in experiment, the Y-coordinate is the diameter used in MoldFlow simulation to model the valve. By using the valve openings and flow diameters, 10^{o} : 0.964mm, 15^{o} : 0.934mm, 30^{o} : 0.496mm, 32.5^{o} : 0.373mm, 35^{o} : 0.259mm, the polynomial fit is given by the following equation:

$$y = 0.00001x^{3} - 0.0018x^{2} + 0.0346x + 0.7906 \qquad \text{(A-1)}$$

The resulting magnitude is very close to all those five points and it is degradable. These decreasing numbers are fit to the desired prediction model.

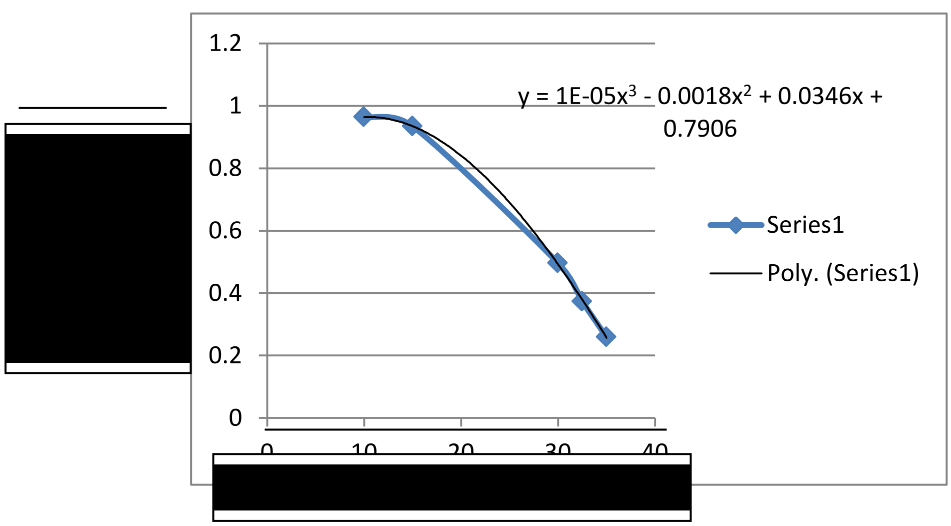

Figure Appendix A2: Polynomial A-1

X Theta	Y Diameter	Polynomial
0	6.35	6.35
1		5.4918
2		4.7046
3		3.9884
4		3.3432
5		2.769
6		2.2658
7		1.8336
8		1.4724
9		1.1822
10	0.964	0.9666
11		0.96671
12		0.96388
13		0.95817
14		0.94964
15	0.934	0.93835
16		0.92436
17		0.90773
18		0.88852
19		0.86679
20		0.8426
21		0.81601
22		0.78708
23		0.75587
24		0.72244
25		0.68685
26		0.64916
27		0.60943
28		0.56772
29		0.52409
30	0.496	0.4786
31		0.43131
32		0.38228
32.5	0.373	0.35713125
33		0.33157
34		0.27924
35	0.259	0.22535

Table Appendix A1: Diameters for MoldFlow Valve

Appendix B: MoldFlow Simulation Model Test

According to Appendix A, the relationship between the valves in MoldFlow and the valves in experiment, here are four cases to exam the relationships. With both experimental test cases and MoldFlow simulation test cases, it can be sure that this prediction model is accurate and very powerful to predict the weld line position. Figure Appendix B1 to B24 shows all the testing results.

Experimental Test Case 1:

Left Valve Opening = 35 degree, Right Valve Opening= 0 degree.

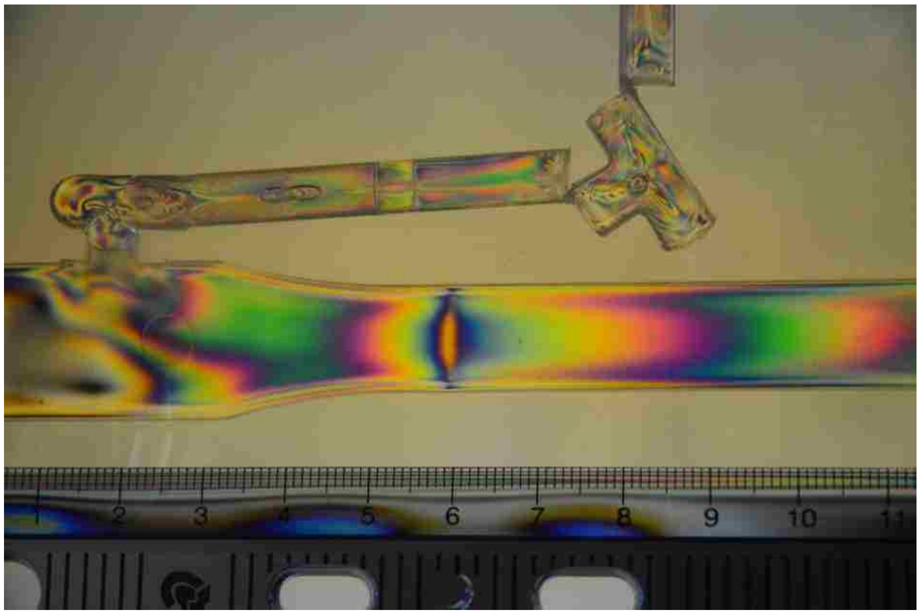

Figure Appendix B1: Experimental Case 1.1

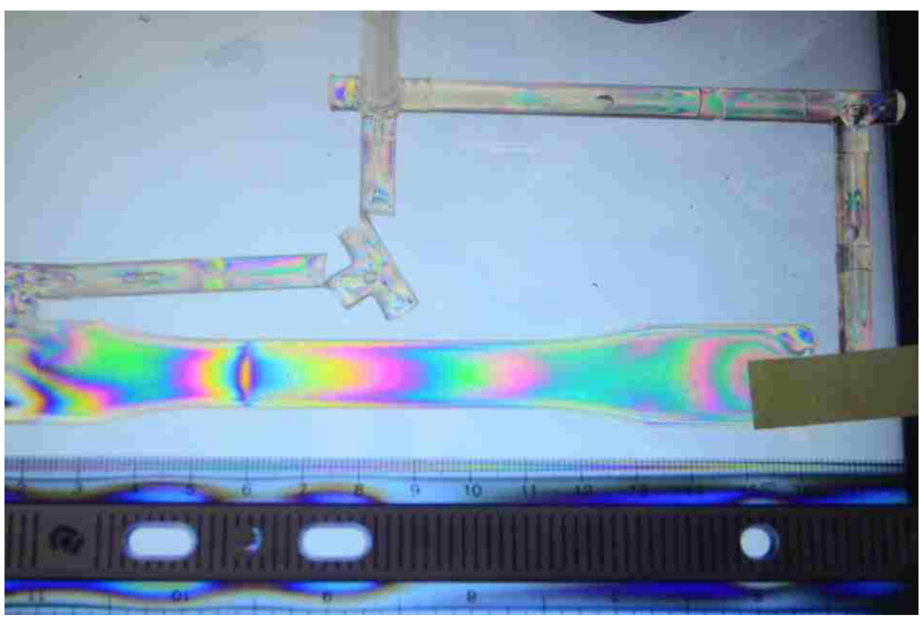

Figure Appendix B2: Experimental Case 1.2

MoldFlow Test Case 1:

Left Valve Opening = 35 degree (35^o = 0.259mm)

Right Valve Opening= 0 degree (0^o = 6.35 mm)

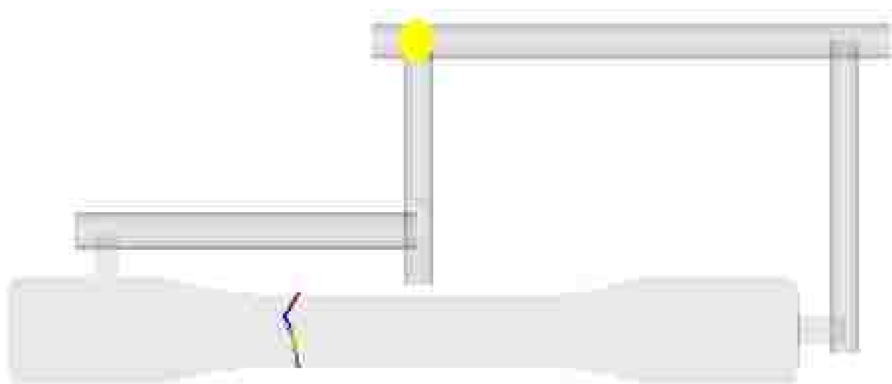

Figure Appendix B3: MoldFlow Test Case 1.1

In Experimental Test Case 1, shown in Figure Appendix B1 and Appendix B2, the weld line locates at 60mm, with left valve opening at 35 degree and right valve opening at 0 degree. In MoldFlow Test Case 1, shown in Figure Appendix B3, the weld line locates at 60mm as well, with left valve diameter in 0.259mm (35^o = 0.259mm), and right valve diameter in 6.35mm (0^o = 6.35 mm). The testing results shows the MoldFlow simulation model works properly and it can predict the weld line exactly as it will be molded in the experimental work.

Experimental Test Case 2:

Left Valve Opening = 35 degree, Right Valve Opening = 30 degree.

Figure Appendix B4: Experimental Case 2.1

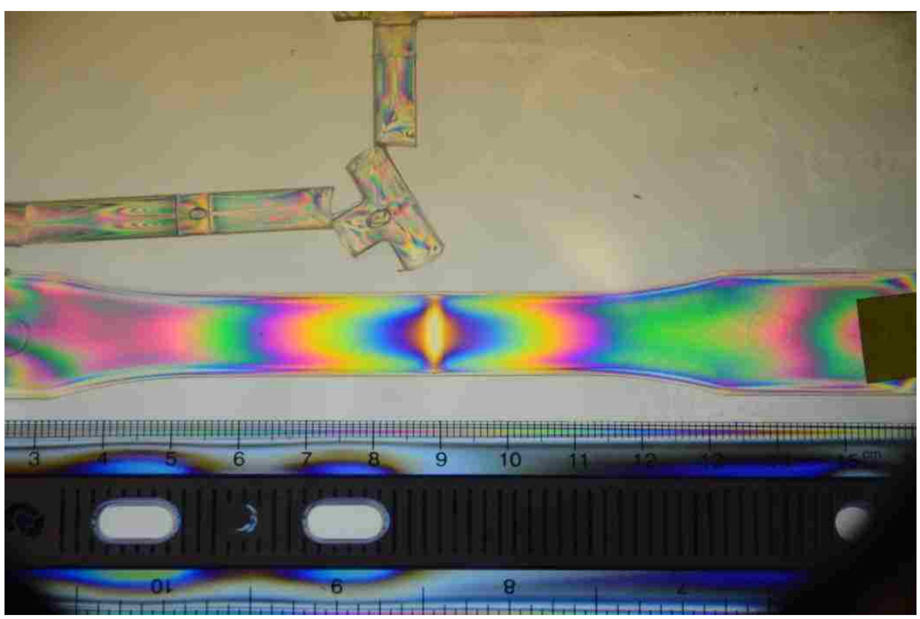

Figure Appendix B5: Experimental Case 2.2

MoldFlow Case 2:

Left Valve Opening = 35 degree (35^o = 0.259mm)

Right Valve Opening= 30 degree (30^o = 0.496mm)

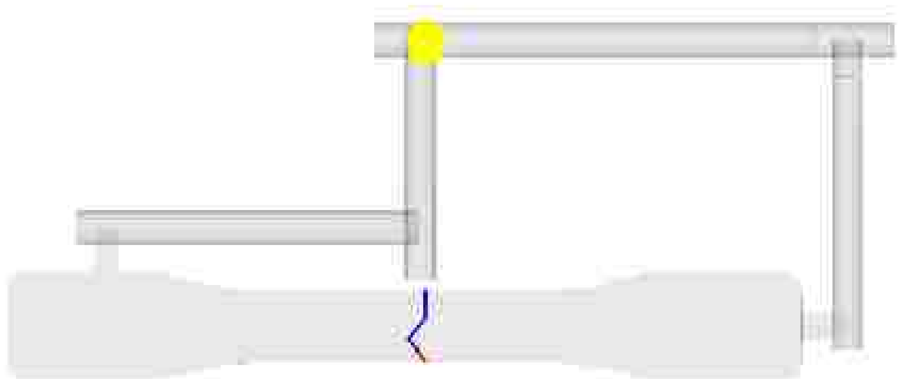

Figure Appendix B6: MoldFlow Test Case 2.1

In Experimental Test Case 2, shown in Figure Appendix B4 and Appendix B5, the weld line locates at 90mm, with left valve opening at 35 degree and right valve opening at 30 degree. In MoldFlow Test Case 2, shown in Figure Appendix B3, the weld line locates at 90mm as well, with left valve diameter in 0.259mm (35^o = 0.259mm), and right valve diameter in 0.496mm (30^o = 0.496mm). The testing results shows the MoldFlow simulation model works properly and it can predict the weld line exactly as it will be molded in the experimental work.

Experimental Test Case 3:

Left Valve Opening = 15 degree, Right Valve Opening = 30 degree.

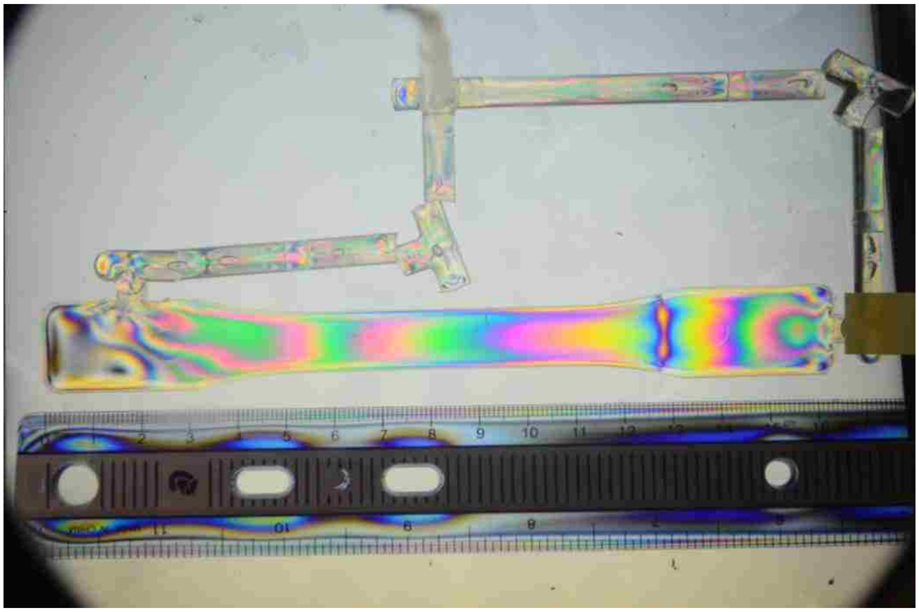

Figure Appendix B7: Experimental Test Case 3.1

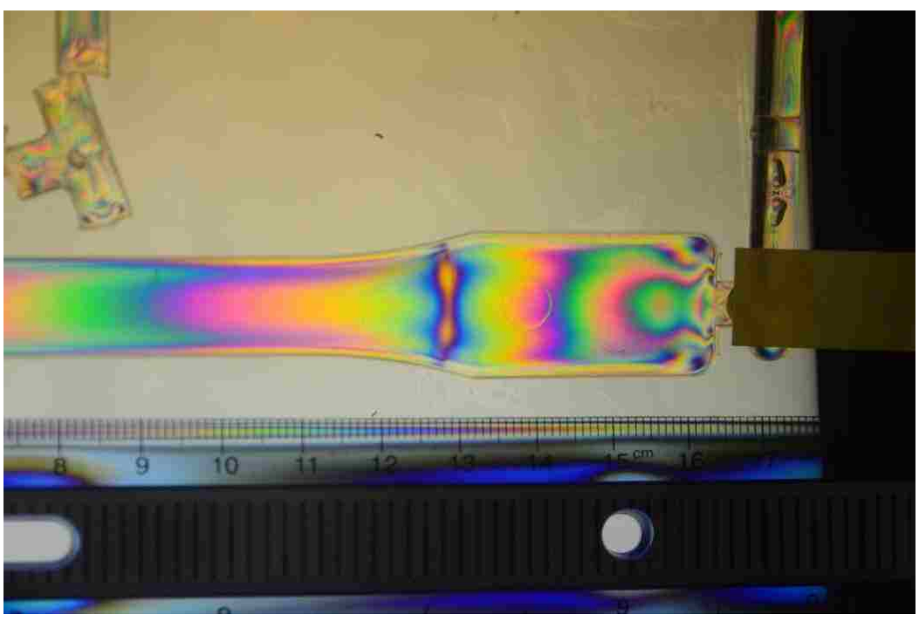

Figure Appendix B8: Experimental Test Case 3.2

MoldFlow Case 3:

Left Valve Opening = 15 degree (0.934mm)

Right Valve Opening = 30 degree (0.496mm)

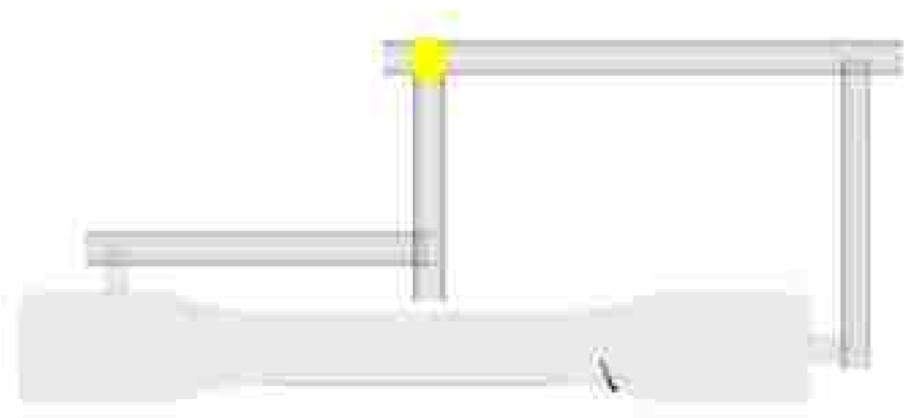

Figure Appendix B9: MoldFlow Test Case 3.1

In Experimental Test Case 3, shown in Figure Appendix B7 and Appendix B8, the weld line locates at 127mm, with left valve opening at 15 degree and right valve opening at 30 degree. In MoldFlow Test Case 2, shown in Figure Appendix B9, the weld line locates at 127mm as well, with left valve diameter in 0.934mm (15^o = 0.934mm), and right valve diameter in 0.496mm (30^o = 0.496mm). The testing results shows the MoldFlow simulation model works properly and it can predict the weld line exactly as it will be molded in the experimental work.

Experimental Test Case 4:

Left Valve Opening = 10 degree, Right Valve Opening = 32.5 degree.

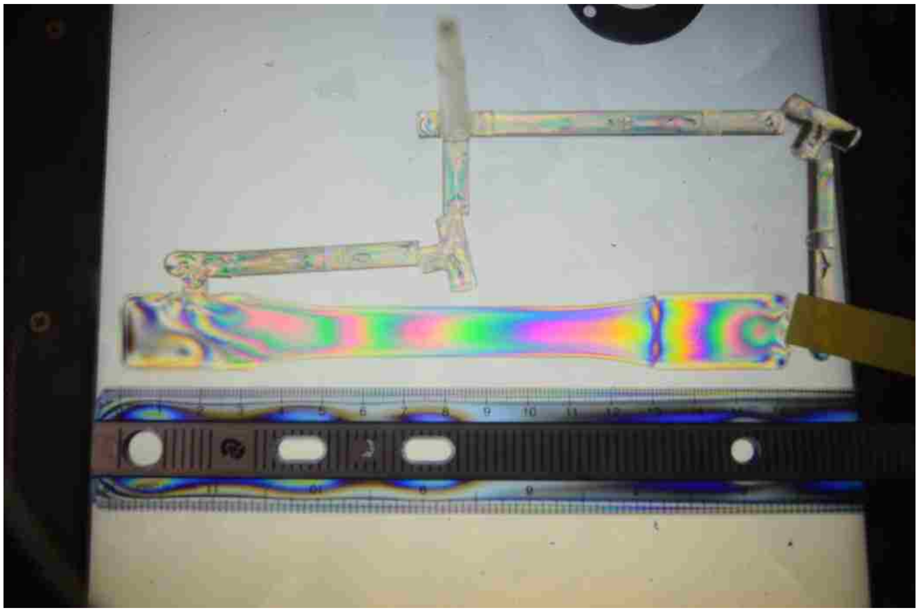

Figure Appendix B10: Experimental Test Case 4.1

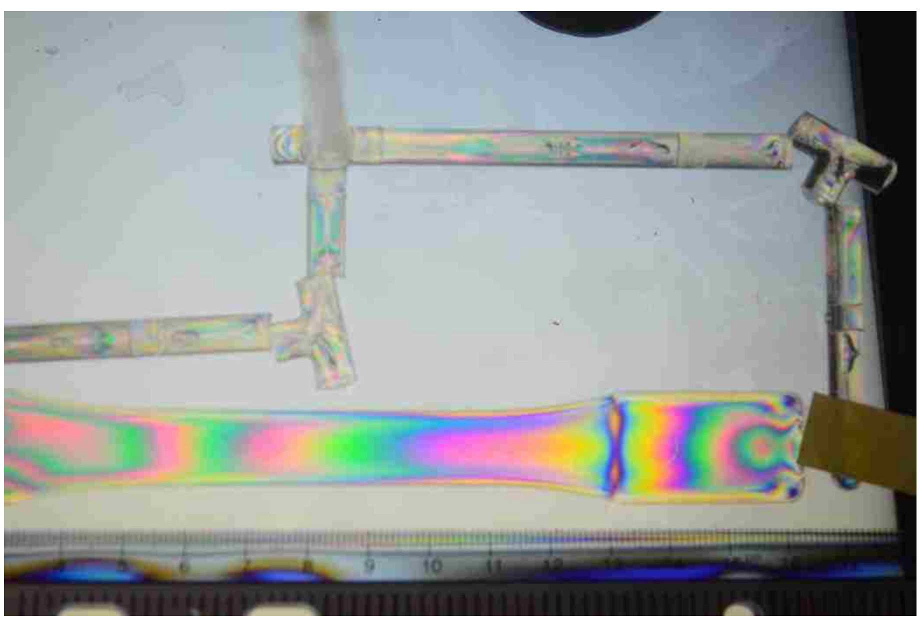

Figure Appendix B11: Experimental Test Case 4.2

MoldFlow Case 4:

Left Valve Opening = 10 degree (0.964mm)

Right Valve Opening = 32.5 degree (0.373mm)

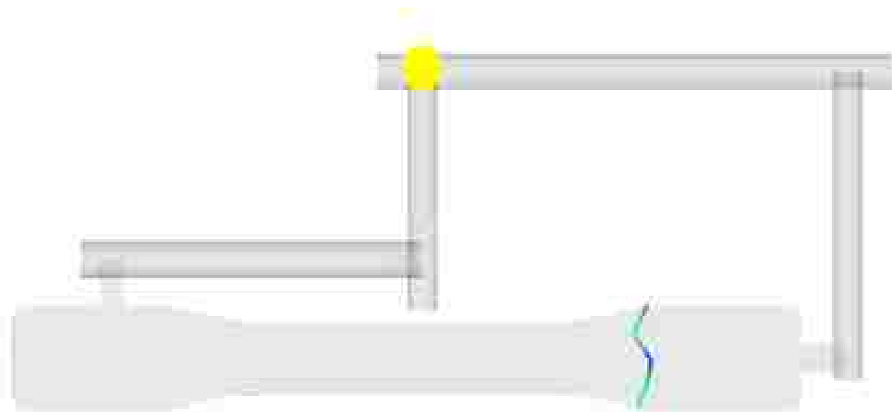

Figure Appendix B12: MoldFlow Test Case 4.1

In Experimental Test Case 3, shown in Figure Appendix B10 and Appendix B11, the weld line locates at 130mm, with left valve opening at 10 degree and right valve opening at 32.5 degree. In MoldFlow Test Case 2, shown in Figure Appendix B12, the weld line locates at 130mm as well, with left valve diameter in 0.964mm (10^o = 0.964mm), and right valve diameter in 0.373mm (32.5^o = 0.373mm). The testing results shows the MoldFlow simulation model works properly and it can predict the weld line exactly as it will be molded in the experimental work.

Appendix C: SolidWork Model Setup

This Solidworks model (Fig. Appendix C1) is based on the molded ASTM 638 Type I Dog Bone (Fig. Appendix C2). By measuring the shape, angle, length, width, and height of the molded dog bone, then plot into the Soliworks to model the part.

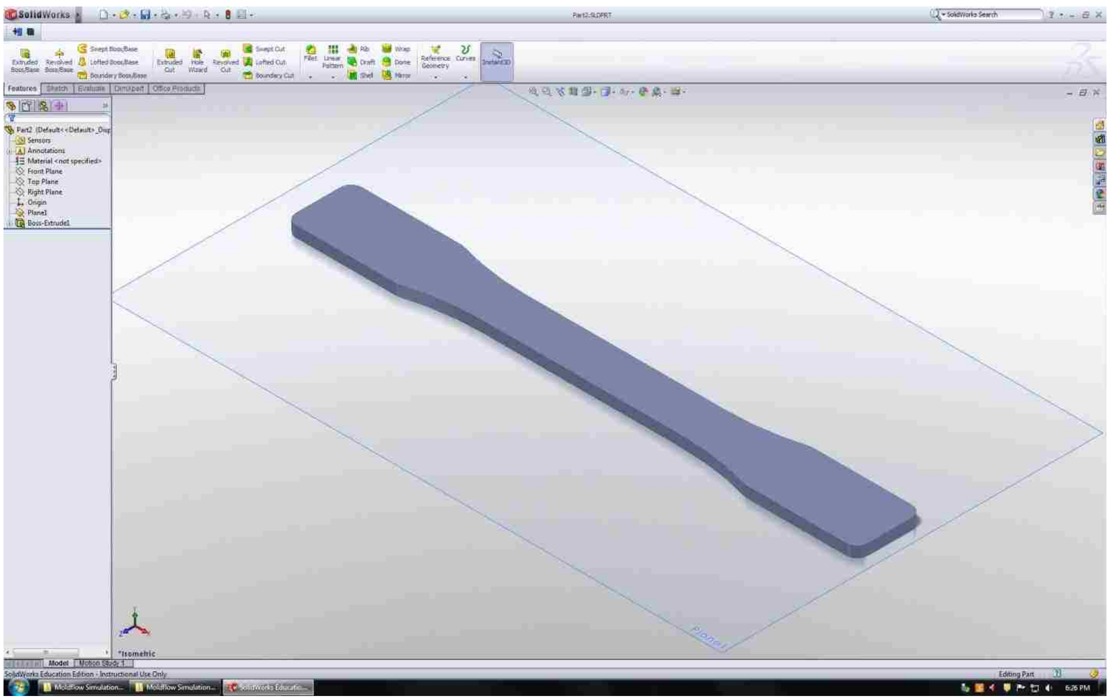

Figure Appendix C1: SolidWorks ASTM 638 Type I Dog Bone Model

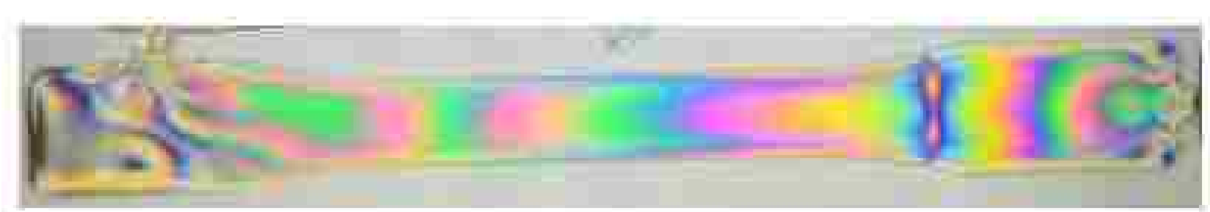

Figure Appendix C2: Molded ASTM 638 Type I Dog Bone

Appendix D:

Nissei 22mm Injection Molding Machine Specs

Machine Specs:

NISSEI Injection Molding Machine

Model: PS40E5ASE

S/N: E04M235

Injection Unit:

Injection Capacity: 35 cm^3/shot or 30 g/shot

Screw DIA: 22mm

Plasticizing Rate: 15 kg/hr

Injection Pressure: 2610 kg/cm^2

Injection Rate: 51 cm^3/sec

Screw Stroke: 92mm

Screw Speeds: 0~335 rpm

Injection Force 9.9 ton

Nozzle Touch Force: 1.7 ton

Hopper Capacity: 15 L

Clamp Unit:

Clamp Force: 40 ton

Clamp Stroke: 300 mm

Mold Thickness: 200 mm

Daylight Open: 500 mm

Distance b/w Tie Rods: (H)310 x (V)310

Platen Size: (H)450 x (V)450

Ejector Stroke: 60mm

Ejector Force: 1.8 ton

Mold Open Force: 3.0 ton

General:

Max Line Pressure 140 kg/cm^2

Pump-Elect Motor: 7.5/4 kw/pole

Heaters: 3.77 kw

Hydraulic Oil Req.: 240 L

Machine Size (L x W x H): 3.07 x 0.85 x 1.82 m

Floor Space: 2.46 x 0.73 m

Machine Weight: 2.2 ton

Vita

The Author was born in Miaoli, Taiwan on September 30, 1985 to Feng-Chiao Huang and Chih-Hung Mai. He earned his Bachelor of Science degree in Mechanical Engineering from Chun Yuan Christian University, Chung Li City, Taiwan, in June, 2007. The author then studied abroad and continued his education at Lehigh University. He was the President of Taiwanese Student Association. He will receive his Masters of Science degree in Mechanical Engineering and Mechanics in September, 2011.