EVALUATION OF ALTERNATIVE INJECTION STRATEGIES WITH VARIABILITY CONSIDERATION IN INJECTION MOLDING

A Thesis

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By

Thania Gaido, B.S.

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The Ohio State University

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Master's Examination Committee:

Dr. Jose M. Castro, Adviser

Dr. Blaine Lilly

Approved By:

José M Castro

Adviser

Graduate Program in Industrial

and Systems Engineering

ABSTRACT

Selecting proper process settings is crucial in injection molding (IM) as part quality is greatly influenced by the process conditions. The locations of the injection gate need to be decided before the mold is made. Other processing variables can be adjusted during start up; however changing the gate location at a later stage involves great cost. In this work, we analyze the effect of gate location on process consistency for an automotive part, using a multi-variable optimization method called Data Envelopment Analysis (DEA).

Dedicated to my mother and family, they are my inspiration for continuing with my education and strive for success.

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There is also the rest of my family and friends, who when I go to Honduras stay close to me, even though everybody knows I am not the best person in keeping in touch, which does not mean that I am not thinking of them, they are always in my thoughts and my life.

VITA

March 8th 1981 .... Born – San Pedro Sula, Honduras

March 2004 .... B.S. Industrial and Systems Engineer, The Ohio State University

March – November 2004 .... Process Coordinator Amiraults Remodeling

September 2005 – September 2006 .... Graduate Administrative Associate, ¿Qué Pasa, OSU? The Ohio State University

FIELDS OF STUDY

Major Field: Industrial and Systems Engineering

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CHAPTER 1

INTRODUCTION AND OBJECTIVES

1.1 Introduction

Injection Molding (IM) is considered to be one of the most important processes in the manufacturing of plastic parts. One of the main advantages of IM is that parts can be manufactured economically with little or virtually no finishing operations needed [1].

Plastics offer several advantages over metals including the ease of manufacturing and low cost associated with the production process, simplification of components, part integration and consistent quality when mass produced. This has led overtime to an increased replacement of metal parts with plastic ones.

Today, more than one-third of all the thermoplastic materials are injection molded and more than half of all the polymer processing equipment is for injection molding [2]. A schematic representation of a typical injection molding machine is shown in Figure 1.1.

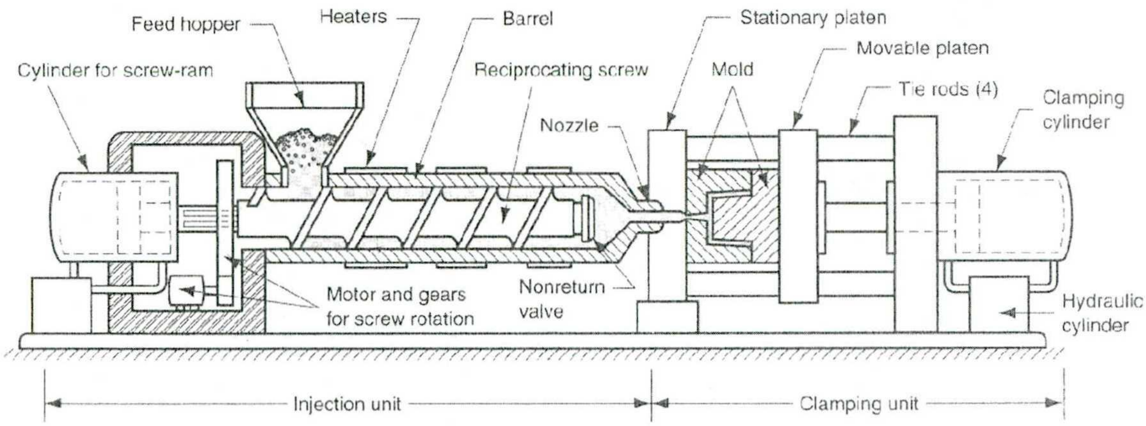


Figure 1.1: Typical injection molding machine [3]

The IM process starts when raw material, typically in the form of pellets is fed into the **hopper**. From the hopper the material falls into the **barrel,** where the material is melted by a combination of electrical and shear heating as the **reciprocating screw** turns. As the screw drags material forward, it pulls back into the chamber in order to allow material to accumulate in the front of the barrel and for pressure to build to the desired value. Once enough material is gathered at the front of the barrel, the screw plunges forward and injects the plastic into the **mold cavity** filling the mold. Once the filling process is completed, the packing phase of the process starts. During the packing phase the pressure is further increased as shown schematically in figure 1.2. This is done in order to continue to feed more material to make up for shrinkage due to the material cooling to room temperature at ejection. The packing pressure and packing time play a critical roll in the part quality. The length of the packing phase can only be controlled if hot runners are used; if a cold runner is used, then the end of the packing stage depends on when the gate freezes. If there is not enough material fed into the mold, this could lead to unacceptable shrinkage of the part. On the other hand, feeding too much material in to the mold can cause flash (excess material that is formed and attached to the part), which will create the need of post finishing operations.

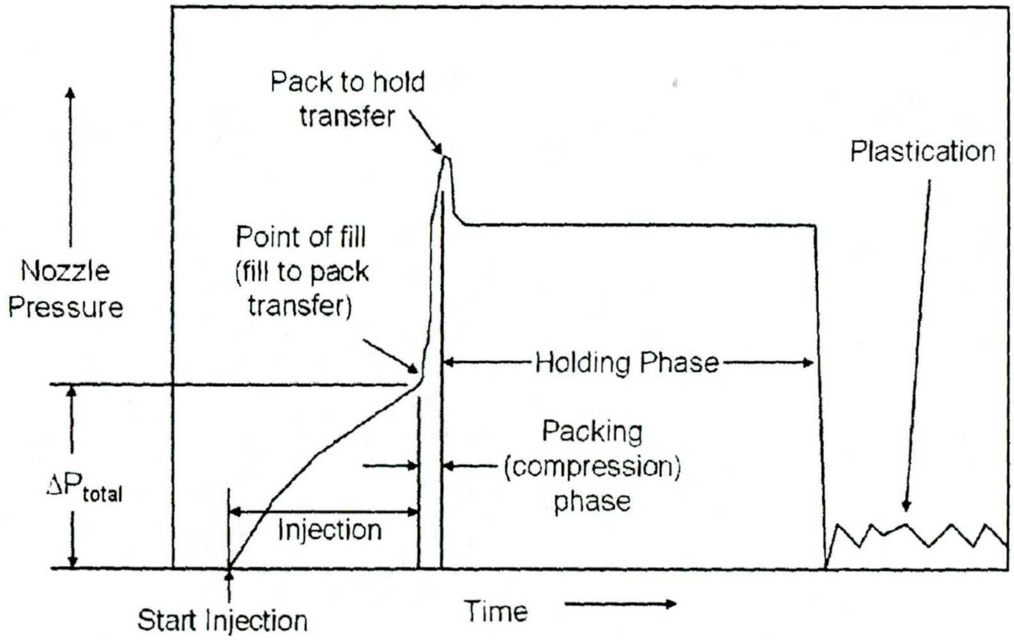


Figure 1.2: Pressure at the injection location for one cycle of IM [4]

The part quality of an injection molded part is greatly affected by the process settings. Selecting the best process settings is complicated by the fact that in most cases, improvement in some quality or performance measures negatively affects the performance of others. A critical issue to keep in mind is part consistency. When selecting the best process conditions, it is important to take into account their variability. For most manufacturing cases when optimizing the performance measures (PM) it is desired to take in to account the conditions that minimize their variability. As a matter of fact in high precision injection molding the critical issue is to minimize variability.

The variability in the PMs arises from inconsistencies in the process settings. These inconsistencies can be caused by many exterior factors such as heat from the environment (other machines). Once the process reaches steady state the machine will only be able to control the set values of either the mold or melt temperature within a range. For example, if the set melt temperature is 100 °F the variability from the environment can cause the melt temperature to vary ± 10 °F, which in turn can cause variability in the PMs of the parts being produced.

There are two approaches that can be used to develop mathematical models to represent the performance measures during injection molding. If the physics are understood, then a physics based model can be used to simulate the PMs; on the other hand, if the physics behind the problem are too complicated or are not fully understood, then an empirical model is used. The empirical models used in this thesis are linear regression models.

As can be deduced from the above discussion optimizing the IM process, involves multiple variables with conflicting effects. One approach would be to develop a single objective function by assigning relative weights to the different PMs. However coming up with adequate weights may be an issue. An alternate approach is to use a technique which selects the best compromises among all the PMs of interest. That is those cases for which no PM can be further improved without a detrimental effect on another. Data envelopment analysis (DEA) is a multi-variable optimization method that is ideally suited for these cases and is the one used in this thesis.

Process settings can be adjusted after the parts are in production. This will cause some delays in production but in most cases does not involve a large cost. However, once the mold is fabricated, it becomes very expensive to change the injection location. Thus it is crucial to properly select injection locations before the mold is machined. A critical reason for identifying the correct injection location in the IM process is the formation of weld lines. Weld lines are visible flaws that are created when two or more flow paths meet during the filling process [5], this in turn becomes the weakest location in the part which can cause structural problems in the finished part. They may also affect part appearance. These flaws can be controlled by selecting the proper gate location. Some injection locations may also conduct to a more robust process operation. .

The problem under analysis in thesis is considered to be a multiple criteria optimization problem, because there is more than one PM under analysis. The part that is studied in this thesis is the Honda Civic bumper, which can be seen in figure 1.3. Combinations of shrinkages at different locations were chosen as the PMs under investigation. Five different injection strategies were analyzed in order to select which strategy resulted in the most consistent process.

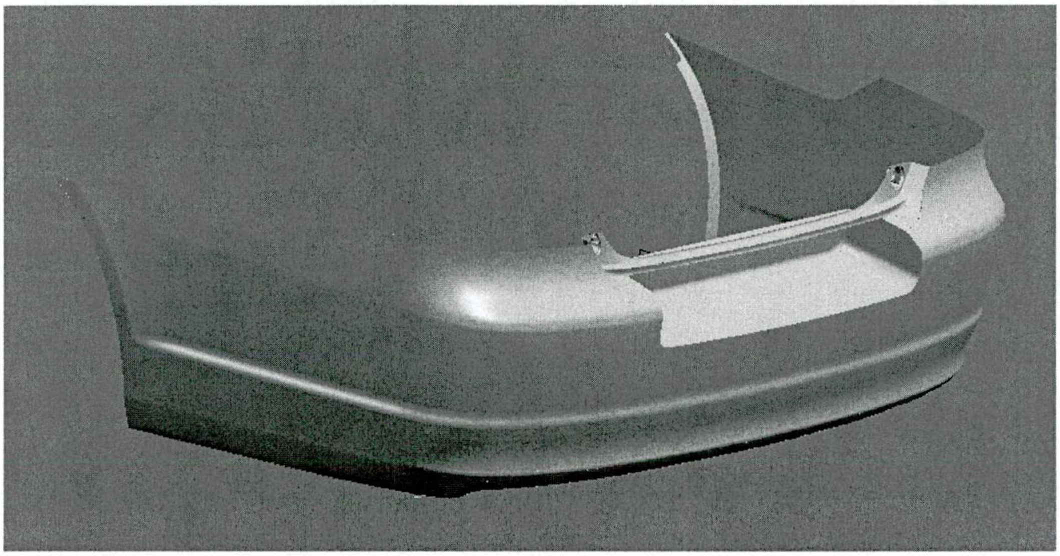


Figure 1.3: Honda Bumper under analysis

1.2 Objectives

The objective of this thesis is to demonstrate a method based on CAE and DEA to find the best compromises between multiple PMs for injection molding the Honda Civic bumper. Several injection strategies will be evaluated in order to identify the injection location which minimizes process variability

In this thesis I will:

- Determine the best injection strategy for the Honda Civic bumper
- Determine the best combination of process variables for the Honda bumper

- Study the effect of introducing variability in the Honda bumper in order to understand how variability affects the analysis
- Use DEA to solve the multiple criterion optimization problem

CHAPTER 2

TECHNICAL BACKGROUND

2.1 Process Modeling

When developing a model to analyze a problem in plastic manufacturing, one must always start with properly defining the problem. Next it needs to be decides if physics based models can be developed or if an empirical model will be needed. A physical based model is chosen if the physics behind the problem are understood. Physics based models are always preferred as they provide more insight into the problem, as well as allow for extrapolation. However, when analyzing most manufacturing problems there needs to be a combination of physics based models and empirical models. The reason being that in most cases, there are some PMs whose physics may not be fully understood or are too complicated to represent with physics based models. Empirical models are based on statistics and a well planned design of experiments is needed to develop a robust empirical model. Figure 2.1 from reference 6, represents the optimization strategy followed in this thesis and the following explanation refers to the mentioned figure.

The first step is to determine the phenomena that will be modeled. Once the phenomena has been identified, it is necessary to determine if the physics behind them are sufficiently understood and documented, if this is true then this will lead to the path of physics modeling. If the physics are not completely understood, this will lead to the empirical modeling path [6].

The complexity of the physics based model will help determine if an analytical solution is feasible or if a numerical solution is required. In the case where a numerical solution is needed, there needs to be a validation process for the extreme cases where analytical solutions can be obtained. The experimental validation is followed by an assessment of the burden to obtain predictions (i.e. to simulate) from a particular model. The result of this assessment will help determine whether it is convenient to summarize the functionality of the physics based model with an empirical model, or if the physics based model is simple enough to be used repeatedly to generate predictions. In the end, the model will be used to simulate a large number of combinations of untried variable levels to ultimately determine the best alternatives in terms of the controllable variables in the process [6].

On the other hand when the physics of the model are not completely understood, an empirical modeling requires the use of statistical designs of experiments to experimentally establish the relationship between process variables and the physical phenomena. It should be noted that an appropriate validation is required in empirical modeling [6].

After following either a numerical or empirical model, this will lead to a model or series of models that will be used to simulate the process to generate the required response predictions of the physical phenomena under study [6]. These predictions will then be used to select the best process compromises; that is the process conditions that give the best compromises among the performance measures of interest.

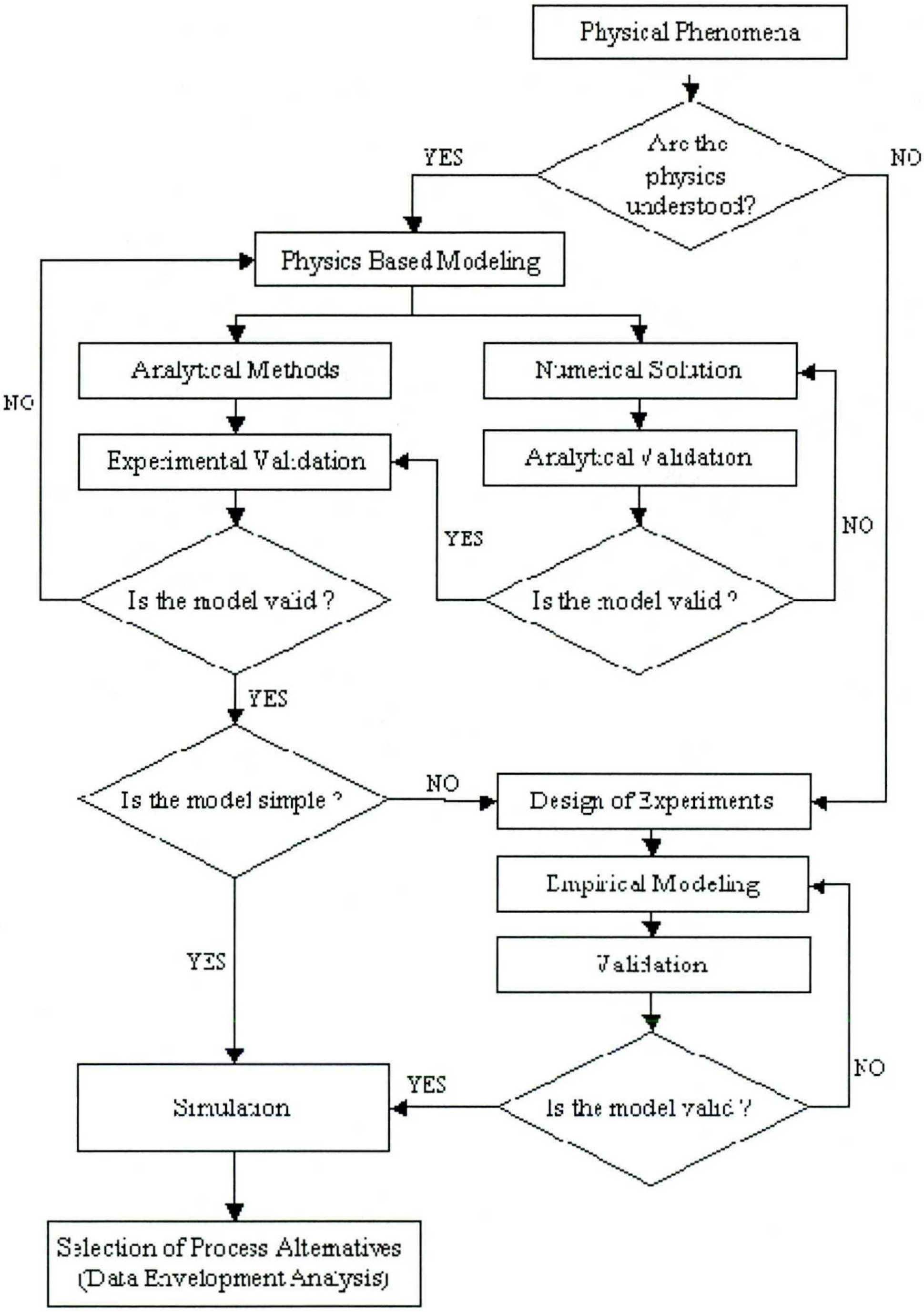


Figure 2.1: Process Modeling Scheme [6]

2.2 Computer Aided Engineering (CAE) - Moldflow

Computer simulations in IM are used to understand the system, solve an existing problem, or improve a manufacturing process. IM simulations are very useful for a number of reasons; they are not only a more economical way to analyze the IM process; but they also have many other advantages as well. For instance, they can be utilized in an experimental try-out of a new injection mold where there might be a need to predict a few pressures and temperatures; they can be used to investigate the effect of different process settings on a particular mold and machine; or to investigate the effect of different injection locations in a mold. [2, 7]

A computer model or simulation is considered to be the combination of a mathematical model, a numerical method to solve the equations, and computer software to carry out the numerical solution. The simulation software used in this thesis was the computer software package Moldflow Plastic Insight. This software, allows the user to input a Computer Aided Design (CAD) drawing of the part being produced, to determine the ideal combination of part geometry, material, mold design, and processing conditions that will produce quality finished parts. [5]

After the CAD drawing is inputted into Moldflow, the drawing needs to be meshed into finite elements. The mesh consists of elements with nodes at every corner of the elements. The mesh provides the basis for the Moldflow analysis, where molding properties are calculated at every node. The equation used for the calculations are the flow equations and the heat transfer equation [1]. It is necessary to have the right combination of elements and nodes in order for the calculations to be as precise as possible.

Moldflow has a fully three dimensional equation solver, however, for most plastic parts, the mid-plane mesh approach suffices. This approach takes advantage of the fact that there is a dimension that is much smaller than the other two. And simplifies the equations to what is commonly known as the Hele-Shaw model. Starting with the general balance equation which can be simplified as follows [8]:

Pressure equation for the cavity

$$\frac{\partial}{\partial_x}\left(S_2\frac{\partial_p}{\partial_x}\right)+\frac{\partial}{\partial_y}\left(S_2\frac{\partial_{op}}{\partial_y}\right)=0 \qquad 2.2.1$$

Where $S_2 = \int_0^h \frac{z'^2}{\eta}dz'$

Energy equation for cavity

$$\rho c_p\left(\frac{\partial T}{\partial t}+v_x\frac{\partial T}{\partial x}+v_y\frac{\partial T}{\partial x}\right)=\eta\dot{\gamma}^2+k\frac{\partial^2 T}{\partial z^2} \qquad 2.2.2$$

Pressure equation for circular runners

$$\frac{\partial}{\partial x}\left(r+S_1\frac{\partial p}{\partial x}\right)=0 \qquad 2.2.3$$

Where $S_1 = \frac{1}{2r^+}\int_0^{r^+}\frac{r'^3}{\eta}dr'$

Energy equation for circular runners

$$\rho c_p\left(\frac{\partial T}{\partial t}+v_r\frac{\partial T}{\partial r}\right)=\eta\dot{\gamma}^2+\frac{k}{r}\frac{\partial}{\partial r}\left(r\frac{\partial T}{\partial r}\right) \qquad 2.2.4$$

2.3 Metamodeling

A metamodel is an empirical expression that approximates the functionalities implied by a mathematical model, they are able to map the relationship of the outputs in relation to variation of the inputs. Metamodels are developed to mimic the behavior of a PM with respect to the independent variables being analyzed. An example of metamodels is linear regression models, neural networks, splines, etc. [9] For this study the metamodel of interest are linear regressions.

2.3.1 Linear Regression Models

The goal of linear regression is to build a probabilistic model that relates the dependable variables (outputs) y to k independent variables (inputs) x_j.

The general additive multiple regression model equation is defined by the following equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad 2.3.1$$

where the parameters β_j (j = 0, 1, …, n) are called the regression coefficients and ε is the random error term which is assumed to be normally distributed with an expected value of 0 and variance σ^2. The parameter β_j represents the expected change in output y per unit change in input x_j when all of the other input variables are held constant. A linear regression model may contain terms that are second order or higher, for example if the term x_j would be squared, it can still be considered linear regression as long as the regression coefficients β_j are kept linear.

For this study a second order linear regression model was used, which follows the equation

$$y = \beta_0 + \sum_{i=1}^{N} \beta_I x_i + \sum_{i=1}^{N-1} \sum_{j=i}^{N} \beta_{ij} x_i x_j + \sum_{i=1}^{N} \beta_{ii} x_i^2 \qquad 2.3.2$$

where N is the total number of independent variables. The coefficient of determination r^2 is the proportion of observed y variation that can be explained by linear regression [10]. r^2 is given by the following equation:

$$r^2 = 1 - \frac{\sum_{i-1}^{N} (y_i - \hat{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \qquad 2.3.3$$

where N is the total number of experimental data points, y_i and $\hat{y}_i$, are the experimental responses and the predicted response at the i[th] experimental point respectively, and $\bar{y}$ is the experimental mean value. The larger the r^2 value, the more successful the linear regression analysis is in predicting the responses. When performing linear regression, one must also verify that the assumptions of the model are met. This means that the analysis of the residuals should be normally and independently distributed with mean 0 and constant σ^2.

The majority of the computer packages that have a regression analysis option provide an analysis of variance (ANOVA) table in the results. An ANOVA table in linear regression helps in understanding how well the model fits the data.

2.4 Data Envelopment Analysis (DEA)

When analyzing a combination of PMs in IM, the improvement in one can negatively affect the improvement in the other. Such is the case when analyzing cycle time vs. shrinkage in a part. In order to have minimal shrinkage, the part needs to have a larger packing time, which in turn increases cycle time. Data envelopment analysis (DEA) is able to find a compromise between such PMs. Also, it has the advantage of not requiring the user to define an overall objective function, as is the case in regular optimization problems, where weights need to be assigned to the PMs in order to analyze the problem.

DEA, a technique first introduced by Charnes, Cooper and Rhodes [11], provides a way to measure the efficiency of a combination of PMs alongside a finite number of PMs.

An example of how DEA solves a multiple criteria optimization problem can be seen in figure 2.2. In this example there are two PMs that are being analyzed, objective 1, in this case is cycle time, which is to be minimized and objective 2, in this case surface quality, is to be maximized. Following the direction of improvement of both PMs, the desired solution should lie in the upper left corner of the dataset. DEA is able to find the best compromise of solutions by means of the efficient frontier, which can only be seen in graphical mode in 2 or 3 dimensions. In this example it can easily be represented graphically as shown in figure 2.2. The points that are on the efficient frontier, which are called the efficient solutions, are the desirable solutions in the problem any other point not located on the efficient frontier is considered inefficient. Points not in the efficient frontier can be improved without a detrimental effect in one of the performance measures.

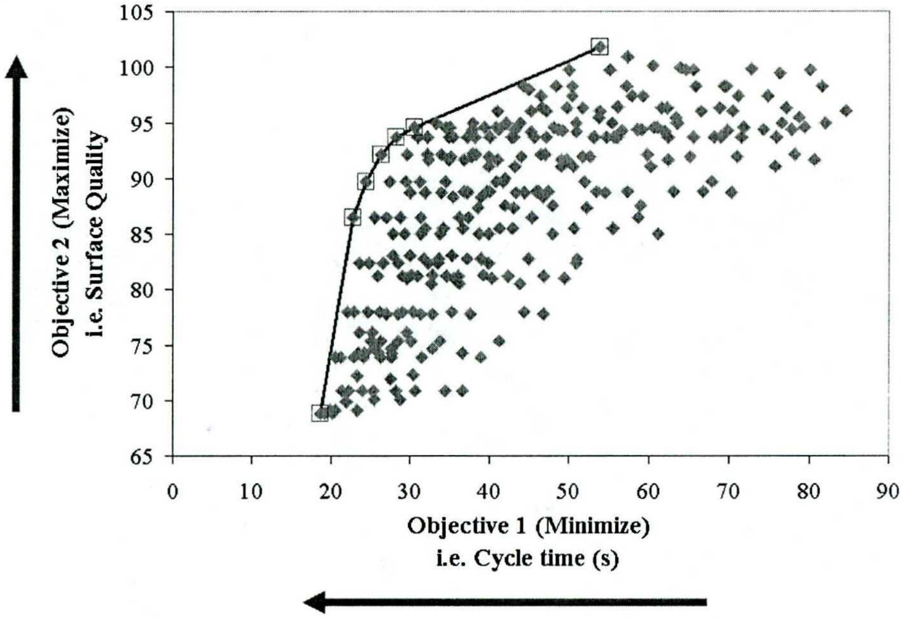


Figure 2.2: DEA example [9]

The efficiency of each combination of PM is computed through the use of two linearized versions of the following mathematical programming problem in ratio form:

Find v, μ, μ_o to

$$\text{Maximize} \quad \frac{\mu^t Y_o^{\max} + \mu_o}{v^T Y_o^{\min}} \tag{2.4.1}$$

s.t.

$$\frac{\mu^T Y_j^{\max} + \mu_o}{v^T Y_j^{\min}} \leq 1 \quad j = 1, \dots, n \tag{2.4.2}$$

$$\frac{\mu^T}{v^T Y_o^{\min}} \geq \varepsilon \cdot 1 \tag{2.4.3}$$

$$\frac{v^T}{v^T Y_o^{\min}} \geq \varepsilon \cdot 1 \tag{2.4.4}$$

$$\mu_o \;\; \text{free} \tag{2.4.5}$$

where, $Y_o^{\max}$ and $Y_o^{\min}$ are vectors containing the values of the PMs currently under analysis to be maximized and minimized respectively, μ is a vector of multipliers for the PMs being maximized, v is a vector of multipliers for the PMs being minimized, μ_o is a scalar variable, n is the number of total combinations in the set, and ε is a very small constant, usually set to a value of 1×10^{-6} [12].

The efficiency score obtained from solving the problem formulated above for each combination ranges from 0 to 1 and is relative to all n combinations. Those combinations with efficiency of 1 are deemed efficient. The collection of the efficient combinations makes up the (piece-wise) efficient frontier of the entire data set. These efficient combinations dominate any other combination not in the frontier.

Linearization becomes necessary because the ratio form of the original formulation results in an infinite number of solutions [13]. The manner in which linearization is achieved is by setting the denominator of Eq. 2.4.1 to a value of 1, while multiplying both sides of Eq. 2.4.2 by the denominator of its left-hand-side; the inequalities in Eqs. 2.4.3

and 2.4.4 are simplified once the denominator takes the value of 1; and Eq. 2.4.5, can be decomposed into the differences of two nonnegative variables. Following these manipulations one obtains the first linear version of the problem called the input-oriented model, which is shown in equations 2.5.1 through 2.5.6.

The second linearization is obtained by inverting the ratios in the original formulation (Eqs. 2.4.1 through 2.4.5) and keeping the variable μ_o in the numerator in Eqs. 2.4.1 and 2.4.2. The rest of the linearization steps are similar to those described above. The second linearization is called the output-oriented model and it is a minimization problem. The efficiency score obtained from the linearized version of the formula ranges from 1 to infinity, with 1 being the perfect efficiency score. A particular combination of PM will be considered efficient when both the input-oriented and output-oriented models identify it as efficient [12].

Find v, μ, μ_0^+, μ_0^- to

$$\text{Maximize} \quad \mu^T Y_0^{\max} + (\mu_0^+ + \mu_0^-) \tag{2.5.1}$$

s.t.

$$\mu^T Y_0^{\min} = 1 \tag{2.5.2}$$

$$\mu^T Y_j^{\max} - v^T Y_j^{\min} + \mu_0^+ - \mu_0^- \leq 0 \quad j = 1,\ldots,n \tag{2.5.3}$$

$$-\mu^T \leq -\varepsilon \cdot 1 \tag{2.5.4}$$

$$-V^t \leq -\varepsilon \cdot 1 \tag{2.5.5}$$

$$-\mu_0^+, -\mu_0^- \leq 0 \tag{2.5.6}$$

Either of these linear versions results in a linear programming problem that can be solved by using traditional linear programming methods such as the Simplex method, which is included in practically all the available commercial optimization software packages.

As can be seen from the equations above, in order to solve the equations there needs to be at least two PM being analyzed one to be maximized and the other to be minimized. However, there are cases where all the PMs that are to be analyzed go in the same direction i.e. they are to be minimized. In this situation a transformation needs to be evaluated on at least one PM so that they are not all in the same direction [9].

The transformation used in all the necessary situations is as follow:

$$\hat{y} = (y_{\max} + y_{\min}) - y_i \qquad 2.5.7$$

where $y_{\max}$ and $y_{\min}$ are the maximum and the minimum of the range for the PM respectively, and y_i and $\hat{y}_i$ are the i^{th} PM and the i^{th} PM transformation [8].

2.5 Variability

In any manufacturing process such as injection molding, it is not possible to always keep the process variables at the specified value. Over some finite time, the process settings can vary, therefore it is important to replicate this scenario in the problem being analyzed. For example, if in real IM production the mold temperature (T_w)

is set to 100 °C, due to a number of external factors, that affect the operation of the IM machine such as ambient temperature, many cycles of the IM machine can cause the temperature of the mold to vary say up to 110 °C, this leads to variability in the process, which in turn can cause changes in the PM of interest. It is critical to minimize this variability in order to obtain a more consistent process.

One of the challenges in this thesis is that when analyzing the problem with the simulation program, the simulation output will always be at the defined process settings; therefore it is necessary to insert the inherent variability to replicate a real world IM process.

A way to introduce variability into the analysis is by adding the variability directly into the simulation software, for example, if we are trying to simulate the example above with T_w set at 100 °C, then it would be necessary to add the variability by performing more simulation repeats, for example by adding ± 10 °C to the original temperature of 100 °C. This would mean for example to simulate the process with T_w at 110 °C, 100 °C and 90 °C and assign all the responses to 100 C. This method of introducing variability is useful when the combinations of runs planned are not that numerous. If a large number of simulations are needed, it is helpful to obtain metamodels that can reproduce the results in a shorter time.

CHAPTER 3

CASE STUDY

3.1 Honda Civic Bumper

This study involves the injection molding of the Honda bumper described in chapter 1 and shown in figure 1.3. The goal of the study is to analyze the five different injection scenarios, illustrated in figure 3.1, in order to investigate which injection location leads to lower variability in the final production of the bumper.

The following is the description of the different scenarios analyzed. The individual points that are located on each side of the mold represent point source gates and the central group of points represents a single fan gate; (1) represents injection from the top; (2) represents injection from the bottom of the mold; (3) represents injection from the bottom of the mold with gate sequencing. Gate sequencing is set up so that the fan gate is the only gate open in the beginning until it fills 50% of the mold, time at which the two side gates open; (4) represents an alternating injection location with the fan gate located at the top of the mold and the point sources located at the bottom of the mold and (5) represents the alternating location with gate sequencing. The gate sequencing functions in the same manner as explained for gate location (3).

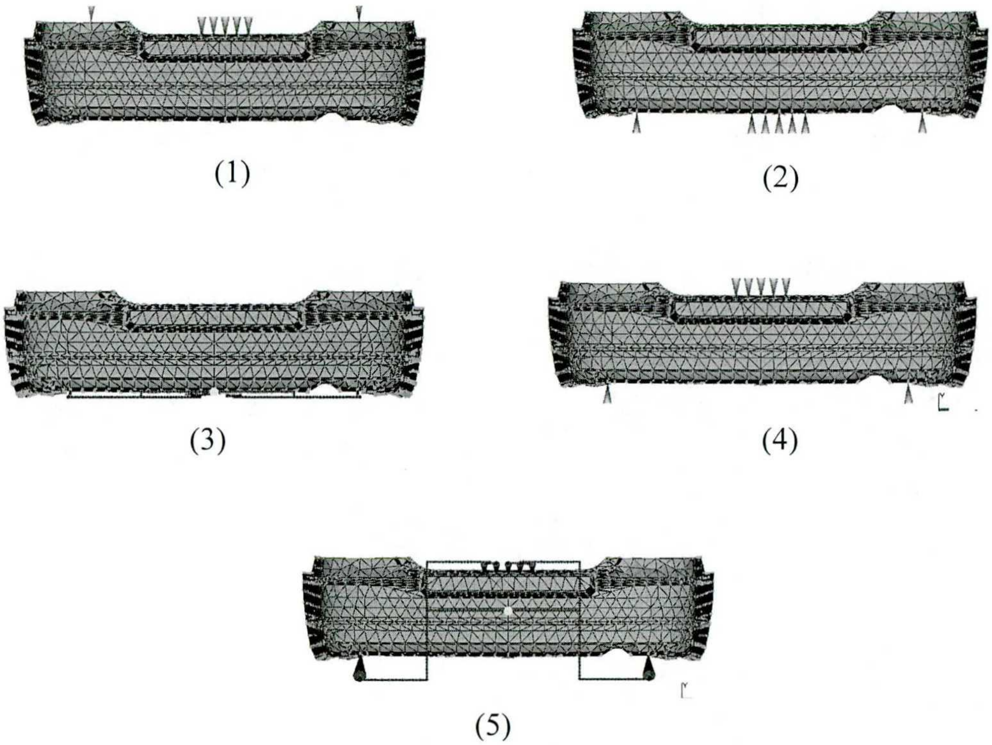


Figure 3.1: Injection locations being evaluated

Each of these injection cases were selected based on the recommendations from Honda of America Manufacturing. The Injection cases (2) and (4) are currently being used in production by Honda. The other represent conditions that they would like to consider as alternatives for future models

The bumper is injection molded using Thermoplastic Polyolefin (TPO) polymer D17133 manufactured by SOLVAY. The fill time was kept constant at 12 seconds for all cases. For simplicity in the analysis, the overall thickness of the bumper was kept constant at 3 mm. The process variables included for most of this study were mold temperature, $T_{w,}$ and melt temperature, T_m with a constant packing pressure of 70 MPa. Initially the packing pressure was also varied; however, packing pressure is easier to control at the set value than temperatures. Thus since the main focus of this work is variability, we decided to analyze the effect of temperatures only. The ranges for the process variables were chosen from the recommended operating range that the Moldflow database suggested.

For each injection location, the control variables were varied at 3 levels, which produced a total of 9 runs per injection location. The levels for each of the control variables are shown in table 3.1.

T_w	T_m
°C	°C
40	215
65	240
90	265

Table 3.1: Levels of the control variables

As a first step in analyzing the problem, the possibility of using deflections as PMs at relevant locations in the mold was evaluated. These locations are shown in Figure 3.2. These points are relevant as they are points that if variability is not controlled, it will affect the bumper quality. The deflections of all these points were predicted using Moldflow. Initially, the packing pressure was also varied, because it was believed that it could have an effect on the quality of the bumper. The data was analyzed using ANOVA tables to verify if they meet the assumptions needed to use linear regression. The results can be seen in Table 3.2. Examples of the statistics tests used are given in appendix A. All of the data points that resulted from this analysis were carefully analyzed, even if there seemed to be outliers in the data points. If these abnormalities came up they were verified in Moldflow to see if a recording mistake was done or if the data point was simply and outlier. When a recording mistake was found, they were immediately corrected, however if no recording mistake was found, the results were left as they were in order to further analyze the reason for the outliers.

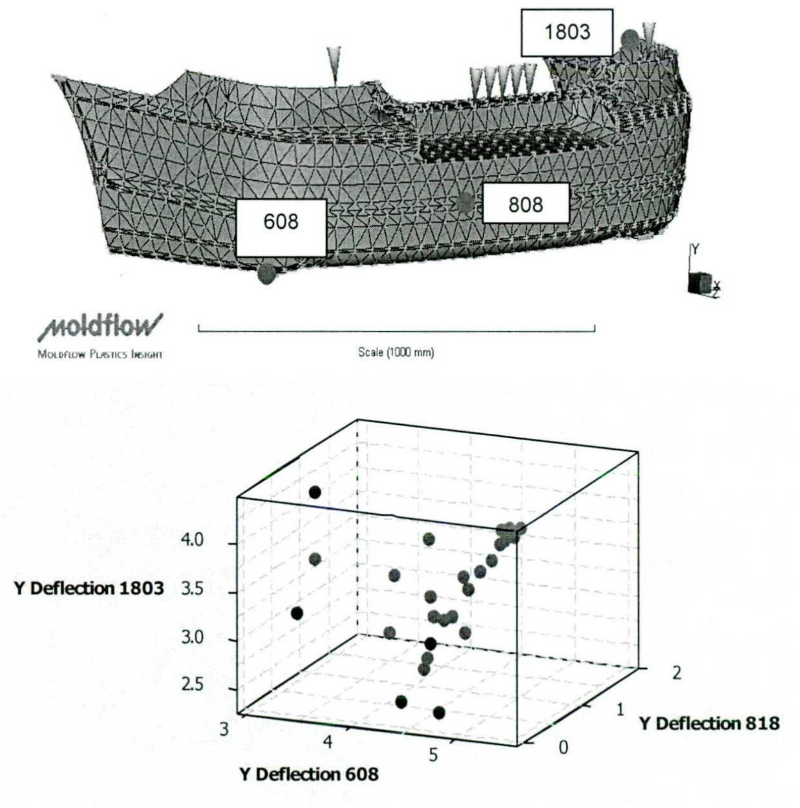


Figure 3.2: Example of possible PMs

The goal of the analysis was to minimize the 3 deflections in the mold, points (1803, 818 and 608). However, once these points were analyzed, there was little confidence in the results because of low r^2 values, as can be seen in table 3.2. From the table, it can be seen that point 818, which is located in the center of the mold, provides a good r^2 value, however the other 2 points 1803 and 608, which are located on edges of the mold provide a lower r^2 value. This does not necessarily mean that points 1803 and 608 are not good values, as it could just mean that they can not be predicted using linear regression. However, it could also mean that due to the mesh, the Moldflow predictions at these points are not very accurate. Another thing that can be seen from table 3.2 is that packing pressure has less effect than the temperatures; therefore it was decided to leave it as a constant for future analysis. Also, maintaining packing pressure at the desired set point is easier than is the case for temperatures and as previously discussed; our main interest is in evaluating conditions that minimize variability.

Controllable Variables			Performance Measures		
T_w ℃	T_m ℃	*Ppack* *MPa*	Y deflection 1803	Y deflection 818	Y deflection 608
40	215	40	-4.152	0.7944	-2.907
40	240	40	-3.574	0.636	-3.528
40	265	40	-3.45	0.4242	-3.543
65	215	40	-3.906	0.5918	-3.617
65	240	40	-3.642	0.3814	-3.617
65	265	40	-3.475	0.307	-3.363
90	215	40	-3.899	0.3368	-3.781
90	240	40	-3.671	0.3205	-3.575
90	265	40	-3.487	0.2979	-3.412
40	215	55	-3.528	0.7533	-3.091
40	240	55	-3.057	0.5621	-3.756
40	265	55	-3.247	0.2708	-3.741
65	215	55	-3.883	0.3887	-3.948
65	240	55	-3.595	0.3669	-3.572
65	265	55	-3.442	0.2968	-3.344
90	215	55	-3.868	0.3277	-3.763
90	240	55	-3.649	0.3131	-3.565
90	265	55	-3.464	0.2843	-3.429
40	215	70	-3.005	0.7121	-3.04
40	240	70	-2.577	0.4397	-3.938
40	265	70	-3.032	0.2082	-3.79
65	215	70	-3.318	0.3081	-3.989
65	240	70	-3.55	0.3519	-3.526
65	265	70	-3.397	0.268	-3.393
90	215	70	-3.839	0.3214	-3.742
90	240	70	-3.616	0.2937	-3.608
90	265	70	-3.45	0.2764	-3.419
r^2			**81.5%**	**90.6%**	**37.1%**
T_w			0.732	0.000	0.001
Ppack			0.035	0.566	0.102
T_m			0.018	0.183	0.477
$T_w * T_w$			0.096	0.010	0.482
Ppack Ppack*			0.077	0.661	0.200
$T_m * T_m$			0.690	0.701	0.688
T_w **Ppack*			0.622	0.000	0.001
$T_w * T_m$			0.000	0.022	0.294
Ppack Tm*			0.021	0.549	0.806

Table 3.2: Possible performance measures and analysis

In order to further evaluate if the low r^2 values were caused by limitations in Moldflow to predict points that are located on an edge of the mold, simulations on a simplified version of the bumper were analyzed. The depiction of the simplified version of the bumper can be seen in figure 3.3. A couple of deflections in the center of the part and close to the edge of the mold were analyzed. The results, which can be seen in appendix B, were consistent with the ones from the original bumper in which the deflections on the center of the mold presented a higher r^2 value than the deflections near the edges.

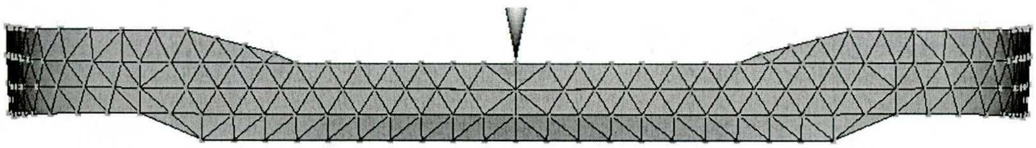


Figure 3.3: Simplified bumper

Based on these results, shrinkages at two different locations on the part were chosen as the PMs, which will be called Shrinkage A and Shrinkage B; they can be seen in figure 3.4. Honda uses shrink lines as quality indicator in their bumper molding. Thus, following the shrinkage of these two lines is consistent with Honda's practice. Both of the PMs are to be minimized, because the goal is to minimize any kind of shrinkage that the part may suffer after injection. In order to gain confidence in the results, that

Moldflow provided, cycle time (seconds) and max tonnage (ton) were also collected in each run. These two values are easier to evaluate for trends than shrinkages.

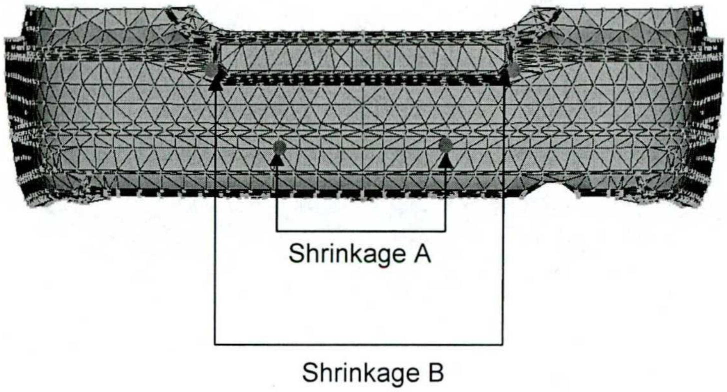


Figure 3.4: Performance measures of interest for Honda bumper

Using the control variables shown in table 3.1 and the PMs discussed above, a full factorial design of experiments was analyzed using the simulation software Moldflow. The resulting number of runs yielded 9 data points per shrinkage, referred from now on as "original points". Packing pressure was not varied as it seemed to have less effect than temperatures; plus pressure should be a lower source of variability than temperatures as it is easier to control. The ANOVA tables for these runs are discussed in the next section.

3.2 Variability

During production of injection molded parts, there is variability around the process settings. Over some finite range of time, the process variables will vary around their set values creating an inconsistency in the process variables which leads to variability in the PMs. Therefore it is important to replicate this scenario in the problem being analyzed. The goal of the problem is to choose an injection location that minimizes the shrinkages while decreasing variability at the same time, thus providing consistency to the process.

Variability was introduced into the problem by varying the process setting levels T_w and T_m by a range of ± 10 °C from the initial process variables. The resulting variance for one set point is shown in figure 3.5.

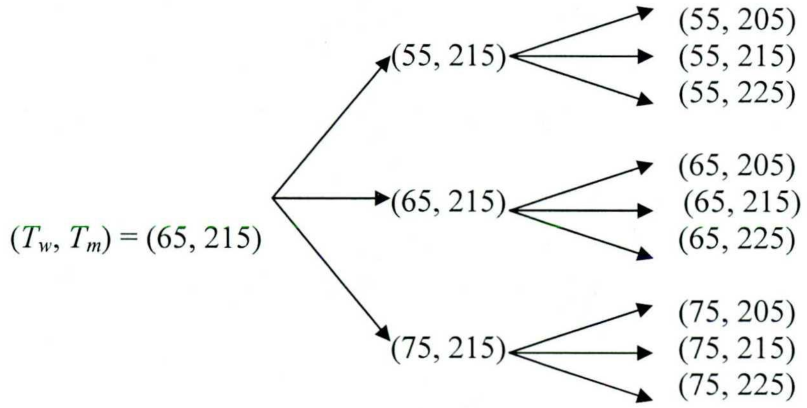


Figure 3.5: Example of variability for on set point

The introduction of variability was done to simulate the variation in process variables in actual manufacturing. Each of the 5 injection locations generated 81 data points per shrinkage. Linear regression analysis was performed on the 81 data points, in order to understand how the points differ from each injection location. Table 3.3 is the resulting ANOVA table for each injection location. For this table, the results are assumed to be at the specific value that is without variability. The ANOVA table gave critical knowledge to understand the importance of the controllable variables in the different PMs, and the differences between the injection locations. It also gave confidence in using these shrinkages as PMs as they all have large r^2 values.

	Performance Measures		
	Shrinkage A	Shrinkage B	
r^2	96.6%	94.2%	Injection Top
T_w	0.000	0.000	
T_m	0.000	0.000	
$T_w * T_w$	0.000	0.000	
$T_m * T_m$	0.000	0.000	
$T_w * T_m$	0.000	0.000	
r^2	92.2%	91.8%	Injection Bottom
T_w	0.000	0.000	
T_m	0.041	0.000	
$T_w * T_w$	0.000	0.000	
$T_m * T_m$	0.033	0.000	
$T_w * T_m$	0.000	0.000	
r^2	90.6%	94.3%	Injection Bottom GS
T_w	0.000	0.000	
T_m	0.000	0.000	
$T_w * T_w$	0.000	0.000	
$T_m * T_m$	0.000	0.008	
$T_w * T_m$	0.000	0.000	
r^2	93.8%	96.1%	Alternate Injection
T_w	0.000	0.000	
T_m	0.001	0.000	
$T_w * T_w$	0.000	0.000	
$T_m * T_m$	0.086	0.001	
$T_w * T_m$	0.000	0.000	
r^2	94.6%	92.4%	Alternate Injection GS
T_w	0.000	0.000	
T_m	0.029	0.099	
$T_w * T_w$	0.000	0.000	
$T_m * T_m$	0.210	0.749	
$T_w * T_m$	0.000	0.000	

Table 3.3: Results of ANOVA table for each injection location per PM

The complete set of data points for all the injection strategies are given in appendix C. Then the average and the standard deviation for each of the PM per shrinkages were found, reducing the dataset to a new set of 9 points per shrinkage corresponding to the "original points" but with variability as an additional PM, collectively called "new points". The values can be seen in appendix D. These new data points or values of PMs include the average shrinkage as well as its corresponding variability measured by the standard deviation. The results are summarized in Table 3.4. DEA was performed on these 9 data points to find the efficient solutions that give the optimal compromises between each of the shrinkages A and B and their variability.

T_w	T_m	Average Shrinkage A	Standard Deviation Shrinkage A	Average Shrinkage B	Standard Deviation Shrinkage B	
40	215	4.1716	0.3896	6.9821	1.2286	Injection Top
65	215	5.4454	0.3495	9.7073	0.7791	
90	215	5.8483	0.1134	10.6722	0.2033	
40	240	4.5917	0.4184	8.5337	0.9403	
65	240	5.3979	0.1421	9.9030	0.2005	
90	240	5.5717	0.1023	10.1904	0.1811	
40	265	4.8806	0.2762	9.1596	0.3503	
65	265	5.2230	0.0844	9.5678	0.1523	
90	265	5.3148	0.0909	9.7291	0.1642	
r^2		95.8%	62.8%	92.4	86.3	
T_w		0.005	0.359	0.009	0.045	
T_m		0.364	0.964	0.193	0.506	
$T_w * T_w$		0.031	0.554	0.092	0.298	
$T_m * T_m$		0.636	0.956	0.338	0.739	
$T_w * T_m$		0.01	0.629	0.014	0.069	
40	215	5.5354	0.2264	8.4456	0.8575	Injection Bottom
65	215	5.8408	0.0977	10.2063	0.4148	
90	215	5.9435	0.1139	10.7267	0.2068	
40	240	5.4821	0.0898	9.2414	0.5505	
65	240	5.5679	0.0975	10.0159	0.1642	
90	240	5.6339	0.1013	10.2038	0.1845	
40	265	5.2663	0.0813	9.3502	0.2067	
65	265	5.3094	0.0858	9.5829	0.1552	
90	265	5.3664	0.0902	9.7287	0.1660	
r^2		95%	38.3%	88.3%	94.3%	
T_w		0.046	0.139	0.016	0.008	
T_m		0.691	0.387	0.296	0.219	
$T_w * T_w$		0.412	0.416	0.143	0.064	
$T_m * T_m$		0.662	0.488	0.43	0.458	
$T_w * T_m$		0.059	0.184	0.025	0.013	

Continued

Table 3.4: Simplified data set with ANOVA table

Table 3.4 continued

40	215	4.3526	0.6270	6.752667	0.825565	Injection Bottom with Gate Sequencing
65	215	5.5000	0.2632	9.400889	0.997023	
90	215	5.8376	0.1068	10.63444	0.196921	
40	240	4.9973	0.3282	7.862667	1.131596	
65	240	5.4557	0.0872	9.823556	0.306971	
90	240	5.5724	0.0975	10.12744	0.185664	
40	265	5.1010	0.1108	8.784333	0.652179	
65	265	5.2473	0.0796	9.521778	0.152015	
90	265	5.3238	0.0874	9.660444	0.164899	
r^2		86.6%	95.3%	97.5%	28.6%	
T_w		0.018	0.005	0.002	0.686	
T_m		0.25	0.107	0.151	0.909	
$T_w * T_w$		0.161	0.06	0.019	0.873	
$T_m * T_m$		0.373	0.237	0.355	0.865	
$T_w * T_m$		0.027	0.008	0.004	0.845	
40	215	3.8232	0.2967	6.1761	0.8624	Alternating Injection
65	215	5.0854	0.4862	9.0631	1.0287	
90	215	5.7963	0.1167	10.6089	0.2269	
40	240	4.2004	0.4880	7.4158	1.1365	
65	240	5.2768	0.2378	9.6518	0.4648	
90	240	5.5407	0.1029	10.1642	0.1886	
40	265	4.6778	0.3970	8.5413	0.7644	
65	265	5.1801	0.0840	9.5084	0.1511	
90	265	5.2901	0.0916	9.7006	0.1659	
r^2		98.7%	9.6%	98.7%	40.1%	
T_w		0.001	0.805	0.001	0.806	
T_m		0.216	0.796	0.097	0.8242	
$T_w * T_w$		0.011	0.868	0.011	0.969	
$T_m * T_m$		0.594	0.803	0.292	0.79	
$T_w * T_m$		0.003	0.722	0.002	0.956	

Continued

Table 3.4 continued

40	215	3.4351	0.2740	5.9327	0.4690	Alternating Injection with Gate Sequencing
65	215	4.3988	0.4967	8.3060	1.2613	
90	215	5.6249	0.2746	10.5000	0.2925	
40	240	3.5710	0.3256	6.4041	1.1410	
65	240	4.8133	0.4998	9.3268	0.8101	
90	240	5.5068	0.0977	10.1077	0.1822	
40	265	3.8461	0.4996	7.7432	1.2290	
65	265	4.9981	0.2478	9.4779	0.1703	
90	265	5.2683	0.0902	9.6673	0.1603	
r^2		94.2	45.5	94.8	0	
T_w		0.053	0.101	0.015	0.431	
T_m		0.672	0.948	0.687	0.71	
$T_w * T_w$		0.264	0.163	0.09	0.655	
$T_m * T_m$		0.821	0.947	0.976	0.76	
$T_w * T_m$		0.152	0.183	0.037	0.423	

Figures 3.6 and 3.7 are the representation of the efficient solutions that resulted from DEA for each injection location for shrinkage A and B respectively, and table 3.5 and 3.6 represent the efficient solution and their corresponding input setting for each injection location.

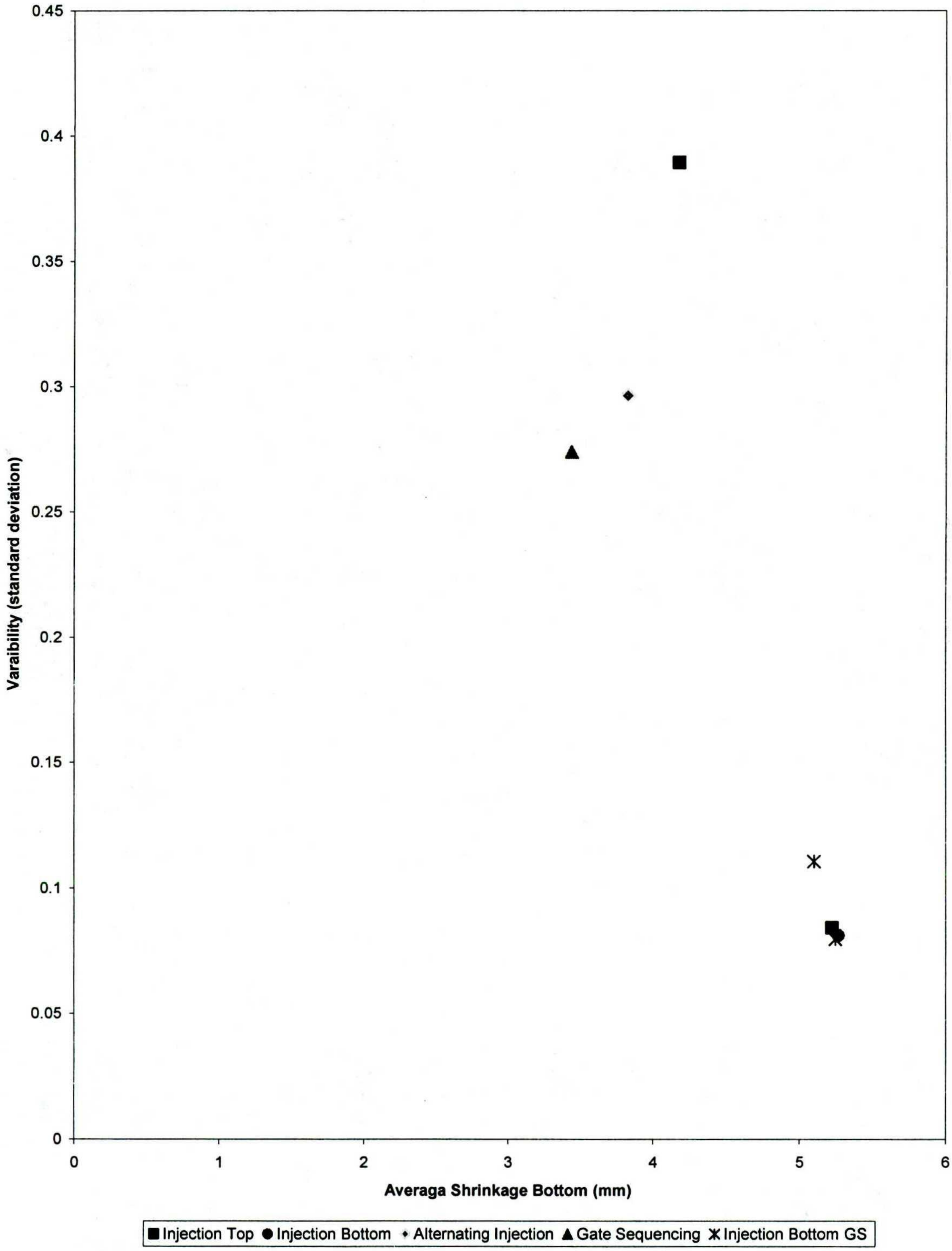


Figure 3.6: Efficient Solutions of "original points" for Shrinkage A

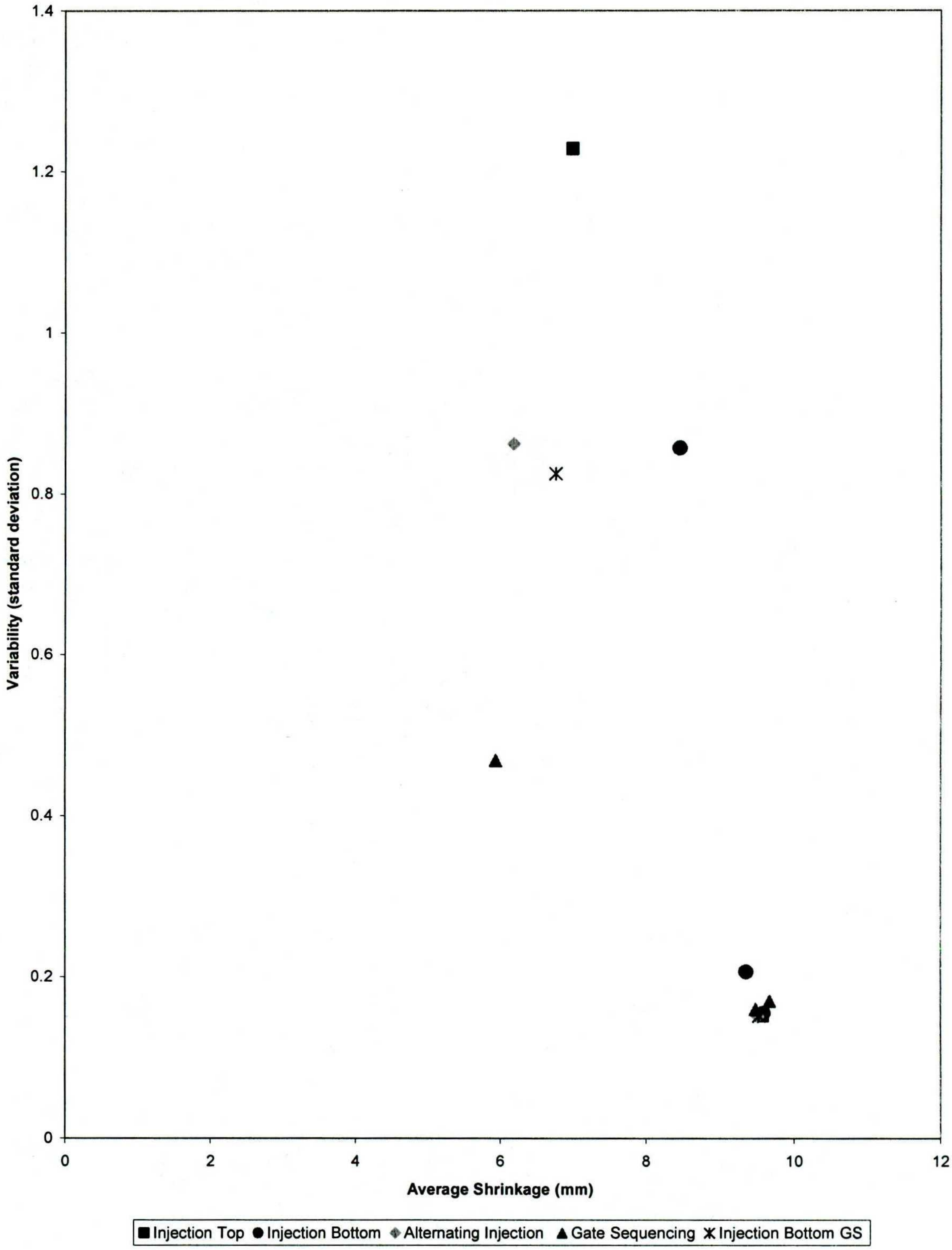


Figure 3.7: Efficient Solutions of "original points" for Shrinkage B

T_w °C	T_m °C	
40 65	215 265	Injection Top
40	265	Injection Bottom
40 65	265 265	Injection Bottom Gate Sequencing
40 65	215 265	Alternating Injection
40 90	215 265	Alternating Injection Gate Sequencing

Table 3.5: Efficient Solutions of "original points" Shrinkage A

T_w °C	T_m °C	
40 65	215 265	Injection Top
40 40 65	215 265 265	Injection Bottom
40 65	215 265	Injection Bottom Gate Sequencing
40 65	215 265	Alternating Injection
40 65 90	215 265 265	Alternating Injection Gate Sequencing

Table 3.6: Efficient Solutions of "original points" Shrinkage B

What we want to observe in the graphical representation of the efficient solutions for each injection location is to see the data points that are close together in the y-axis, which is the standard deviation. As can be seen from figure 3.6, it appear that injection from the bottom results in less variability in the process. This can be confirmed when looking at the efficient solutions in tables 3.5. From figure 3.7 there appears that a combination of injection from the bottom and alternating injection with gate sequencing, provides a good solution in terms of variability. There is an important factor to notice, which is that some of the temperature combinations that are efficient for shrinkage A and B are the same in both instances, as can be seen by comparing tables 3.5 and 3.6. Therefore there is confidence that the solutions obtained by DEA represent the best choices for both shrinkages

3.3 Multiple Criteria Optimization with DEA

In order to solve a multiple criteria optimization problem, a large dataset is needed, and since the "new points" were reduced to 9 data points after analyzing the variability, there was a necessity to populate the dataset to improve the location of the efficient frontier and to validate the data set. Consequently, second order linear regression metamodels were used to generate these extra data points at the levels shown in table 3.7.

T_w	T_m
°C	°C
50	215
60	225
70	235

Table 3.7: Levels of the control variable for the validation set

These predicted data points, which can be seen in table 3.8, were combined with the "new points" described above to populate the data set which now makes-up a total of 18 data points for each gate per shrinkage, becoming the new input for the multiple criteria optimization problem, which is also solved using DEA.

T_w	T_m	Average Shrinkage A	Standard Deviation Shrinkage A	Average Shrinkage B	Standard Deviation Shrinkage B	
50	215	4.86016	0.36404	8.02	0.91997	Injection Top
60	215	5.06626	0.31224	9.02	0.78857	
70	215	5.27236	0.26044	9.86	0.65717	
50	225	4.85706	0.33734	8.38	0.81697	
60	225	5.06316	0.28554	9.26	0.68557	
70	225	5.26926	0.23374	9.98	0.55417	
50	235	4.85396	0.31064	8.66	0.71397	
60	235	5.06006	0.25884	9.43	0.58257	
70	235	5.26616	0.20704	10.03	0.45117	
50	215	5.6127	0.1193	10.48	0.58737	Injection Bottom
60	215	5.7006	0.0994	10.95	0.51687	
70	215	5.7765	0.0875	11.31	0.44637	
50	225	5.5444	0.0816	10.78	0.52397	
60	225	5.6203	0.0667	11.16	0.45347	
70	225	5.6842	0.0598	11.44	0.38297	
50	235	5.4701	0.0499	11.04	0.46057	
60	235	5.534	0.04	11.34	0.39007	
70	235	5.5859	0.0381	11.54	0.31957	
50	215	4.2238	0.39683	8.28	0.89417	Injection Bottom with Gate Sequencing
60	215	4.6058	0.34523	8.74	0.75667	
70	215	4.9278	0.29363	9.21	0.61917	
50	225	4.3018	0.34893	8.35	0.82417	
60	225	4.6338	0.29733	8.82	0.68667	
70	225	4.9058	0.24573	9.29	0.54917	
50	235	4.3398	0.30103	8.43	0.75417	
60	235	4.6218	0.24943	8.90	0.61667	
70	235	4.8438	0.19783	9.37	0.47917	

Continued

Table 3.8: Predicted data points per injection strategy

Table 3.8 Continued

50	215	4.51846	0.39748	9.06	0.94538	Alternating Injection
60	215	4.78016	0.33948	10.20	0.79988	
70	215	5.04186	0.28148	11.13	0.65438	
50	225	4.54796	0.37568	9.62	0.87628	
60	225	4.80966	0.31768	10.62	0.73078	
70	225	5.07136	0.25968	11.43	0.58528	
50	235	4.57746	0.35388	10.13	0.80718	
60	235	4.83916	0.29588	11.01	0.66168	
70	235	5.10086	0.23788	11.68	0.51618	
50	215	3.94376	0.44469	7.27	0.93239	Alternating Injection with Gate Sequencing
60	215	4.31366	0.49809	8.36	0.78549	
70	215	4.68356	0.50149	9.25	0.63859	
50	225	3.98736	0.45459	7.61	0.90149	
60	225	4.35726	0.49199	8.60	0.75459	
70	225	4.72716	0.47939	9.38	0.60769	
50	235	4.03096	0.46649	7.96	0.87059	
60	235	4.40086	0.48789	8.83	0.72369	
70	235	4.77076	0.45929	9.50	0.57679	

Figure 3.8 and 3.9 show all the efficient solutions for each injection location for shrinkages A and B respectively.

It can be seen from figure 3.8, that the efficient solutions of gate location 2 (injecting from the bottom) produce less variability for shrinkage A. In addition, figure 3.8 shows that gate location 1 (injecting from the top), gate location 2 (injection from the bottom), gate location 3 (injecting from the bottom with gate sequencing) and gate location 5 (alternating injection with gate sequencing) produce less variability for shrinkage B. Table 3.9 summarizes the temperature levels for the efficient solution for each gate location for both shrinkages.

The addition of these validation points in the data set, were used as confirmation of the efficient solutions that DEA would give.

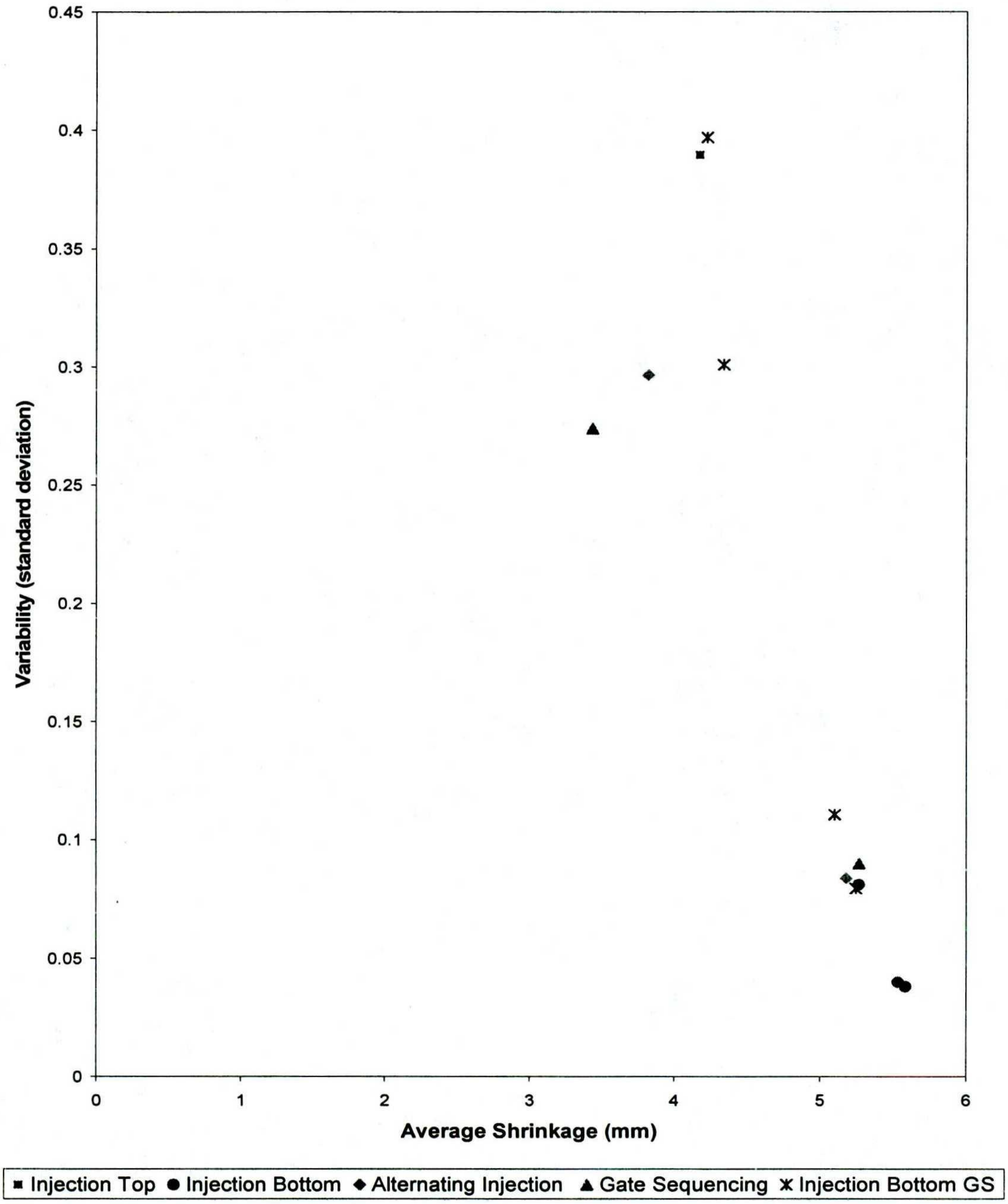


Figure 3.8: Efficient Solutions for Shrinkage A

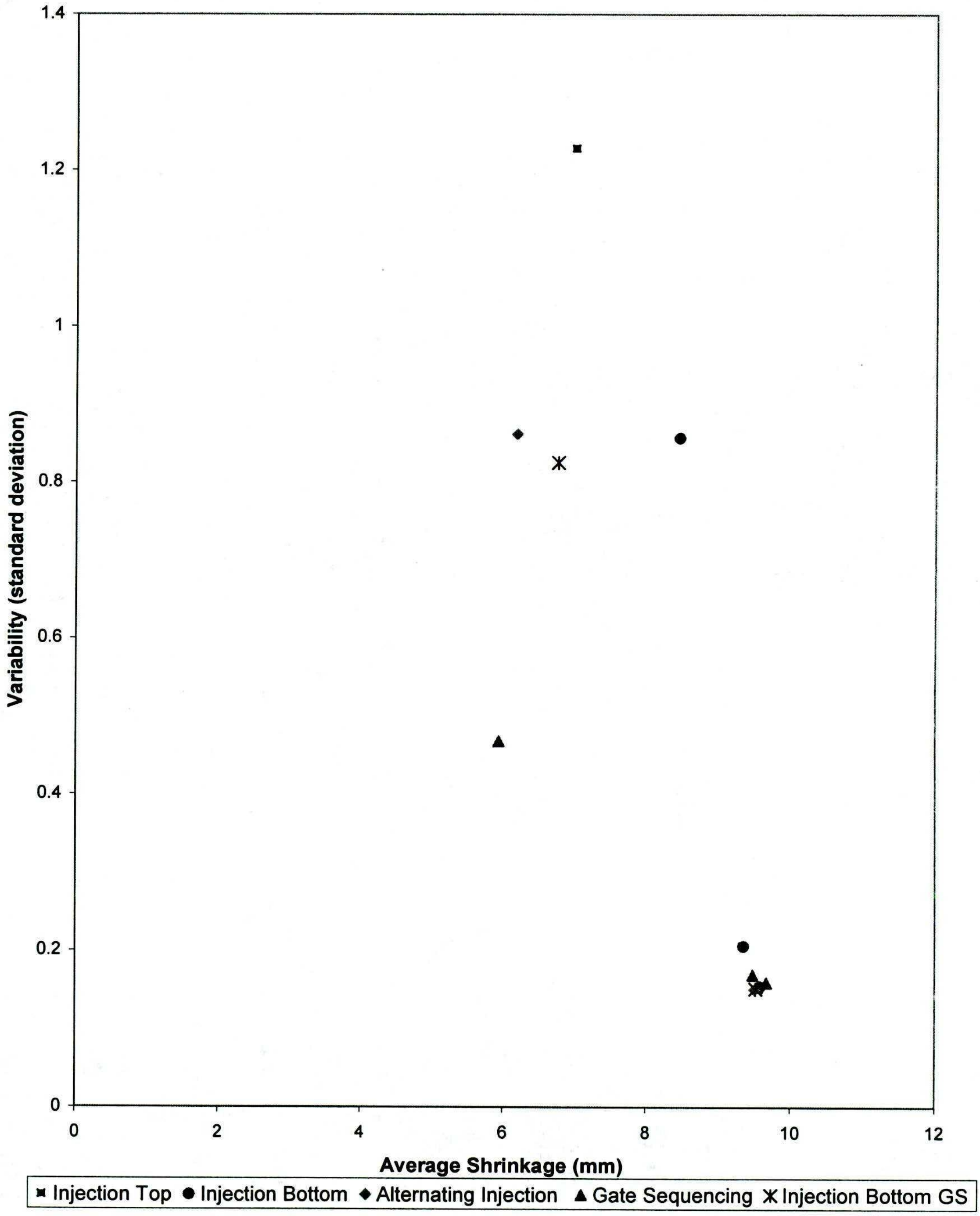


Figure 3.9: Efficient Solutions for Shrinkage B

T_w °C	T_m °C	
40	215	Injection Top
65	265	
40	215	Injection Bottom
40	265	
65	265	
60	235	
70	235	
40	215	Injection Bottom Gate Sequencing
40	265	
65	265	
50	215	
50	235	
40	215	Alternating Injection
65	265	
90	265	
40	215	Alternating Injection Gate Sequencing
65	265	
90	265	

Table 3.9: Efficient Solution of both Shrinkages for each gate

CHAPTER 4

PROCESSING AND DESIGN CONSIDERATIONS

4.1 Weld Line Analysis

The objective of using a tool like DEA in a multiple criteria optimization problem, as mentioned before, is to provide the user with a set of optimal solution or efficient frontier, which is a set of points that are efficient with regards to any other point in the data set. The researcher must then choose between these compromises the one that best fits his specific goals. In this study, a group of efficient solutions per injection location per shrinkage was found; the field of efficient solutions can be further narrowed down by studying the location of the weld lines corresponding to the efficient solutions with least variability.

It is significant to mention, that the location of the weld lines in a finished product is important for the overall appearance and strength of the part. However, there are locations on the finished part were the position of the weld lines do not cause critical weakness to the overall part, therefore these are the locations were the weld lines can be accepted.

Figure 4.10 depicts the weld line analysis performed, based on the results of the efficient solutions identified by DEA. Parts (5) and (6) exhibit clearly visible and prominent weld lines whereas part (7) shows that injecting from the bottom with gate sequencing, produces little or no weld lines. Therefore, the weld line analysis can be used in addition to DEA to further optimize the solution.

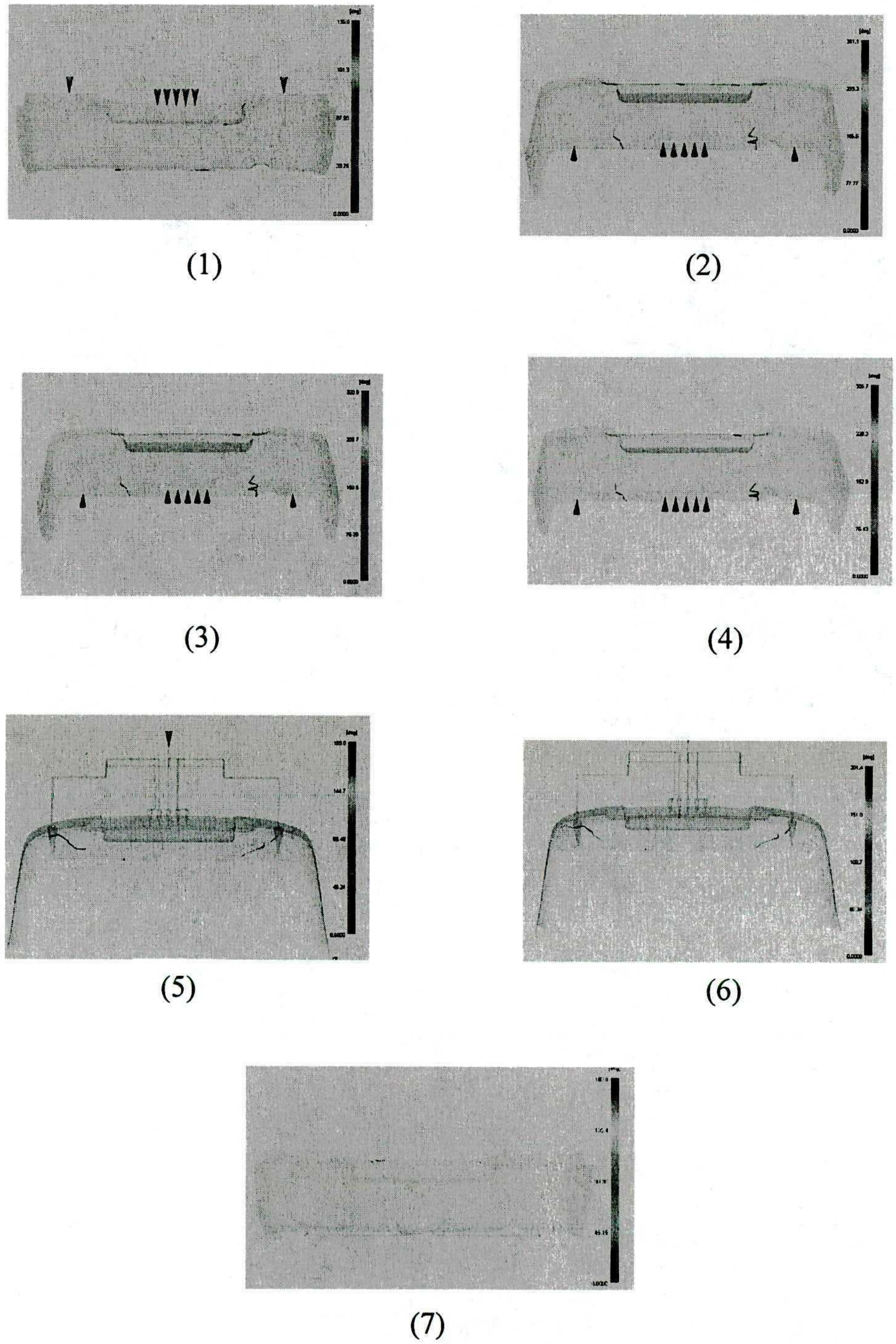


Figure 4.10: Weld line analyses for efficient solutions with least variability

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

Selection of the best injection location or locations, for IM in a given plastic part is of critical importance. The economic penalty for making the erroneous choice is very large. Process variables can be optimized after the part is in production; however, modifying the injection location or locations, after the mold is in production is very costly in both time and actual cost. The locations of the injection location greatly affect part quality. Previous work in our group (Carlos Castro) has shown that some injection locations will also result in a more consistent process.

In this thesis we used CAE, linear regression metamodels and a multivariable optimization technique, DEA, to study several injection locations and strategies for the Honda accord bumper. The main goal was to establish which injection locations produced a more consistent process.

In order to obtain the results of the best injection location, the Honda bumper was analyzed extensively using Moldflow plastic insight simulation software. After careful analysis of the validity of the results obtained from Moldflow, 2 shrinkages were chosen as the PMs of interest. This created a multiple criteria optimization problem which was analyzed by using DEA. This technique selects the best compromises among the possible solutions. That is those solutions where no improvement can be made in one performance measure without an adverse effect in another.

Variability was inserted into the problem by way of perturbations in the process settings; this was done to simulate real manufacturing conditions. After the variability was inserted the data was analyzed using DEA, this enabled us to find the combination of PMs that gave the best compromises that is those solutions with the more consistent process results. Since DEA needs many data points to work best, more data points were needed in order to find the improve solutions. Second order linear regression metamodels were used to find the extra data points. The process controllable variables selected were the mold and material temperatures as these are more difficult to keep at the selected set point.

Specific conclusions from this thesis are:

- The use of statistical analysis, namely the ANOVA tables to understand how well the linear regression model fits the data in the multiple criteria optimization problem.
- The introduction of variability into an IM problem in order to mimic the real world settings.
- DEA is demonstrated to be a good technique to use in a multiple criteria optimization problem, to choose the best compromise of solutions without the need of having weights assigned to the PMs being analyzed.

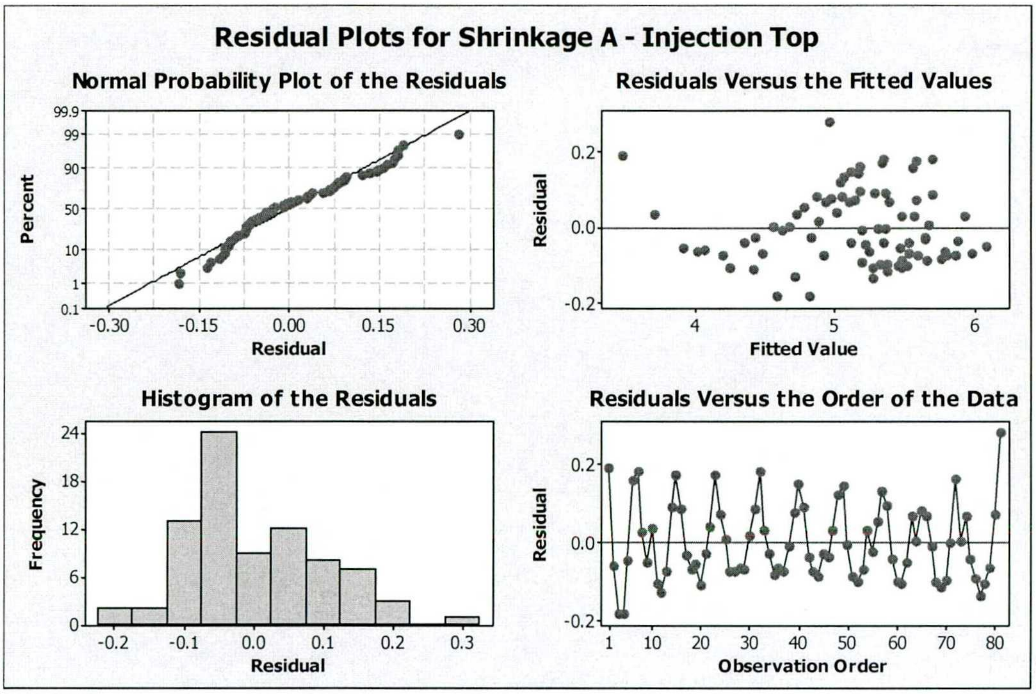
- The use of weld line analysis in IM was proven to be a good tool to choose between the best compromises of solutions that DEA provided, in order to choose an optimal solution in the injection location problem.

5.2 Future Work

Future work on this project will involve, validating using experiments the efficient frontier obtained using CAE. We will use a smaller mold initially and then work with Honda for a validation using the actual bumper mold. We will investigate how to go from efficient frontier to process windows. That is study the mapping of the performance measures to the control variables. As well as study the effect of material variability on the efficient frontier.

APPENDIX A

SAMPLE VERIFICATION OF ASSUMPTIONS FOR LINEAR REGRESSION



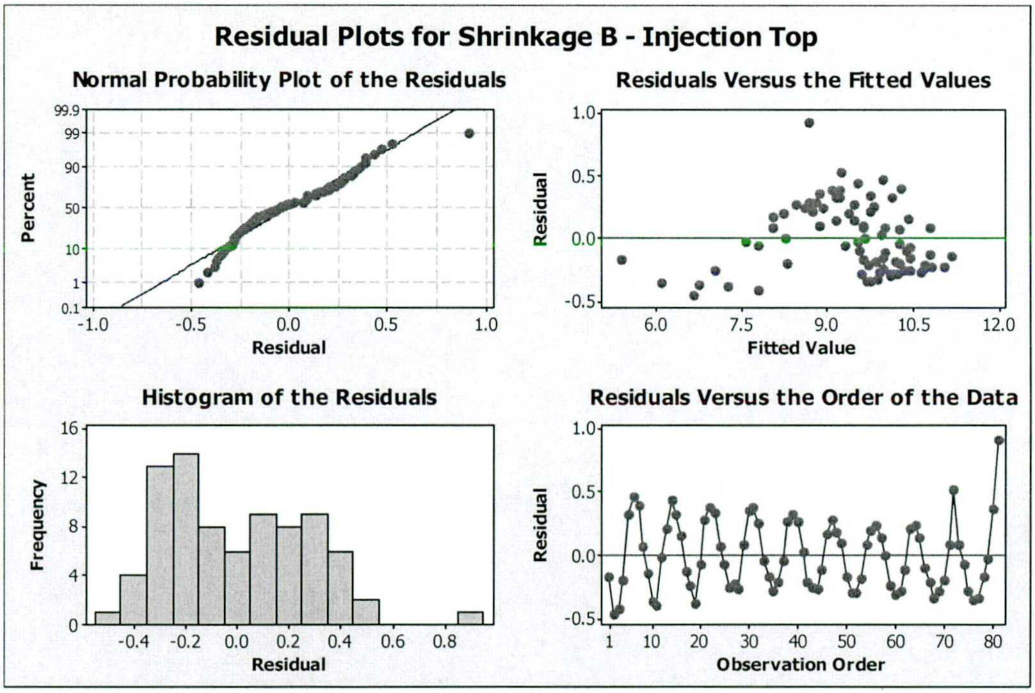
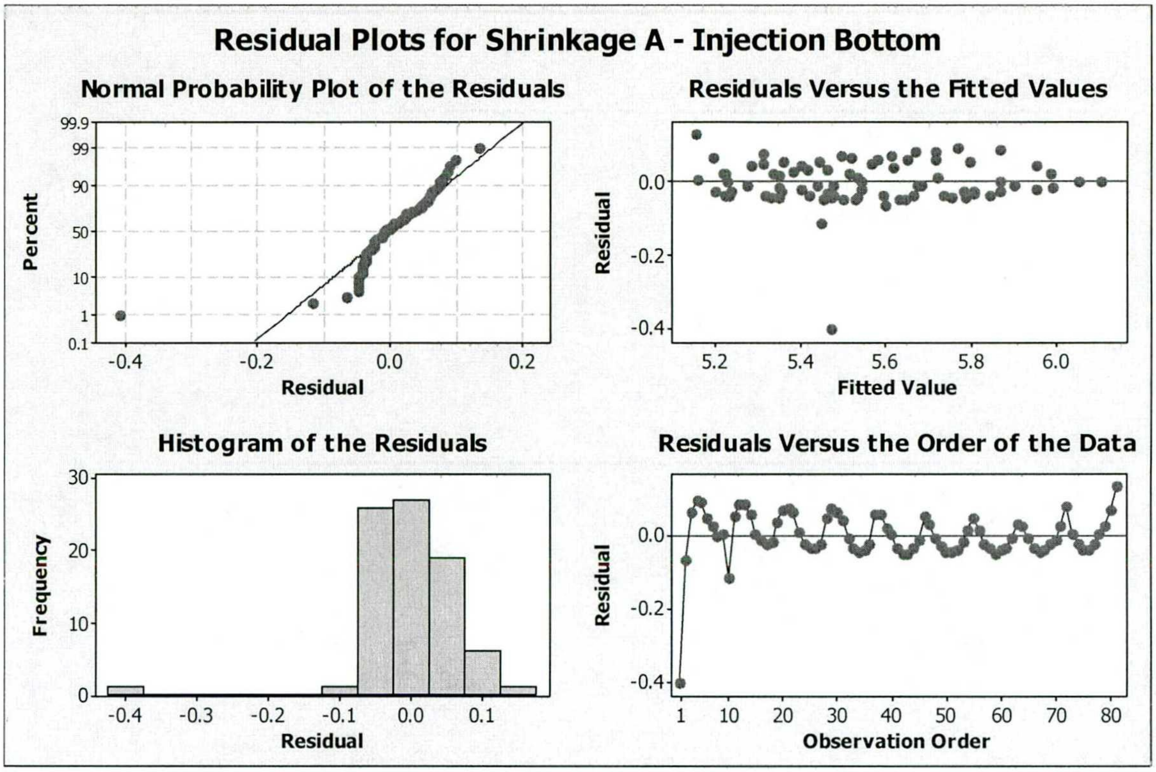


Figure A.1 Verification of assumptions – Injection Top



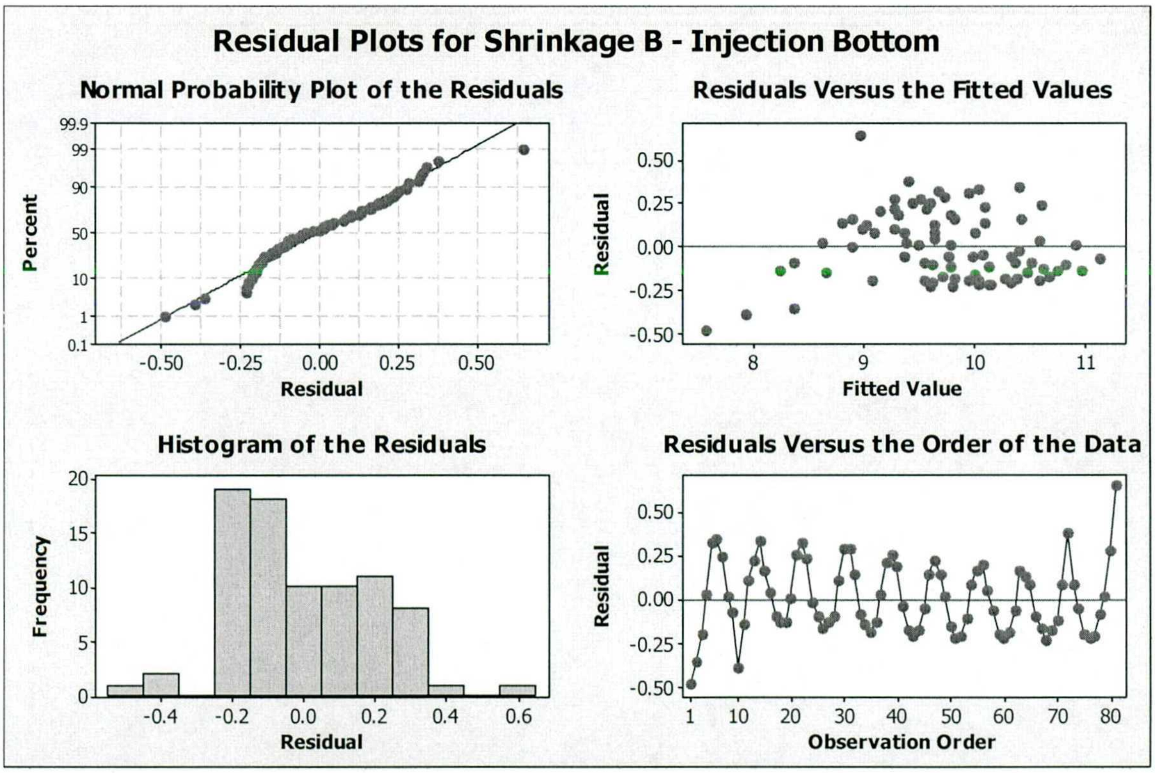


Figure A.2 Verification of assumptions – Injection Bottom

APPENDIX B

SIMPLE BUMPER ANALYSIS

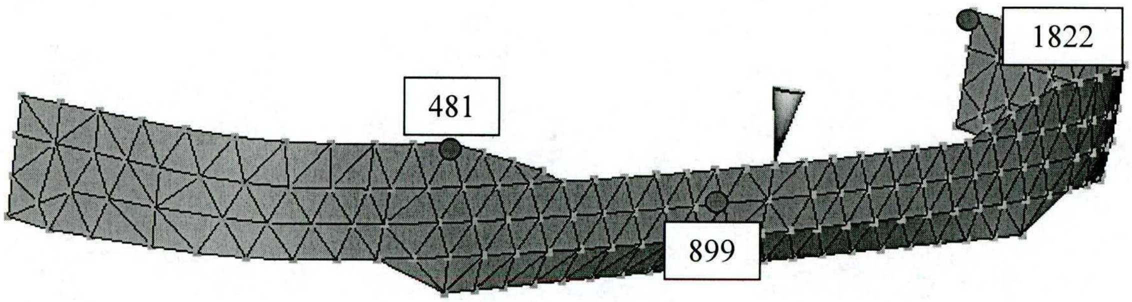


Figure B.1: Simplified bumper

Controllable Variables				Performance Measures		
T_w ℃	T_m ℃	*Ppack MPa*	*t pack s*	Y deflection 481	Y deflection 899	Y deflection 1822
33	200	60	7	0.0632	-2.218	-4.745
33	200	80	7	0.0835	-1.961	-4.053
33	200	100	7	0.0481	-1.882	-4.018
33	200	60	10	0.1312	-4.202	-3.484
33	200	80	10	0.7705	-6.345	-5.112
33	200	100	10	1.63	-2.893	-5.449
33	200	60	13	1.002	-2.694	3.577
33	200	80	13	1.147	-2.724	3.392
33	200	100	13	1.294	-2.674	3.075
33	230	60	7	0	-1.691	-1.882
33	230	80	7	-0.065	-1.165	-1.845
33	230	100	7	-0.113	-0.737	-1.853
33	230	60	10	-0.118	-3.434	-5.183
33	230	80	10	0.0129	-2.911	-4.956
33	230	100	10	-0.047	-2.761	-4.99
33	230	60	13	0.2691	-4.577	-0.405
33	230	80	13	0.4929	-4.542	-0.32
33	230	100	13	0.6544	-4.467	-0.506
33	260	60	7	-0.026	-1.854	-1.162
33	260	80	7	-0.116	-1.358	-1.12
33	260	100	7	-0.358	-0.968	-1.546
33	260	60	10	0.1142	-2.668	-2.688
33	260	80	10	0.1782	-2.21	-2.33
33	260	100	10	0.0323	-1.959	-2.483
33	260	60	13	-0.328	-3.188	-5.108
33	260	80	13	-0.2	-3.116	-5.673
33	260	100	13	0.1786	-2.146	-5.856
53	200	60	7	-0.109	-1.12	-2.567
53	200	80	7	-0.124	-0.653	-2.561
53	200	100	7	-0.046	-0.405	-2.574
53	200	60	10	-0.904	-2.8	-6.128
53	200	80	10	-0.505	-0.827	-6.235
53	200	100	10	-0.28	-2.873	-5.676
53	200	60	13	0.6433	-3.659	1.855
53	200	80	13	-0.092	-2.525	-0.639
53	200	100	13	0.9912	-3.431	1.376

Continued

Table B.1: Simplified bumper data points and analysis

Table B.1 continued

53	230	60	7	-0.322	-1.269	-1.459
53	230	80	7	-0.396	-0.832	-1.361
53	230	100	7	-0.457	-0.436	-1.487
53	230	60	10	0.0352	-2.176	-2.701
53	230	80	10	0.0299	-1.889	-2.469
53	230	100	10	0.119	-1.38	-2.516
53	230	60	13	-1.11	-2.496	-6.416
53	230	80	13	-0.624	-5.182	-6.723
53	230	100	13	-0.063	-0.543	-5.704
53	260	60	7	-0.317	-1.305	-1.006
53	260	80	7	-0.398	-0.997	-0.97
53	260	100	7	-0.552	-0.475	-0.885
53	260	60	10	-0.04	-2.263	-1.748
53	260	80	10	0.0247	-1.65	-1.2
53	260	100	10	0.0624	-1.263	-1.221
53	260	60	13	0.2769	-3.208	-2.34
53	260	80	13	0.3388	-3.113	-3.012
53	260	100	13	0.3481	-2.453	-2.525
73	200	60	7	0.5684	-0.817	-1.681
73	200	80	7	0.6181	-0.4	-1.722
73	200	100	7	-0.7	-0.124	-1.605
73	200	60	10	0.1602	-2.051	-2.726
73	200	80	10	0.2102	-1.638	-2.584
73	200	100	10	0.2824	-1.114	-2.77
73	200	60	13	0.669	-3.481	-5.892
73	200	80	13	0.3301	-3.33	-5.834
73	200	100	13	0.3118	-2.576	-4.384
73	230	60	7	0.66	-0.747	-1.131
73	230	80	7	0.7188	-0.479	-1.029
73	230	100	7	-0.817	-0.275	-1.028
73	230	60	10	0.2428	-1.543	-1.407
73	230	80	10	0.3241	-1.013	-1.397
73	230	100	10	0.3909	-0.641	-1.25
73	230	60	13	0.0658	-2.462	-2.736
73	230	80	13	0.0235	-2.09	-2.659
73	230	100	13	0.068	-1.553	-2.652

Continued

Table B.1 continued

73	260	60	7	0.6169	-0.948	-0.693
73	260	80	7	-0.701	-0.533	-0.719
73	260	100	7	-0.783	-0.217	-0.718
73	260	60	10	0.2381	-1.634	-0.897
73	260	80	10	0.3693	-1.059	-0.897
73	260	100	10	-0.414	-0.924	-0.842
73	260	60	13	0.031	-2.447	-1.708
73	260	80	13	0.0955	-2.018	-1.694
73	260	100	13	0.1871	-1.876	-1.843
r^2				41.0%	63.8%	23.2%
T_w				0.048	0.109	0.175
T_m				0.181	0.765	0.791
Ppack				0.518	0.504	0.788
t pack				0.649	0.080	0.260
$T_w * T_w$				0.001	0.357	0.500
$T_m * T_m$				0.143	0.780	0.567
Ppack Ppack*				0.899	0.460	0.774
t pack t pack*				0.659	0.222	0.031
$T_w * T_m$				0.090	0.350	0.011
T_w **Ppack*				0.003	0.861	0.709
T_w **t pack*				0.138	0.826	0.005
Ppack Tm*				0.165	0.633	0.977
t pack Tm*				0.306	0.566	0.000
Ppack t pack*				0.002	0.992	0.968

APPENDIX C

DATA SET OF PERFORMANCE MEASURES

Controllable Variables			Performance Measures			
T_w ℃	T_m ℃	*Ppack MPa*	t cycle *s*	Max *Tonne*	Shrinkage A	Shrinkage B
30	205	70	21.80	5624.80	3.669	5.21
40	205	70	22.52	5547.80	4.008	6.211
50	205	70	23.50	5430.20	4.405	7.395
55	205	70	23.98	5365.30	4.636	8.123
65	205	70	25.19	5198.80	5.183	9.549
75	205	70	26.89	5034.50	5.721	10.44
80	205	70	27.87	4952.80	5.885	10.68
90	205	70	30.57	4781.70	5.961	10.88
100	205	70	35.26	4566.50	6.037	11.02
30	215	70	22.31	5322.50	3.745	5.744
40	215	70	23.03	5244.00	4.146	6.893
50	215	70	24.00	5100.40	4.592	8.285
55	215	70	24.72	5029.70	4.858	8.952
65	215	70	25.94	4904.10	5.383	9.958
75	215	70	27.64	4732.20	5.756	10.47
80	215	70	28.61	4644.50	5.785	10.56
90	215	70	31.32	4476.90	5.844	10.67
100	215	70	36.26	4289.00	5.916	10.8
30	225	70	22.81	5037.20	3.863	6.38
40	225	70	23.53	4902.02	4.306	7.74
50	225	70	24.50	4785.60	4.81	8.981
55	225	70	25.22	4716.90	5.062	9.474
65	225	70	26.42	4574.60	5.509	10.08
75	225	70	28.38	4446.30	5.652	10.32
80	225	70	29.36	4358.70	5.68	10.37
90	225	70	32.06	4192.40	5.733	10.47
100	225	70	37.00	4012.10	5.794	10.6
30	230	70	23.06	4886.10	3.952	6.792
40	230	70	23.78	4780.50	4.421	8.122
50	230	70	24.74	4638.40	4.904	9.228
55	230	70	25.47	4585.70	5.145	9.618
65	230	70	26.92	4439.30	5.532	10.09
75	230	70	28.63	4278.70	5.601	10.23
80	230	70	29.61	4230.40	5.626	10.27
90	230	70	32.56	4057.00	5.678	10.37
100	230	70	37.24	4062.40	5.735	10.49

Continued

Table C.1: Injection Top – Data Set of Performance measures

Table C.1. continued

30	240	70	23.57	4585.40	4.124	7.556
40	240	70	24.29	4495.90	4.614	8.729
50	240	70	25.50	4354.70	5.053	9.489
55	240	70	25.97	4307.80	5.272	9.74
65	240	70	27.43	4172.10	5.459	9.971
75	240	70	29.14	4013.80	5.499	10.06
80	240	70	30.36	4000.00	5.523	10.11
90	240	70	33.05	4064.00	5.569	10.19
100	240	70	37.99	4098.90	5.619	10.28
30	250	70	23.83	4315.70	4.322	8.229
40	250	70	24.79	4201.20	4.771	9.08
50	250	70	25.75	4086.70	5.164	9.578
55	250	70	26.48	4043.70	5.313	9.717
65	250	70	27.94	3987.20	5.36	9.816
75	250	70	29.64	4036.90	5.4	9.885
80	250	70	30.87	4057.60	5.42	9.924
90	250	70	33.80	4109.90	5.466	10
100	250	70	38.50	4142.90	5.509	10.08
30	255	70	24.08	4177.50	4.41	8.46
40	255	70	25.04	4075.90	4.843	9.181
50	255	70	26.00	3964.80	5.201	9.604
55	255	70	26.73	3967.00	5.278	9.671
65	255	70	28.19	4007.70	5.312	9.729
75	255	70	29.89	4065.20	5.353	9.8
80	255	70	31.12	4080.10	5.371	9.835
90	255	70	34.05	4131.10	5.415	9.909
100	255	70	38.75	4175.70	5.454	9.98
30	265	70	24.59	3932.10	4.57	8.844
40	265	70	25.56	3957.30	4.954	9.307
50	265	70	26.50	4000.00	5.173	9.48
55	265	70	27.23	4009.50	5.187	9.506
65	265	70	28.69	4068.80	5.222	9.563
75	265	70	30.38	4112.20	5.257	9.629
80	265	70	31.61	4131.90	5.275	9.663
90	265	70	34.55	4131.90	5.314	9.727
100	265	70	39.49	4208.20	5.351	9.792

Continued

Table C.1. continued

30	275	70	24.84	3956.00	4.682	8.977
40	275	70	25.80	4008.50	5.007	9.26
50	275	70	27.00	4043.90	5.085	9.323
55	275	70	27.48	4072.00	5.1	9.347
65	275	70	29.18	4114.30	5.132	9.401
75	275	70	30.88	4142.80	5.166	9.464
80	275	70	32.10	4173.90	5.183	9.495
90	275	70	35.05	4164.80	5.219	9.551
100	275	70	39.75	4237.80	5.251	9.61

Controllable Variables			Performance Measures			
T_w ℃	T_m ℃	*Ppack MPa*	t cycle *s*	Max *Tonne*	Shrinkage A	Shrinkage B
30	205	70	21.79	4560.6	36.19	7.071
40	205	70	22.50	4435.8	31.18	7.998
50	205	70	23.51	4763.0	28.61	8.867
55	205	70	24.00	4782.1	21.66	9.41
65	205	70	25.23	4814.6	8.498	10.26
75	205	70	26.94	4755.9	11.74	10.75
80	205	70	27.91	4705.6	18.29	10.84
90	205	70	30.62	4558.4	20.4	10.93
100	205	70	35.31	4388.2	21.89	11.06
30	215	70	22.31	4217.8	30.65	7.521
40	215	70	23.04	4333.3	28.19	8.496
50	215	70	24.02	4522.1	17.91	9.382
55	215	70	24.51	4534.3	10.6	9.777
65	215	70	25.98	4494.5	5.578	10.37
75	215	70	27.70	4473.3	17.71	10.59
80	215	70	28.66	4415.0	18.98	10.62
90	215	70	31.37	4272.9	20.58	10.72
100	215	70	36.07	4126.2	22.47	10.83
30	225	70	22.80	3916.7	26.88	8.093
40	225	70	23.55	4191.9	19.55	8.887
50	225	70	24.52	4304.1	7.619	9.695
55	225	70	25.26	4294.1	4.116	10
65	225	70	26.48	4258.5	16.02	10.32
75	225	70	28.20	4211.4	18.48	10.38
80	225	70	29.42	4128.7	19.32	10.42
90	225	70	32.12	3982.3	21.17	10.51
100	225	70	36.81	4056.5	22.3	10.61
30	230	70	23.05	3833.9	24.96	8.272
40	230	70	23.80	4063.2	14.73	9.085
50	230	70	24.79	4174.7	4.576	9.783
55	230	70	25.52	4188.2	5.162	10.01
65	230	70	26.73	4144.0	16.49	10.23
75	230	70	28.44	4065.6	18.75	10.28
80	230	70	29.66	4004.3	20.2	10.32
90	230	70	32.37	4015.5	20.91	10.4
100	230	70	37.31	4059.7	22.22	10.49

Continued

Table C.2: Injection Bottom – Data Set of Performance measures

Table C.2. continued

30	240	70	23.32	3725.7	16.88	8.636
40	240	70	24.31	3906.7	5.968	9.356
50	240	70	25.29	3970.7	8.801	9.842
55	240	70	26.03	3958.8	14.61	9.963
65	240	70	27.48	3902.6	18.24	10.03
75	240	70	29.18	3991.1	19.66	10.09
80	240	70	30.17	4025.2	20.17	10.12
90	240	70	33.10	4069.3	20.68	10.2
100	240	70	37.81	4116.2	21.91	10.28
30	250	70	23.83	3774.20	5.365	-2.05
40	250	70	24.81	3845.3	5.414	-1.956
50	250	70	25.79	3906.7	5.432	-1.905
55	250	70	26.52	3940.9	5.437	-1.817
65	250	70	27.98	3990.3	5.456	-1.661
75	250	70	29.67	4015.5	5.482	-1.646
80	250	70	30.92	4059.7	5.494	-1.644
90	250	70	33.60	4125.7	5.522	-1.646
100	250	70	38.54	4171.5	5.55	-1.669
30	255	70	24.08	3808.0	5.331	-2.047
40	255	70	25.07	3878.3	5.367	-1.952
50	255	70	26.03	3939.4	5.379	-1.835
55	255	70	26.77	3669.3	5.386	-1.74
65	255	70	28.23	3991.7	5.405	-1.635
75	255	70	29.92	4071.5	5.43	-1.628
80	255	70	31.16	4093.8	5.442	-1.626
90	255	70	33.86	4137.2	5.468	-1.631
100	255	70	38.80	4190.7	5.495	-1.653
30	265	70	24.59	3891.9	5.249	-1.903
40	265	70	25.32	3949.2	5.268	-1.879
50	265	70	26.53	4002.5	5.279	-1.704
55	265	70	27.26	4002.1	5.287	-1.627
65	265	70	28.72	4080.8	5.308	-1.596
75	265	70	30.42	4124.9	5.329	-1.592
80	265	70	31.65	4146.6	5.341	-1.59
90	265	70	34.59	4146.7	5.364	-1.599
100	265	70	39.28	4224.0	5.39	-1.616

Continued

Table C.2. continued

30	275	70	24.84	3964.1	5.165	-1.821
40	275	70	25.83	4012.0	5.173	-1.738
50	275	70	27.04	4056.9	5.186	-1.594
55	275	70	27.52	4083.2	5.194	-1.577
65	275	70	28.97	4129.7	5.213	-1.561
75	275	70	30.93	4161.7	5.233	-1.559
80	275	70	32.15	4186.0	5.244	-1.56
90	275	70	34.84	4212.6	5.265	-1.593
100	275	70	39.79	4248.2	5.289	-1.59

Controllable Variables			Performance Measures			
T_w ℃	T_m ℃	*Ppack MPa*	t cycle *s*	Max *Tonne*	Shrinkage A	Shrinkage B
30	205	70	11.57	4159.0	3.295	6.188
40	205	70	11.54	4209.7	3.964	6.391
50	205	70	11.51	4167.8	4.626	7.119
55	205	70	11.48	4149.5	4.965	7.671
65	205	70	11.44	4100.9	5.498	8.985
75	205	70	11.40	4034.4	5.802	10.31
80	205	70	11.39	3998.1	5.872	10.68
90	205	70	11.35	3928.9	5.943	10.84
100	205	70	11.32	3825.8	6.016	10.96
30	215	70	11.59	4037.8	3.741	5.839
40	215	70	11.57	4019.5	4.379	6.465
50	215	70	11.53	3973.1	5.02	7.672
55	215	70	11.51	3938.8	5.256	8.268
65	215	70	11.45	3892.6	5.601	9.626
75	215	70	11.43	3822.8	5.749	10.47
80	215	70	11.39	3787.7	5.783	10.58
90	215	70	11.36	3699.8	5.835	10.63
100	215	70	11.31	3612.7	5.899	10.74
30	225	70	11.61	3862.2	4.148	5.862
40	225	70	11.58	3816.1	4.776	6.982
50	225	70	11.56	3774.1	5.224	8.256
55	225	70	11.52	3730.8	5.387	8.928
65	225	70	11.49	3681.5	5.583	10
75	225	70	11.45	3618.6	5.659	10.35
80	225	70	11.41	3581.4	5.678	10.34
90	225	70	11.36	3503.0	5.728	10.42
100	225	70	11.32	3420.5	5.784	10.52
30	230	70	11.62	3736.5	4.339	6.025
40	230	70	11.59	3710.5	4.911	7.316
50	230	70	11.55	3654.5	5.283	8.572
55	230	70	11.53	3630.6	5.417	9.216
65	230	70	11.48	3574.1	5.555	10.07
75	230	70	11.44	3504.9	5.608	10.24
80	230	70	11.41	3463.3	5.627	10.24
90	230	70	11.35	3395.2	5.676	10.32
100	230	70	11.31	3312.9	5.727	10.42

Continued

Table C.3: Injection Bottom Gate Sequencing – Data Set of Performance measures

Table C.3. continued

30	240	70	11.63	3544.9	4.691	6.67
40	240	70	11.59	3514.0	5.084	7.929
50	240	70	11.57	3470.2	5.327	9.094
55	240	70	11.53	3427.4	5.4	9.571
65	240	70	11.48	3376.0	5.477	9.996
75	240	70	11.45	3320.1	5.507	10.01
80	240	70	11.43	3284.1	5.527	10.04
90	240	70	11.37	3203.3	5.571	10.12
100	240	70	11.32	3124.5	5.615	10.21
30	250	70	11.63	3351.70	4.887	7.274
40	250	70	11.60	3316.6	5.151	8.47
50	250	70	11.56	3266.6	5.303	9.414
55	250	70	11.54	3234.3	5.343	9.675
65	250	70	11.51	3193.7	5.382	9.809
75	250	70	11.45	3130.5	5.412	9.825
80	250	70	11.42	3100.1	5.431	9.857
90	250	70	11.37	3016.0	5.47	9.93
100	250	70	11.30	2940.0	5.508	10.01
30	255	70	11.63	3248.6	4.935	7.585
40	255	70	11.61	3217.3	5.154	8.655
50	255	70	11.56	3171.8	5.275	9.466
55	255	70	11.55	3145.3	5.306	9.641
65	255	70	11.50	3091.3	5.335	9.704
75	255	70	11.45	3035.2	5.366	9.735
80	255	70	11.41	2998.2	5.383	9.766
90	255	70	11.36	2923.8	5.42	9.837
100	255	70	11.30	3001.5	5.456	9.914
30	265	70	11.66	3072.8	4.988	8.07
40	265	70	11.61	3030.3	5.139	8.987
50	265	70	11.58	2988.6	5.208	9.448
55	265	70	11.56	2970.4	5.223	9.503
65	265	70	11.52	2924.7	5.243	9.501
75	265	70	11.44	2860.8	5.274	9.559
80	265	70	11.43	2824.8	5.29	9.588
90	265	70	11.36	2964.1	5.322	9.658
100	265	70	11.30	3136.3	5.356	9.728

Continued

Table C.3. continued

30	275	70	11.66	2897.0	4.996	8.443
40	275	70	11.63	2860.1	5.086	9.091
50	275	70	11.59	2827.6	5.128	9.314
55	275	70	11.56	2793.8	5.137	9.327
65	275	70	11.52	2765.7	5.157	9.336
75	275	70	11.45	2867.6	5.185	9.39
80	275	70	11.42	2928.1	5.2	9.421
90	275	70	11.36	3099.2	5.228	9.484
100	275	70	11.30	3267.6	5.259	9.548

Controllable Variables			Performance Measures			
T_w ℃	T_m ℃	*Ppack MPa*	t cycle *s*	Max *Tonne*	Shrinkage A	Shrinkage B
30	205	70	11.17	5074.3	3.544	5.177
40	205	70	11.13	4992.4	3.731	5.734
50	205	70	11.12	5010.2	3.998	6.559
55	205	70	11.09	4884.3	4.183	7.063
65	205	70	11.05	4770.6	4.698	8.335
75	205	70	11.02	4736.8	5.395	9.77
80	205	70	10.99	4628.8	5.738	10.37
90	205	70	10.95	4550.5	5.91	10.83
100	205	70	10.90	4439.5	6.002	11
30	215	70	11.18	4860.5	3.507	5.264
40	215	70	11.15	4835.5	3.752	6.05
50	215	70	11.11	4733.8	4.123	7.018
55	215	70	11.09	4869.9	5.298	8.884
65	215	70	11.06	4598.0	5.021	9.087
75	215	70	11.02	4476.0	5.635	10.19
80	215	70	10.99	4329.8	5.73	10.50
90	215	70	10.95	4279.6	5.806	10.64
100	215	70	10.90	4143.6	5.885	10.79
30	225	70	11.18	4609.8	3.515	5.519
40	225	70	11.15	4551.1	3.873	6.502
50	225	70	11.10	4373.2	4.366	7.762
55	225	70	11.09	4408.9	4.663	8.402
65	225	70	11.05	4314.5	5.276	9.577
75	225	70	11.01	4198.8	5.6	10.26
80	225	70	10.99	4145.9	5.631	10.32
90	225	70	10.94	4019.5	5.697	10.46
100	225	70	10.89	4079.7	5.768	10.57
30	230	70	11.18	4480.6	3.55	5.723
40	230	70	11.14	4420.3	3.951	6.762
50	230	70	11.11	4325.0	4.475	8.054
55	230	70	11.09	4259.5	4.774	8.673
65	230	70	11.05	4197.2	5.376	9.766
75	230	70	11.01	4077.5	5.551	10.19
80	230	70	10.99	4026.0	5.583	10.25
90	230	70	10.94	4053.4	5.643	10.36
100	230	70	10.88	4104.0	5.71	10.47

Continued

Table C.4: Alternating Injection – Data Set of Performance measures

Table C.4. continued

30	240	70	11.18	4186.2	3.68	6.186
40	240	70	11.16	4209.4	4.161	7.402
50	240	70	11.11	4090.8	4.737	8.649
55	240	70	11.09	4039.7	5.042	9.199
65	240	70	11.05	3958.10	5.402	9.915
75	240	70	11.01	4004.5	5.455	10.01
80	240	70	10.99	4034.4	5.483	10.06
90	240	70	10.94	4101.7	5.538	10.16
100	240	70	10.89	4149.1	5.597	10.26
30	250	70	11.19	4009.80	3.85	6.819
40	250	70	11.15	3939.4	4.415	8.043
50	250	70	11.11	3952.8	4.985	9.104
55	250	70	11.08	3963.9	5.218	9.517
65	250	70	11.05	4016.8	5.311	9.755
75	250	70	11.00	4071.9	5.362	9.841
80	250	70	10.99	4071.9	5.386	9.886
90	250	70	10.93	4145.0	5.438	9.972
100	250	70	10.88	4190.0	5.488	10.06
30	255	70	11.19	3916.5	3.983	7.158
40	255	70	11.15	3928.1	4.553	8.308
50	255	70	11.12	3972.7	5.06	9.243
55	255	70	11.09	3991.7	5.22	9.554
65	255	70	11.05	4038.9	5.267	9.673
75	255	70	11.01	4098.0	5.315	9.755
80	255	70	10.98	4117.4	5.337	9.798
90	255	70	10.93	4161.7	5.388	9.879
100	255	70	10.88	4204.6	5.435	9.959
30	265	70	11.18	3932.3	4.239	7.724
40	265	70	11.15	3979.8	4.759	8.704
50	265	70	11.11	4012.0	5.116	9.375
55	265	70	11.09	4045.9	5.137	9.438
65	265	70	11.05	4099.50	5.179	9.509
75	265	70	11.00	4124.3	5.222	9.587
80	265	70	10.98	4161.7	5.244	9.625
90	265	70	10.93	4176.60	5.29	9.699
100	265	70	10.88	4230.9	5.332	9.77

Continued

Table C.4. continued

30	275	70	11.20	3982.0	4.457	8.155
40	275	70	11.16	4032.3	4.897	8.952
50	275	70	11.11	4075.8	5.036	9.253
55	275	70	11.09	4101.8	5.054	9.286
65	275	70	11.06	4101.8	5.095	9.351
75	275	70	11.01	4183.5	5.132	9.423
80	275	70	10.98	4201.2	5.154	9.457
90	275	70	10.94	4229.0	5.196	9.527
100	275	70	10.88	4250.9	5.235	9.591

Controllable Variables			Performance Measures			
T_w °C	T_m °C	*Ppack MPa*	t cycle *s*	Max *Tonne*	Shrinkage A	Shrinkage B
30	205	70	12.65	4565.6	2.979	5.503
40	205	70	12.50	4818.3	3.283	5.957
50	205	70	12.42	4317.2	3.712	6.379
55	205	70	12.43	4554.7	3.791	6.592
65	205	70	12.37	4493.0	4.149	7.596
75	205	70	12.29	4281.5	4.724	9.119
80	205	70	12.25	4200.8	5.089	9.94
90	205	70	12.17	4048.5	5.771	10.83
100	205	70	12.11	4035.2	5.952	10.9
30	215	70	12.56	4452.1	3.182	5.553
40	215	70	12.49	4286.2	3.478	5.86
50	215	70	12.41	4102.4	3.749	6.37
55	215	70	12.36	4086.4	3.903	6.917
65	215	70	12.36	4162.5	4.316	8.213
75	215	70	12.31	4086.0	4.959	9.749
80	215	70	12.26	3994.5	5.32	10.35
90	215	70	12.18	3912.3	5.763	10.55
100	215	70	12.09	3832.3	5.839	10.7
30	225	70	12.58	3922.4	3.294	5.337
40	225	70	12.47	4028.4	3.477	5.709
50	225	70	12.44	3956.4	3.762	6.726
55	225	70	12.41	3981.3	3.974	7.447
65	225	70	12.33	3778.5	4.56	8.961
75	225	70	12.28	3736.8	5.213	10.16
80	225	70	12.23	3705.7	5.494	10.35
90	225	70	12.16	3550.0	5.668	10.38
100	225	70	12.10	3618.0	5.728	10.5
30	230	70	12.52	3827.8	3.297	5.204
40	230	70	12.47	3846.9	3.481	5.815
50	230	70	12.41	3722.7	3.821	7.03
55	230	70	12.39	3699.6	4.047	7.735
65	230	70	12.33	3668.2	4.669	9.273
75	230	70	12.27	3628.9	5.316	10.21
80	230	70	12.27	3677.5	5.501	10.22
90	230	70	12.16	3516.3	5.613	10.28
100	230	70	12.10	3465.6	5.675	10.4

Continued

Table C.5: Alternating Injection with Gate Sequencing – Data Set of Performance measures

Table C.5 continued

30	240	70	12.57	3810.2	3.222	5.163
40	240	70	12.48	3506.8	3.494	6.19
50	240	70	12.44	3534.9	3.941	7.668
55	240	70	12.43	3567.9	4.233	8.438
65	240	70	12.36	3497.60	4.877	9.693
75	240	70	12.28	3473.1	5.378	10.01
80	240	70	12.22	3319.1	5.462	9.999
90	240	70	12.18	3381.1	5.508	10.1
100	240	70	12.11	3316.1	5.565	10.2
30	250	70	12.55	3377.70	3.2	5.376
40	250	70	12.49	3437.1	3.564	6.835
50	250	70	12.45	3400.9	4.119	8.356
55	250	70	12.42	3394.4	4.424	8.997
65	250	70	12.36	3334.9	5.037	9.798
75	250	70	12.27	3228.5	5.339	9.787
80	250	70	12.24	3139.2	5.365	9.834
90	250	70	12.17	3092.1	5.411	9.926
100	250	70	12.13	3134.1	5.461	10.01
30	255	70	12.55	3315.9	3.205	5.665
40	255	70	12.52	3324.0	3.639	7.2
50	255	70	12.45	3290.4	4.232	8.654
55	255	70	12.42	3228.2	4.537	9.223
65	255	70	12.38	3243.8	5.079	9.744
75	255	70	12.28	3133.8	5.294	9.704
80	255	70	12.25	3130.8	5.316	9.749
90	255	70	12.19	2998.8	5.362	9.838
100	255	70	12.12	2921.2	5.412	9.923
30	265	70	12.56	3096.8	3.286	6.409
40	265	70	12.52	3152.9	3.808	7.872
50	265	70	12.46	3054.9	4.413	9.06
55	265	70	12.42	3095.7	4.712	9.42
65	265	70	12.35	2994.0	5.121	9.529
75	265	70	12.28	2880.6	5.206	9.552
80	265	70	12.26	2960.1	5.223	9.586
90	265	70	12.19	2876.90	5.265	9.666
100	265	70	12.11	2861.6	5.312	9.741

Continued

Table C.5. continued

30	275	70	12.56	2921.5	3.433	7.149
40	275	70	12.51	2955.5	4.003	8.422
50	275	70	12.46	2930.6	4.596	9.258
55	275	70	12.41	2835.0	4.842	9.401
65	275	70	12.35	2834.7	5.076	9.333
75	275	70	12.31	2793.5	5.116	9.395
80	275	70	12.26	2716.3	5.135	9.432
90	275	70	12.18	2784.4	5.174	9.503
100	275	70	12.11	2968.1	5.216	9.568

APPENDIX D

SIMPLIFICATION OF THE NEW POINTS

T_w °C	T_m °C	**Shrinkage A**	**Average**	**Standard Deviation**	**Shrinkage B**	**Average**	**Standard Deviation**
		3.669			5.21		
		4.008			6.211		
		4.405			7.395		
		3.745			5.744		
40	215	4.146	4.171556	0.389564	6.893	6.982111	1.228634
		4.592			8.285		
		3.863			6.38		
		4.306			7.74		
		4.81			8.981		
		5.183			8.123		
		5.721			9.549		
		5.885			10.44		
		4.858			8.952		
65	215	5.383	5.445444	0.349497	9.958	9.707333	0.779077
		5.756			10.47		
		5.062			9.474		
		5.509			10.08		
		5.652			10.32		
		5.885			10.68		
		5.961			10.88		
		6.037			11.02		
		5.785			10.56		
90	215	5.844	5.848333	0.113375	10.67	10.67222	0.203272
		5.916			10.8		
		5.68			10.37		
		5.733			10.47		
		5.794			10.6		
		3.952			6.792		
		4.421			8.122		
		4.904			9.228		
		4.124			7.556		
40	240	4.614	4.591667	0.418381	8.729	8.533667	0.940316
		5.053			9.489		
		4.322			8.229		
		4.771			9.08		
		5.164			9.578		

Continued

Table D.1: Simplification of new points - Injection Top

Table D.1 continued

		5.145			9.618		
		5.532			10.09		
		5.601			10.23		
		5.272			9.74		
65	240	5.459	5.397889	0.142146	9.971	9.903	0.200454
		5.499			10.06		
		5.313			9.717		
		5.36			9.816		
		5.4			9.885		
		5.626			10.27		
		5.678			10.37		
		5.735			10.49		
		5.523			10.11		
90	240	5.569	5.571667	0.102255	10.19	10.19044	0.181057
		5.619			10.28		
		5.42			9.924		
		5.466			10		
		5.509			10.08		
		4.41			8.46		
		4.843			9.181		
		5.201			9.604		
		4.57			8.844		
40	265	4.954	4.880556	0.276154	9.307	9.159556	0.350267
		5.173			9.48		
		4.682			8.977		
		5.007			9.26		
		5.085			9.323		
		5.278			9.671		
		5.312			9.729		
		5.353			9.8		
		5.187			9.506		
65	265	5.222	5.223	0.084379	9.563	9.567778	0.15227
		5.257			9.629		
		5.1			9.347		
		5.132			9.401		
		5.166			9.464		
		5.371			9.835		
		5.415			9.909		
		5.454			9.98		
		5.275			9.663		
190	265	5.314	5.314778	0.090891	9.727	9.729111	0.164152
		5.351			9.792		
		5.183			9.495		
		5.219			9.551		
		5.251			9.61		

T_w ℃	T_m ℃	Shrinkage A	Average	Standard Deviation	Shrinkage B	Average	Standard Deviation
		5.065			7.071		
		5.535			7.998		
		5.78			8.867		
		5.333			7.521		
40	215	5.618	5.535444	0.226365	8.496	8.445556	0.857458
		5.755			9.382		
		5.454			8.093		
		5.592			8.887		
		5.687			9.695		
		5.869			9.41		
		5.959			10.26		
		5.999			10.75		
		5.801			9.777		
65	215	5.856	5.840778	0.097655	10.37	10.20633	0.414814
		5.874			10.59		
		5.716			10		
		5.736			10.32		
		5.757			10.38		
		6.013			10.84		
		6.053			10.93		
		6.107			11.06		
		5.89			10.62		
90	215	5.931	5.9435	0.113923	10.72	10.72667	0.206761
		5.974			10.83		
		5.773			10.42		
		5.807			10.51		
		5.845			10.61		
		5.449			8.272		
		5.575			9.085		
		5.644			9.783		
		5.418			8.636		
40	240	5.504	5.482111	0.089799	9.356	9.241444	0.550514
		5.538			9.842		
		5.365			8.944		
		5.414			9.486		
		5.432			9.769		

Continued

Table D.2: Simplification of new points - Injection Bottom

Table D.2 continued

65	240	5.661 5.677 5.701 5.549 5.561 5.587 5.437 5.456 5.482	5.567889	0.097526	10.01 10.23 10.28 9.963 10.03 10.09 9.797 9.841 9.902	10.01589	0.164161
90	240	5.713 5.747 5.782 5.601 5.633 5.663 5.494 5.522 5.55	5.633889	0.10127	10.32 10.4 10.49 10.12 10.2 10.28 9.934 10.01 10.08	10.20378	0.184536
40	265	5.331 5.367 5.379 5.249 5.268 5.279 5.165 5.173 5.186	5.266333	0.081322	9.047 9.503 9.688 9.138 9.442 9.51 9.173 9.307 9.344	9.350222	0.206665
65	265	5.386 5.405 5.43 5.287 5.308 5.329 5.194 5.213 5.233	5.309444	0.085795	9.706 9.75 9.811 9.53 9.577 9.634 9.363 9.41 9.465	9.582889	0.155202
190	265	5.442 5.468 5.495 5.341 5.364 5.39 5.244 5.265 5.289	5.366444	0.090165	9.843 9.912 9.979 9.666 9.725 9.788 9.494 9.547 9.604	9.728667	0.165991

T_w °C	T_m °C	Shrinkage A	Average	Standard Deviation	Shrinkage B	Average	Standard Deviation
40	215	3.295	4.352555	0.626988	6.188	6.752666	0.825565
		3.964			6.391		
		4.626			7.119		
		3.741			5.839		
		4.379			6.465		
		5.02			7.672		
		4.148			5.862		
		4.776			6.982		
		5.224			8.256		
65	215	4.965	5.5	0.26318	7.671	9.400888	0.997023
		5.498			8.985		
		5.802			10.31		
		5.256			8.268		
		5.601			9.626		
		5.749			10.47		
		5.387			8.928		
		5.583			10		
		5.659			10.35		
90	215	5.872	5.837556	0.106791	10.68	10.63444	0.196921
		5.943			10.84		
		6.016			10.96		
		5.783			10.58		
		5.835			10.63		
		5.899			10.74		
		5.678			10.34		
		5.728			10.42		
		5.784			10.52		
40	240	4.339	4.997333	0.328198	6.025	7.862666	1.131596
		4.911			7.316		
		5.283			8.572		
		4.691			6.67		
		5.084			7.929		
		5.327			9.094		
		4.887			7.274		
		5.151			8.47		
		5.303			9.414		

Continued

Table D.3: Simplification of new points – Injection Bottom with Gate Sequencing

Table D.3 continued

65	240	5.417 5.555 5.608 5.4 5.477 5.507 5.343 5.382 5.412	5.455666	0.087167	9.216 10.07 10.24 9.571 9.996 10.01 9.675 9.809 9.825	9.823555	0.306971
90	240	5.627 5.676 5.727 5.527 5.571 5.615 5.431 5.47 5.508	5.57244	0.097545	10.24 10.32 10.42 10.04 10.12 10.21 9.857 9.93 10.01	10.12744	0.185664
40	265	4.935 5.154 5.275 4.988 5.139 5.208 4.996 5.086 5.128	5.101	0.110839	7.585 8.655 9.466 8.07 8.987 9.448 8.443 9.091 9.314	8.784333	0.652179
65	265	5.306 5.335 5.366 5.223 5.243 5.274 5.137 5.157 5.185	5.247333	0.079648	9.641 9.704 9.735 9.503 9.501 9.559 9.327 9.336 9.39	9.521778	0.152015
190	265	5.383 5.42 5.456 5.29 5.322 5.356 5.2 5.228 5.259	5.323778	0.087408	9.766 9.837 9.914 9.588 9.658 9.728 9.421 9.484 9.548	9.660444	0.164899

T_w °C	T_m °C	Shrinkage A	Average	Standard Deviation	Shrinkage B	Average	Standard Deviation
40	215	3.544	3.823222	0.296656	5.177	6.176111	0.862406
		3.731			5.734		
		3.998			6.559		
		3.507			5.264		
		3.752			6.05		
		4.123			7.018		
		3.515			5.519		
		3.873			6.502		
		4.366			7.762		
65	215	4.183	5.085444	0.486213	7.063	9.063111	1.028743
		4.698			8.335		
		5.395			9.77		
		5.298			8.884		
		5.021			9.087		
		5.635			10.19		
		4.663			8.402		
		5.276			9.577		
		5.6			10.26		
90	215	5.738	5.796333	0.116717	10.37	10.60889	0.22685
		5.91			10.83		
		6.002			11		
		5.73			10.5		
		5.806			10.64		
		5.885			10.79		
		5.631			10.32		
		5.697			10.46		
		5.768			10.57		
40	240	3.55	4.200444	0.488027	5.723	7.415778	1.136512
		3.951			6.762		
		4.475			8.054		
		3.68			6.186		
		4.161			7.402		
		4.737			8.649		
		3.85			6.819		
		4.415			8.043		
		4.985			9.104		

Continued

Table D.4: Simplification of new points – Alternate Injection

Table D.4 continued

		4.774			8.673		
		5.376			9.766		
		5.551			10.19		
		5.042			9.199		
65	240	5.402	5.276778	0.237771	9.915	9.651778	0.464755
		5.455			10.01		
		5.218			9.517		
		5.311			9.755		
		5.362			9.841		
		5.583			10.25		
		5.643			10.36		
		5.71			10.47		
		5.483			10.06		
90	240	5.538	5.540667	0.102883	10.16	10.16422	0.188567
		5.597			10.26		
		5.386			9.886		
		5.438			9.972		
		5.488			10.06		
		3.983			7.158		
		4.553			8.308		
		5.06			9.243		
		4.239			7.724		
40	265	4.759	4.677778	0.396967	8.704	8.541333	0.764383
		5.116			9.375		
		4.457			8.155		
		4.897			8.952		
		5.036			9.253		
		5.22			9.554		
		5.267			9.673		
		5.315			9.755		
		5.137			9.438		
65	265	5.179	5.180111	0.083974	9.509	9.508444	0.151099
		5.222			9.587		
		5.054			9.286		
		5.095			9.351		
		5.132			9.423		
		5.337			9.798		
		5.388			9.879		
		5.435			9.959		
		5.244			9.625		
190	265	5.29	5.290111	0.091566	9.699	9.700556	0.165872
		5.332			9.77		
		5.154			9.457		
		5.196			9.527		
		5.235			9.591		

T_w °C	T_m °C	Shrinkage A	Average	Standard Deviation	Shrinkage B	Average	Standard Deviation
40	215	2.979 3.283 3.712 3.182 3.478 3.749 3.294 3.477 3.762	3.435111	0.2740431	5.503 5.957 6.379 5.553 5.86 6.37 5.337 5.709 6.726	5.932667	0.4689523
65	215	3.791 4.149 4.724 3.903 4.316 4.959 3.974 4.56 5.213	4.39877	0.4966683	6.592 7.596 9.119 6.917 8.213 9.749 7.447 8.961 10.16	8.306	1.2613141
90	215	5.089 5.771 5.952 5.32 5.763 5.839 5.494 5.668 5.728	5.624889	0.2745507	9.94 10.83 10.9 10.35 10.55 10.7 10.35 10.38 10.5	10.5	0.2924893
40	240	3.297 3.481 3.821 3.222 3.494 3.941 3.2 3.564 4.119	3.571	0.325634	5.204 5.815 7.03 5.163 6.19 7.668 5.376 6.835 8.356	6.404111	1.1410094

Continued

Table D.5: Simplification of new points – Alternate Injection with Gate Sequencing

Table D.5 continued

65	240	4.047	4.813333	0.4997992	7.735	9.326778	0.8101061
		4.669			9.273		
		5.316			10.21		
		4.233			8.438		
		4.877			9.693		
		5.378			10.01		
		4.424			8.997		
		5.037			9.798		
		5.339			9.787		
90	240	5.501	5.506777	0.0977123	10.22	10.10767	0.18221
		5.613			10.28		
		5.675			10.4		
		5.462			9.999		
		5.508			10.1		
		5.565			10.2		
		5.365			9.834		
		5.411			9.926		
		5.461			10.01		
40	265	3.205	3.846111	0.499622	5.665	7.743222	1.2289549
		3.639			7.2		
		4.232			8.654		
		3.286			6.409		
		3.808			7.872		
		4.413			9.06		
		3.433			7.149		
		4.003			8.422		
		4.596			9.258		
65	265	4.537	4.998111	0.247798	9.223	9.477889	0.1703456
		5.079			9.744		
		5.294			9.704		
		4.712			9.42		
		5.121			9.529		
		5.206			9.552		
		4.842			9.401		
		5.076			9.333		
		5.116			9.395		
190	265	5.316	5.268333	0.0901901	9.749	9.667333	0.1602576
		5.362			9.838		
		5.412			9.923		
		5.223			9.586		
		5.265			9.666		
		5.312			9.741		
		5.135			9.432		
		5.174			9.503		
		5.216			9.568		

APPENDIX E

EFFICIENT SOLUTIONS PER –INJECTION LOCATION FOR "ORIGINAL POINTS"

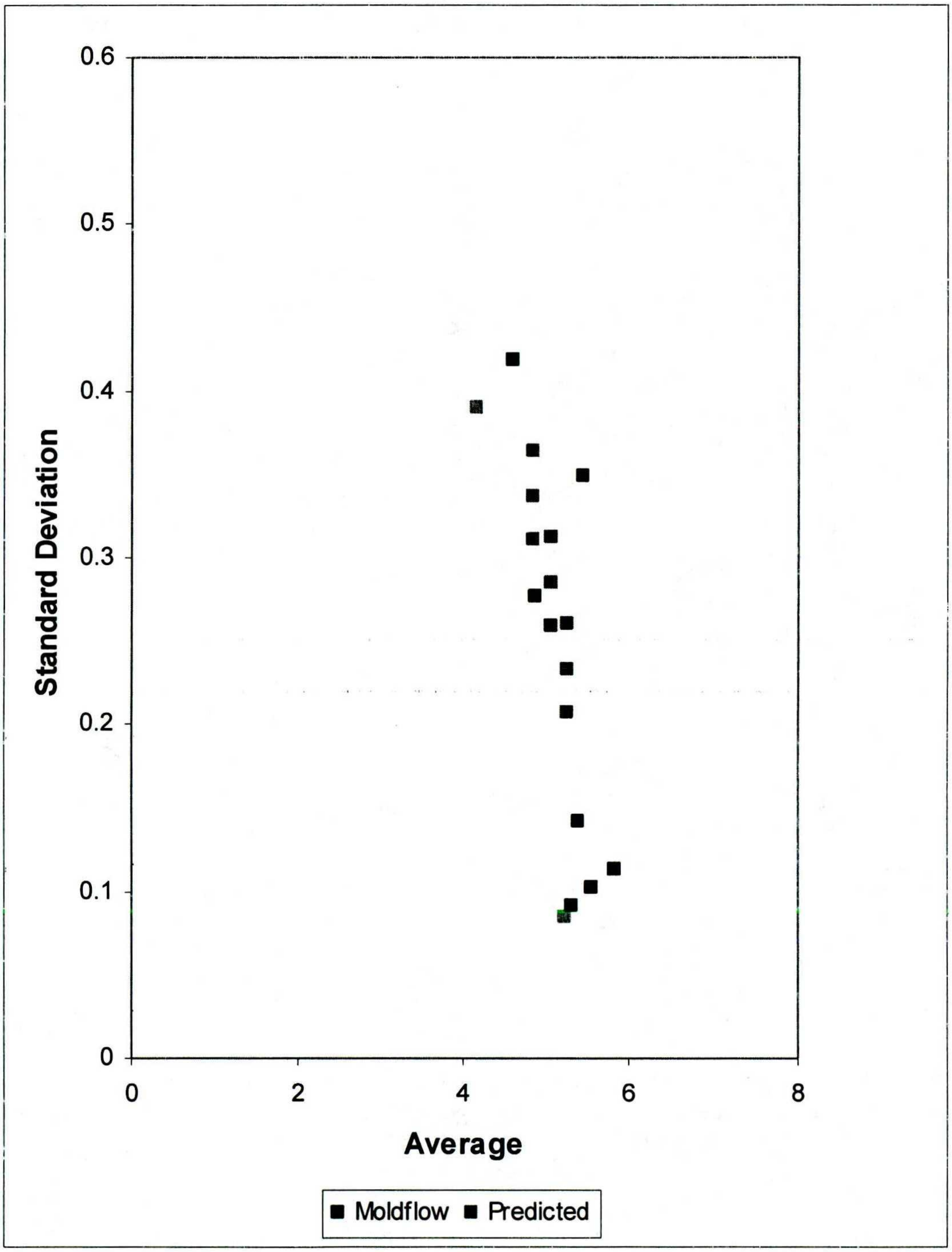


Figure E1 Efficient solution for shrinkage A – Injection top

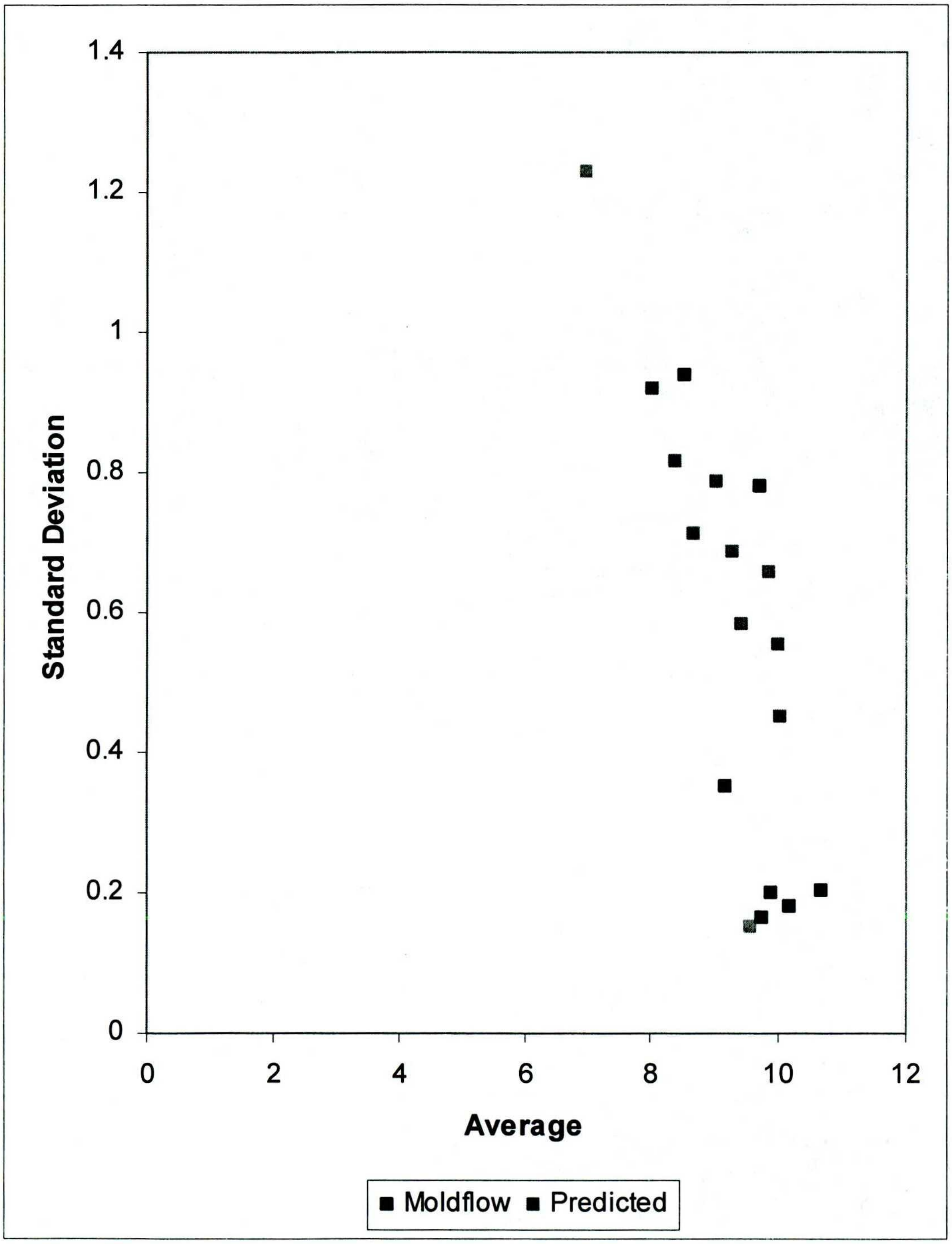


Figure E.2 Efficient solution for shrinkage B – Injection top

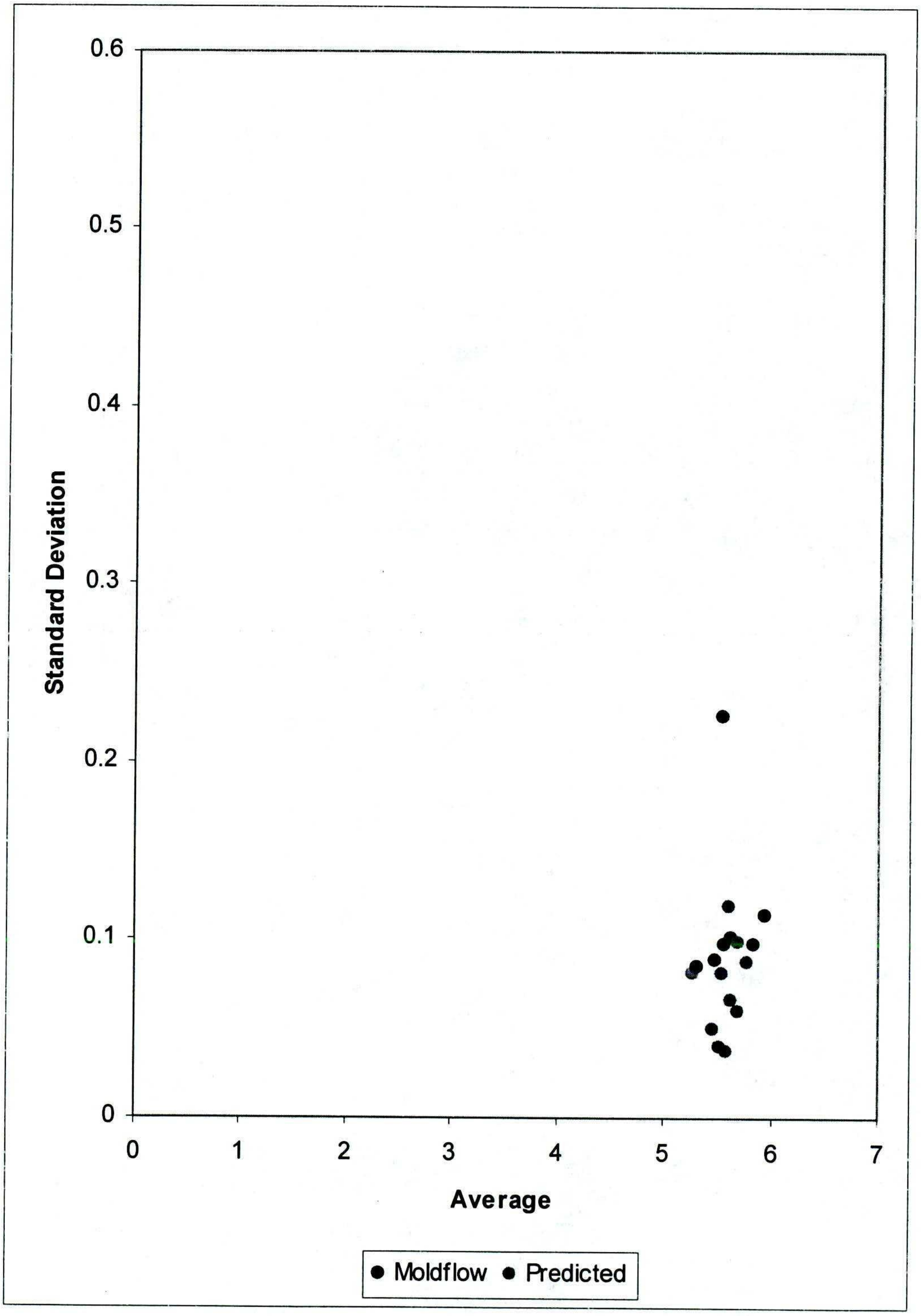


Figure E.3 Efficient solution for shrinkage A – Injection Bottom

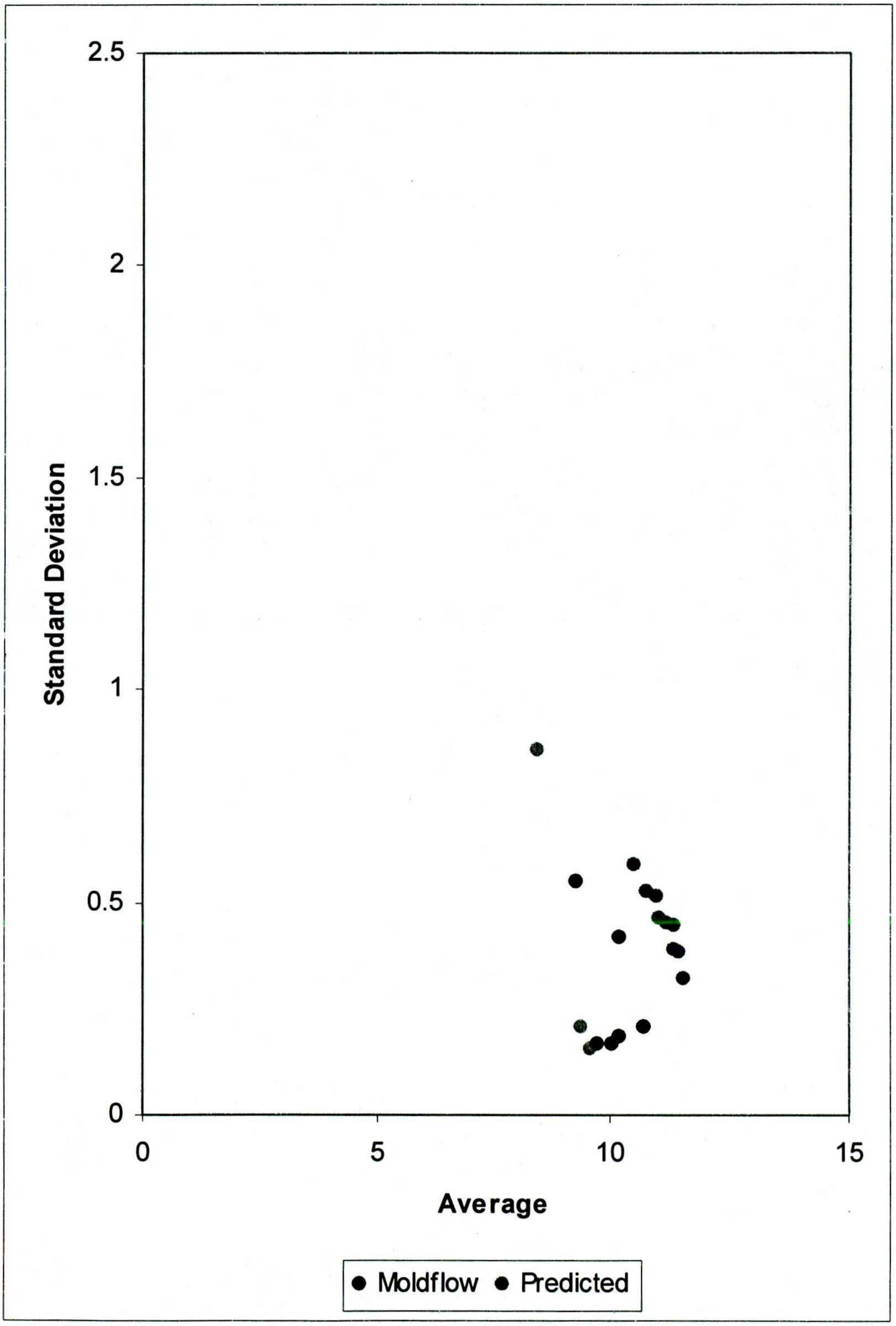


Figure E.4 Efficient solution for shrinkage B – Injection Bottom

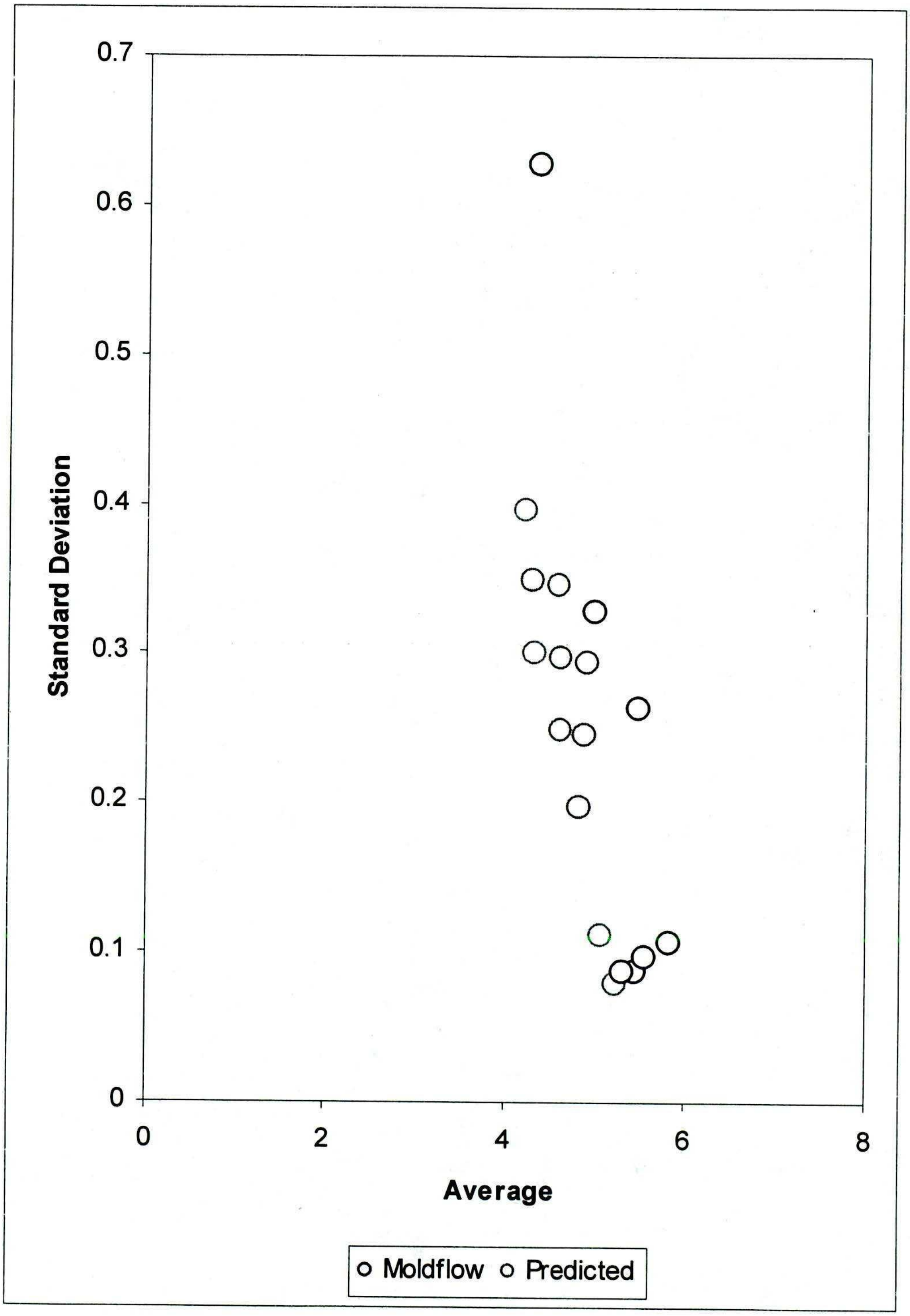


Figure E.5 Efficient solution for shrinkage A – Injection Bottom with Gate Sequencing

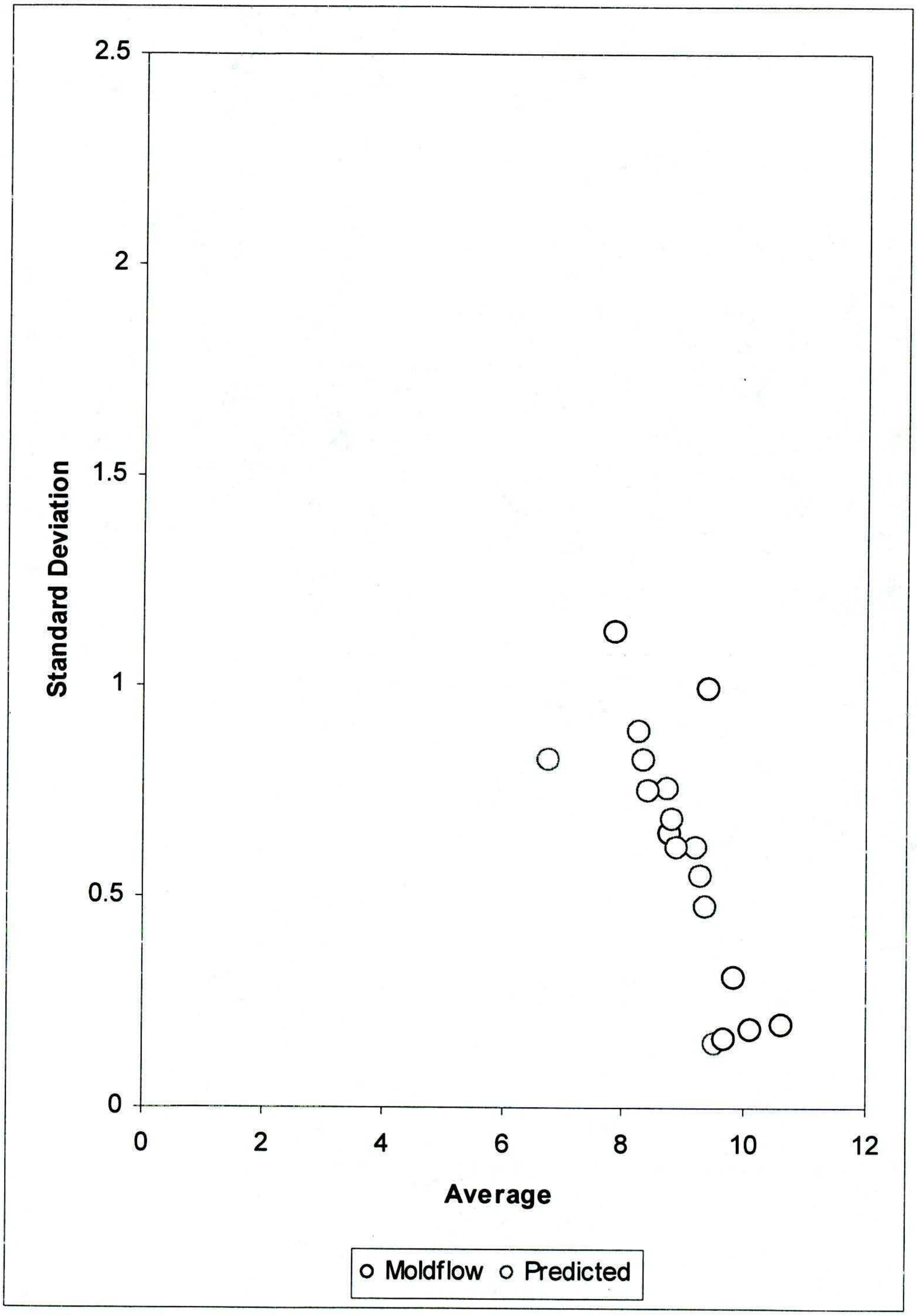


Figure E.6 Efficient solution for shrinkage B – Injection Bottom with Gate Sequencing

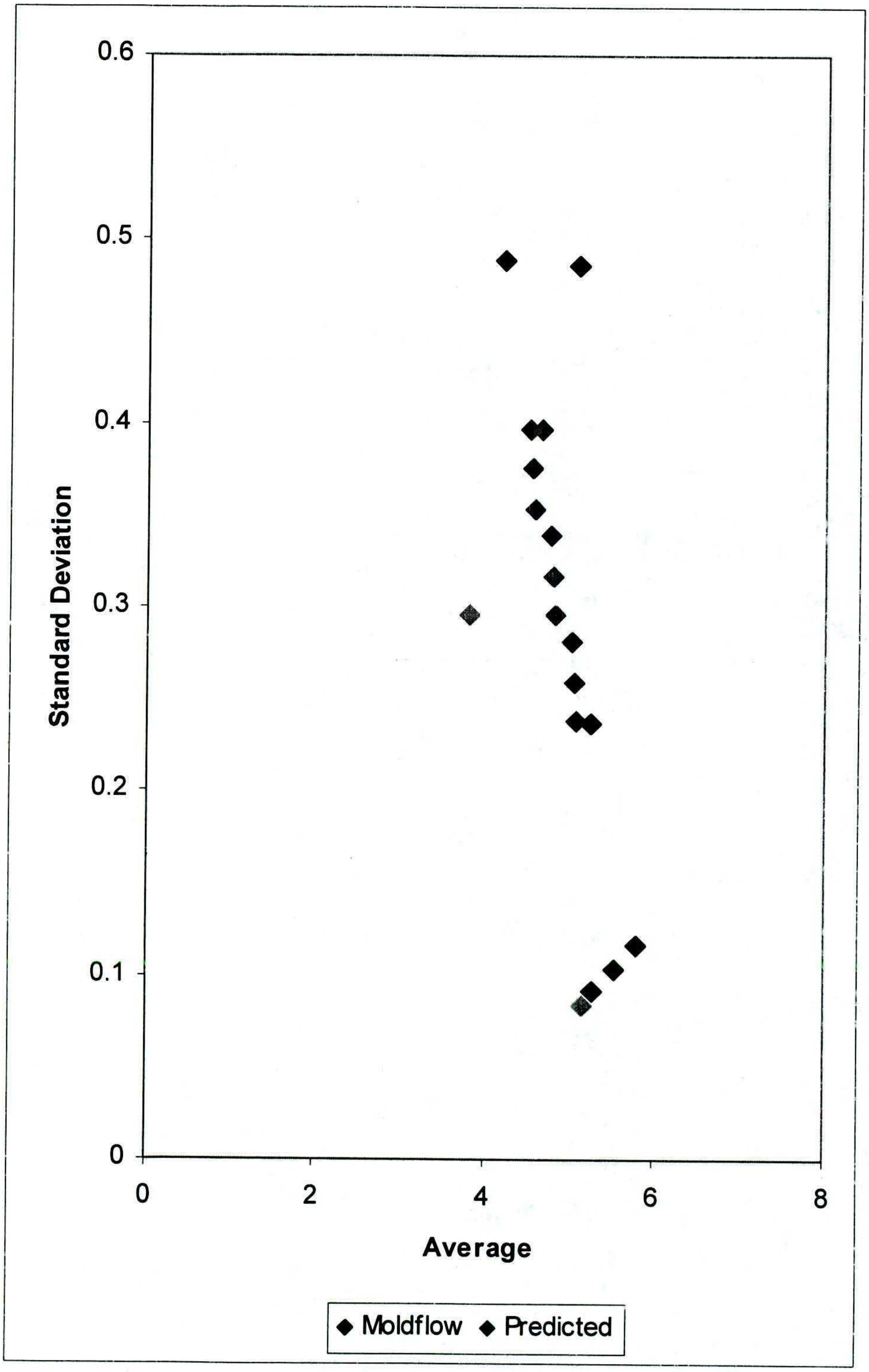


Figure E.7 Efficient solution for shrinkage A – Alternate Injection

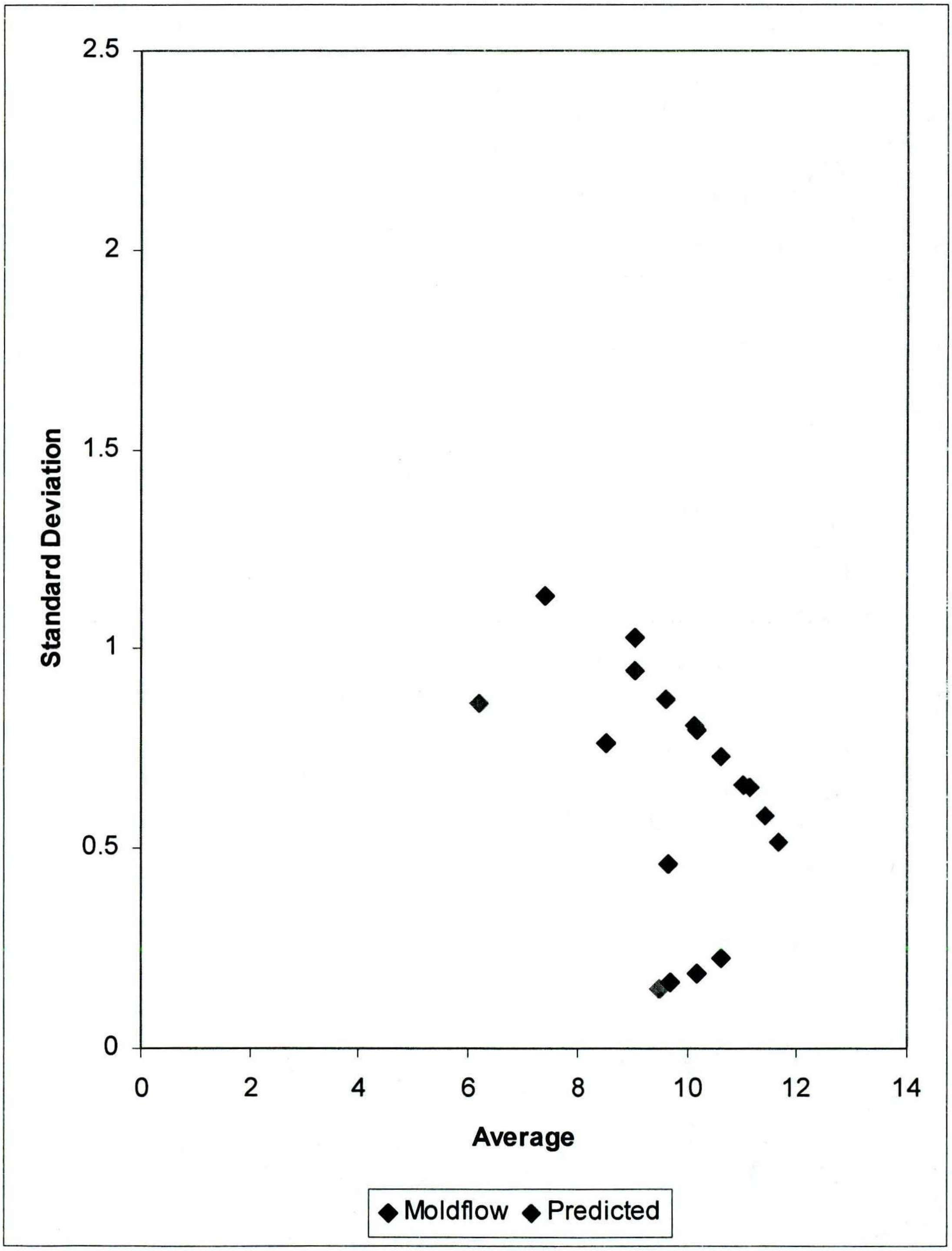


Figure E.8 Efficient solution for shrinkage B – Alternate Injection

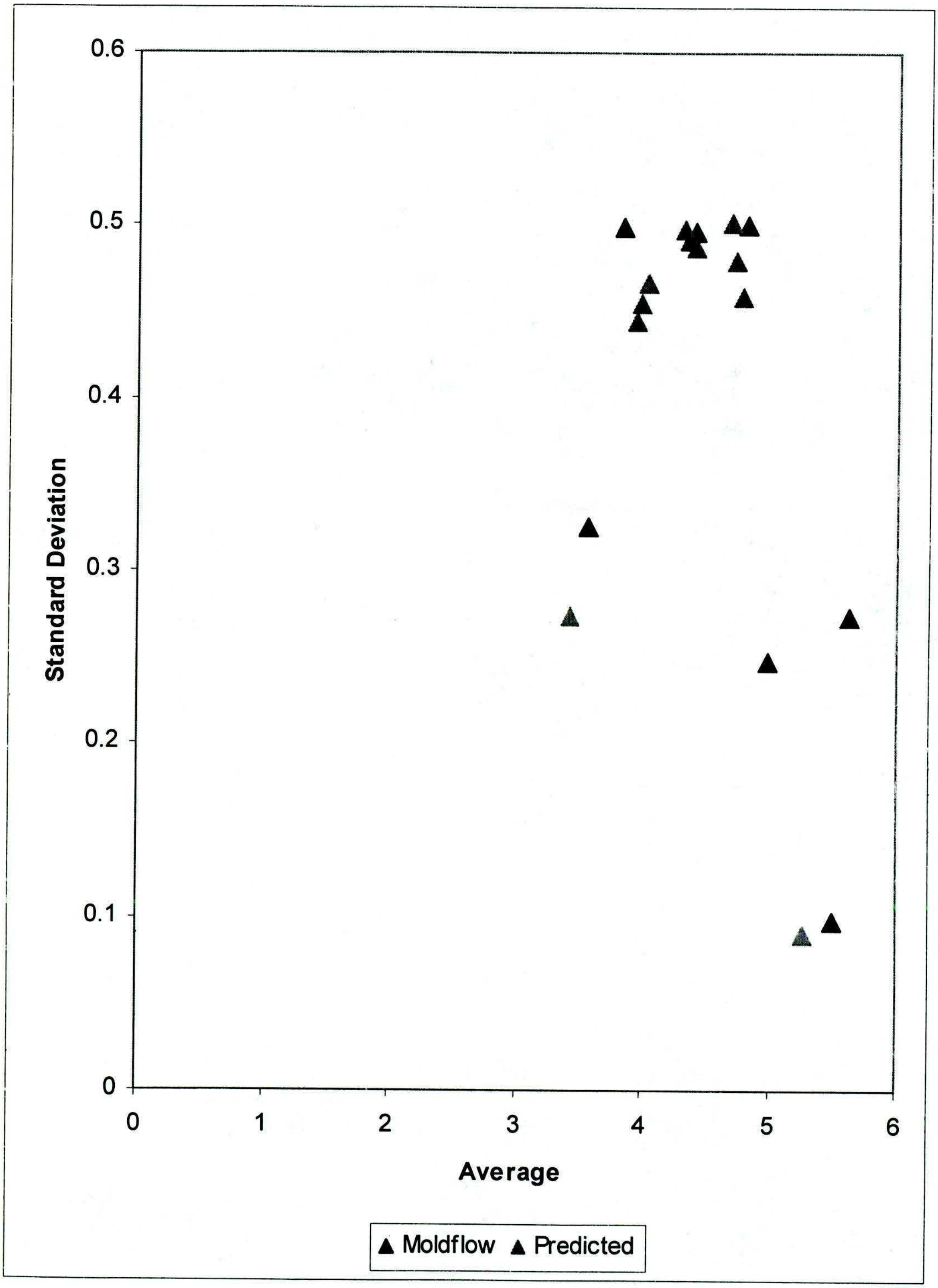


Figure E.9 Efficient solution for shrinkage A – Alternate Injection with Gate Sequencing

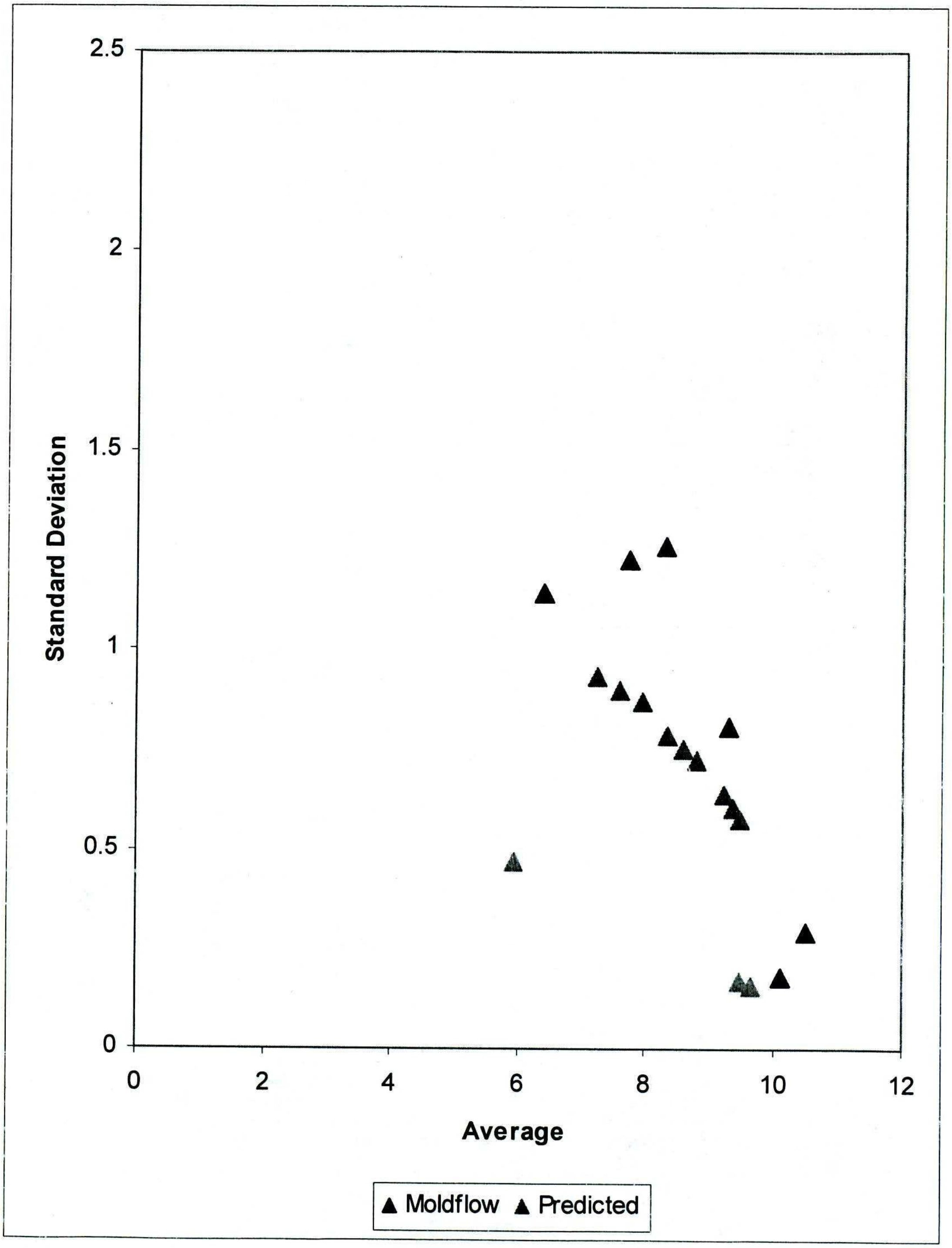


Figure E.10 Efficient solution for shrinkage B – Alternate Injection with Gate Sequencing

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