OPTIMIZATION OF INJECTION MOLDING PROCESS PARAMETERS FOR CYCLE TIME

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ABSTRACT

OPTIMIZATION OF INJECTION MOLDING PROCESS PARAMETERS FOR CYCLE TIME

Plastic, an integral part of modern life, is widely used in various sectors such as automotive, aerospace, and healthcare. The rapid advancements in the plastic industry have improved plastic processing technologies. Among contemporary production methods, plastic injection molding has become one of the most commonly used techniques. As industrial markets evolve rapidly, the need to shorten product cycle times, reduce production costs, and increase production speeds to respond swiftly to demand has become increasingly urgent. In this context, the thesis addresses the reduction of cycle times through the optimization of process parameters in the injection molding process. By utilizing experimental data available in the literature, a mathematical model of the injection molding process has been developed using a hybrid method known as Neuro-regression approach and cross-validation technique. To minimize the cycle time of the injection molding process, multi-objective optimization scenarios were created using seven different process parameters and two parameters affecting product quality. Optimization studies were carried out using stochastic optimization methods with the "Simulated Annealing," "Random Search," "Nelder-Mead," and "Differential Evolution" algorithms in the "Wolfram Mathematica" program with the help of the "NMinimize" tool. When comparing the obtained optimization results with those in the literature, it was found that the model and optimization methods used in the study are reliable and applicable.

ÖZET

ÇEVRİM SÜRESİ İÇİN ENJEKSİYON KALIPLAMA PROSES PARAMETRELERİNİN OPTİMİZASYONU

Modern yaşamın en önemli parçası haline gelen plastik, otomotiv, havacılık, tıp gibi çeşitli sektörlerde sıkça kullanılmaktadır. Plastik endüstrisindeki hızlı gelişmeler, plastik işleme teknolojilerini geliştirmiştir. Günümüzün üretim yöntemlerinde, plastik enjeksiyon kalıplama, en yaygın kullanılan üretim yöntemlerinden olmuştur. Endüstriyel pazarlar hızla gelişirken, ürün çevrim sürelerini kısaltma, üretim maliyetlerini düşürmek ve üretim hızlarının arttırılmasıyla talebe hızlı cevap verme ihtiyacı giderek daha acil hale gelmiştir. Bu bağlamda, tez çalışmasında enjeksiyon kalıplama prosesinin proses parametrelerinin optimizasyonu ile çevrim süresinin kısaltılması ele alınmıştır. Literatürde bulunan deneysel veriler kullanılarak, hibrit bir yöntem olan Nöro-regresyon yaklaşımı ve çapraz doğruluma tekniği ile enjeksiyon kalıplama prosesinin matematiksel modellemesi yapılmıştır. Enjeksiyon kalıplama prosesinin çevrim süresinin minimize etme amacıyla, yedi farklı proses parametresi ve iki adet ürün kalitesine etki eden parameter kullanılarak çok amaçlı optimizasyon senaryoları oluşturulmuştur. Optimizasyon çalışmaları, "Simulated Annealing", "Random Search", "Nelder-Mead" ve "Differential Evolution" algoritmaları kullanılarak "Wolfram Mathematica" programında "NMinimize" aracı yardımıyla stokastik optimizasyon yöntemleri ile gerçekleştirilmiştir. Elde edilen optimizasyon sonuçları ve literatürdeki sonuçlar karşılaştırıldığında çalışmada kullanılan modelin ve optimizasyon yöntemlerinin güvenilir ve uygulanabilir olduğu görülmüştür.

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CHAPTER 1

INTRODUCTION

1.1. Literature Survey

Throughout history, humans have continuously developed new materials to meet their evolving needs. Plastic, which has become an integral part of modern life, reflects humanity's ingenuity and finds applications in various sectors such as automotive, aerospace, medicine, and even in sensitive areas like the human body. The rapid advancement of plastics can be attributed to the incorporation of special additives into base materials like PP, PVC, and PE, allowing for customizable production based on specific requirements. Its flexibility, high insulation properties, ease of cleaning, reusability, and durability contribute to its value addition to the economy, offering effective solutions to users needs. [1]

The rapid advancements in the plastic industry also encompass plastic processing technologies. Particularly, significant progress has been made in the not-so-new plastic injection technology, making it the most widely used processing technique. This progress extends beyond just manufacturing products; it has also influenced every aspect from product design to material and machinery selection. Across Europe and many parts of the world, considerable importance is placed on the advancements in the plastic industry. [2]

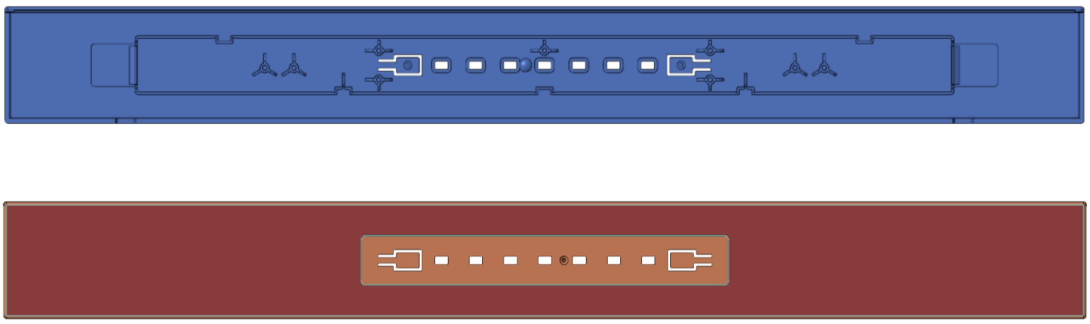

Figure 1.1. 3D model of a part that can be produced by injection molding

Nowadays manufacturing method, plastic injection molding serves as a cornerstone for crafting top-tier plastic products. As markets evolve rapidly, the need to trim down product cycle times becomes increasingly pressing. In this context, injection molding is a widely used manufacturing process, and optimizing its parameters is crucial for enhancing production efficiency. Several studies have successfully tackled this challenge, each employing different methodologies and achieving notable improvements in cycle time reduction.

Figure 1.2. 3D model of a part produced by injection molding

Mukras et al. an experimental-based multi-objective optimization framework for determining the optimal injection molding process parameters to reduce product defects. The research focuses on two main defects affecting product quality: warpage and volumetric shrinkage. Seven critical injection molding process parameters were analyzed: mold temperature, melt temperature, packing pressure, packing time, cooling time, injection speed, and injection pressure. The methodology employed a face-centered central composite design (FCCCD) approach to establish specific test points within a defined domain. These test points were used to conduct injection molding experiments, and the resulting products were evaluated for warpage and volumetric shrinkage. Distinct relationships between the process parameters and defects were developed based on experimental data, forming the foundation for the optimization process. A genetic algorithm (GA) was utilized to formulate and solve a multi-objective optimization problem aimed at minimizing both defects simultaneously. The optimization results indicated a significant trade-off between minimizing warpage and volumetric shrinkage. To validate these results, additional experiments were conducted under the assumption of equal importance for both defects. The experimental results closely matched the optimization results, with a discrepancy of about 7%. [3]

Xu et al. due to, injection molding is a widely used process in manufacturing polymer products and warpage during the process can negatively affect mechanical performance study on this topic. They proposed using a combination of artificial neural network (ANN) and particle swarm optimization (PSO) algorithms for this optimization. Optimizing process parameters is essential for improving product performance. Their approach includes an integrated finite element analysis (FEA) to evaluate the injection molding process, residual stresses, and mechanical performance. A back propagation neural network (BPNN) model maps the relationship between process parameters and mechanical performance, while the PSO algorithm optimizes these parameters. In a case study of a polycarbonate (PC) vehicle window, optimized parameters reduced the maximum von Mises stress by 12.9%. This study demonstrates that optimizing process parameters can significantly enhance the mechanical performance of polymer products. [4]

Ozcelik and Erzurumlu have developed various optimization methods to minimize distortion of thin-shelled plastic parts produced by injection molding. In this context, they proposed an effective optimization methodology using artificial neural network (ANN) and genetic algorithm (GA). In their study, PC Button Base was used as an example and process condition parameters such as mold temperature, melt temperature, printing pressure, printing time, runner type, entry location and cooling time were evaluated to ensure minimum distortion. Finite element analysis was performed for the process parameter combinations arranged using a three-level full factorial experimental design, and according to the analysis of variance (ANOVA) results, the effects of printing pressure, mold temperature, melt temperature, printing time, cooling time, runner type and inlet location on distortion were , respectively. 33.7%, 21.6%, 20.5%, 16.1%, 5.1%, 1.5% and 1.3%. The artificial neural network model created using the most important process parameters was integrated with the genetic algorithm, optimum process parameter values were found and a significant improvement was achieved by reducing the distortion of the initial model by 51%. This study makes a significant contribution to the literature by providing an optimization method that can be applied to solving warpage problems of thin-shelled plastic parts with complex geometries. [5]

In another study optimize the tensile strength and flexural modulus in the injection molding process for recycled polypropylene. Seven process parameters were examined, namely melting temperature, injection pressure, injection speed, injection time, holding pressure, holding time and cooling time. Suitable values were determined by experiments and optimized using Taguchi methods and desirability functions. The results show that the factors that most affect tensile strength are melting temperature, injection time and holding time; It has been shown that the factors that most affect the flexural modulus are melting temperature, holding time and injection pressure. The best parameters were determined as 180°C melting temperature, 55 MPa injection pressure, 30 mm/s injection speed, 8 sec injection time, 20 MPa holding pressure, 3 sec holding time and 25 sec cooling time. These parameters resulted in a tensile strength of 199 kgf/cm² and a flexural modulus of 10,050 kgf/cm². Regression analysis showed that there is a quantitative relationship between process parameters and product quality, with tensile strength at 85% R^2 value and flexural modulus at 59% R^2 value. [6]

In another study used the Taguchi method and analysis of variance (ANOVA) to determine the most important parameters that cause skew during the molding process. Process parameters were then optimized to reduce warpage through a numerical approach using SolidWorks Plastics. The results show that ambient temperature is the most important parameter for warpage (42.116%), followed by melting temperature (41.278%). Among other parameters, mold temperature contributed 5.16%, injection pressure 1.32%, cooling time 1.19%, and pressure holding time 0.59%. Warpage decreased by 7.72% from 1.4556 mm to 1.33803 mm with optimized parameters. [7]

In another study, various optimization methods were developed to minimize warpage of injection molding parts. An adaptive optimization method using the Kriging backup model was used in the study. The Kriging surrogate model was used to approximate the relationship between warpage and process parameters, replacing the time-consuming MoldFlow analysis. In his experiments on a mobile phone model, he observed that the warpage was reduced by 38% compared to the lowest warpage value in the samples. This finding shows that the optimization method is effective in reducing warpage of injection molding parts. Examining the optimization results, he determined that the mold temperature had little effect on the warpage, while the injection time was a very important factor in the selected range; but the injection time causes sharp changes in warpage. Packing time also emerged as an important factor, and after a certain value but it was understood that long pressing times had no effect on warpage. At the end of the study, a problem was identified. When the total packing time is too short, the performance of the parts is bad affected, and when packing time is too long, it causes waste of energy and material. [8]

Kurtaran et al. conducted a comprehensive study to determine the optimum values of process parameters in the injection molding of a bus roof lamp base. They discussed basic process parameters such as mold temperature, melt temperature, packaging pressure, packaging pressure time and cooling time. In their approach, they took advantage of the finite element software MoldFlow, statistical experimental design, artificial neural networks and genetic algorithms. They performed finite element analyzes for the designed process parameter combinations using a statistical three-level full factorial experimental design. Based on the results of these analyses, they created a prediction model for deformation using a feed-forward artificial neural network. This artificial neural network model was validated for predictive ability and then integrated with an efficient genetic algorithm to find optimal process parameter values. The optimization results showed that the genetic algorithm reduced the deformation of the initial bus ceiling lamp base model by 46.5%. [9]

Kurtaran and Erzurumlu developed an effective optimization methodology using response surface methodology (RSM) and genetic algorithm (GA) to minimize the warpage of thin-shelled plastic parts produced by injection molding. In this study, a bus ceiling lamp base is considered as an example of a thin-shelled plastic part. Process condition parameters such as mold temperature, melt temperature, packing pressure, packing time and cooling time were determined to ensure minimum warpage. Finite element (FE) analyzes were performed for the combinations of process parameters organized using the statistical three-level full factorial experimental design method, and the most critical process parameters affecting warpage were determined by analysis of variance (ANOVA). From the ANOVA results, it is shown that packaging pressure, mold temperature, melting temperature, packaging time, and cooling time affect warping by 37.39%, 31.35%, 26.94%, 3.65%, and 0.6%, respectively by the warpage. A prediction model was created in terms of the most important process parameters for warpage (packing pressure, mold temperature, and melt temperature), and this model was combined with an effective GA to find the optimum process parameter values. GA improved the warpage by approximately 46%, significantly reducing the warpage of the initial model. This study reveals that the proposed optimization methodology can also be used for the improvement of other thin-shell plastic parts. [10]

In this study, a method to optimize injection molding parameters to reduce product cycle time while ensuring product quality by minimizing defects like volumetric shrinkage and warpage. Seven parameters were considered, and experiments were conducted to determine their effects on defects. Using the kriging technique, relationships between parameters, cycle time, and defects were established. An optimization problem was formulated to minimize cycle time while keeping defects within acceptable limits. The problem was solved using the Fmincon function from Matlab. Results revealed a trade off between cycle time and defects, showing that reducing cycle time led to increased defects and vice versa. Validation experiments closely matched simulation results, with small differences observed in cycle time and defects. Specifically, the validation experiment showed differences of 6.7% in cycle time, 3.2% in warpage, and 8% in volumetric shrinkage compared to the simulation optimization results. [11]

1.2. The Aim of Thesis

This study introduces a method for enhancing the efficiency of injection molding by reducing cycle time. The method entails establishing connections between process parameters and both product quality and cycle time.

- Investigating the correlation between injection molding process variables and cycle time, shrinkage, and warpage through mathematical modeling.
- Comparing cycle times, shrinkage, and warpage achieved using stochastic methods such as Differential Evolution (DE), Nelder-Mead (NM), Simulated Annealing (SA), and Random Search (RS).
- Assessing the outcomes of the optimization algorithms in comparison with each other and with existing findings in the literature. [11]

CHAPTER 2

INJECTION MOLDING AND PROCESS PARAMETERS

The plastic injection process involves creating plastic items by melting thermoplastic raw materials using a mold. This process is carried out using plastic injection machines, enabling serial production with high precision and efficiency. Moreover, it has the potential to deliver environmental advantages by incorporating recycled material. [12]

The plastic injection process starts by melting and transforming thermoplastic materials, typically in granular or powdered form, into a liquid state. Following this, the liquid plastic is transferred into the funnel of a high-pressure injection machine. The machine then injects the material into the mold cavity, maintaining pressure for a specific duration. After this period, the mold is opened, and the finished product is removed. [13]

Advantages of Plastic Injection Molding;

- Suitable for mass production.
- Enables the easy production of complex shapes.
- High tolerance quality.
- Low probability of faulty production.
- Capable of reaching high production numbers compared to other manufacturing methods.
- Suitable for additive manufacturing (such as flame-retardant additives).

Disadvantages of Plastic Injection Molding;

- Investment costs are high.
- Extensive knowledge and experience are necessary for the production of plastic injection molds.
- The preparatory stage for plastic injection mold production can be costly due to the tests and processes.

The manufacturing process of a plastic injection part consists of four stages as clamping, injection, cooling and ejection. The initial stage in the injection molding procedure is clamping. Injection molds are commonly crafted in two sections resembling a clamshell. During the clamping step, the two metallic plates of the mold are brought together using a machine press. After the two metallic plates are pressed together, the injection process starts. Initially, the plastic material, often in granular or powdered form, undergoes melting until it becomes a fully liquid state. Subsequently, this liquid is injected into the mold. The cooling stage, the mold is left undisturbed, allowing the hot plastic within to cool and solidify into a finished product that can be safely extracted from the mold. After the product has cooled down, a clamping mechanism gradually separates the two halves of the mold and the mold opened, facilitating the safe and easy extraction of the finished product. After the mold is open, a ejector mechanism gently pushes the solidified product out of the mold cavity and the process is completed.

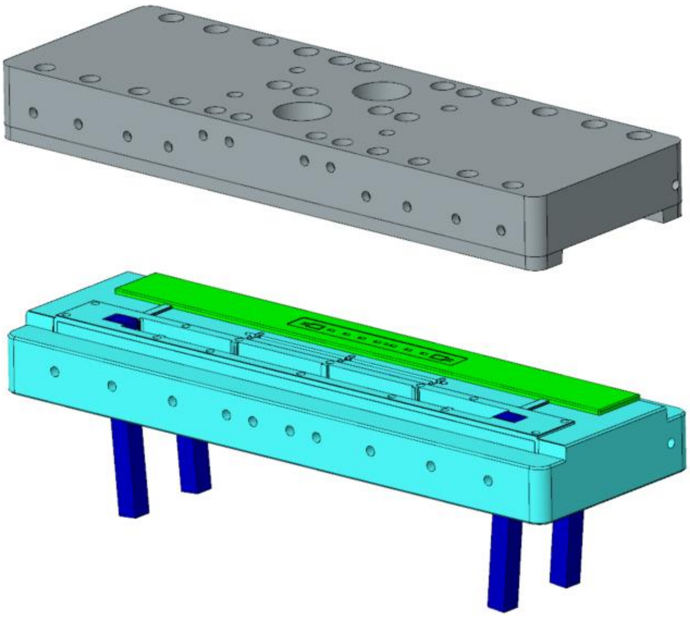

Figure 2.1. 3D Model of an injection mold

2.1. Process Parameters

The quality of products produced by injection molding depends on many factors. In addition to product geometry and material properties, the injection molding process itself is also a crucial factor. In this section, we will examine seven parameters of the injection molding process. These parameters are injection speed, injection pressure, cooling time, packing pressure, mold temperature, packing time, and melt temperature. [12]

Determining the injection time in injection molding is indeed a critical step. Choosing an appropriate injection time for homogeneous filling of the material directly affects the quality of the product. Especially in the production of parts with different thicknesses or complex geometries, the correct adjustment of the injection time ensures that the part has the desired properties. [12]

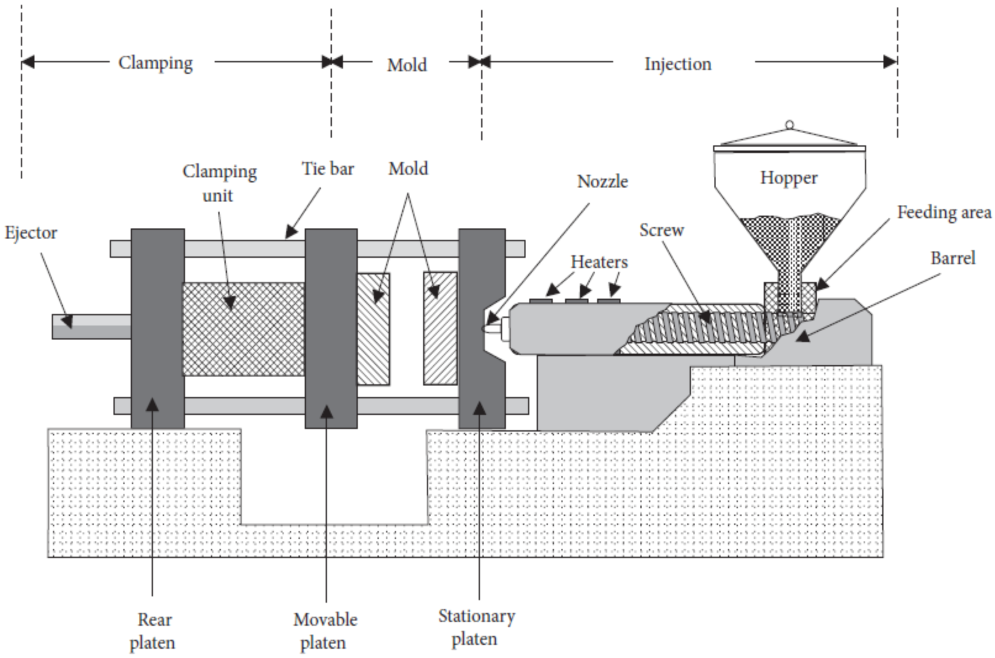

Figure 2.2. Parts of a injection molding machine [11]

Starting with a slow injection allows the material to fill the mold successfully without damaging it. Then, a fast injection ensures complete filling of the material, followed by a slow injection again to complete the process, allowing the material to settle and fill properly. This process should be adjusted according to the flow properties of the material, mold geometry, and product requirements. Failure to determine the optimum injection time can result in non-uniform filling of the material in the mold, leading to a decrease in product quality. Variations in filling in different parts of the material can lead to problems such as warping, shrinking, or draw ratio in the product. Therefore, determining the appropriate injection time for each product is of critical importance to improve product quality and ensure the production of parts with desired properties. [12]

Injection speed is the velocity at which thermoplastic material is introduced into the injection mold. Employing a high injection speed is advantageous for thin-walled part production as it allows swift filling of the mold, ensuring complete cavity filling before material solidification. Conversely, for thick-walled parts, high injection speeds are undesirable as they may hinder thorough cavity filling and lead to unwanted material accumulation within the mold, resulting in surface defects and uneven thickness. [2]

Thus, for thick-walled part manufacturing, employing a slower injection speed yields superior outcome. A slower injection speed promotes more uniform material distribution and improved cavity filling, resulting in a more consistent structure and reduced surface imperfections, ultimately enhancing part quality and functionality. [2]

Injection pressure represents the force required to fill the injection mold. This pressure pushes the injected material towards the mold, ensuring it fills all the cavities. If the injection pressure is too high, it can lead to deformations in the product. These deformations often result in unwanted changes in the shape or dimensions of the part. Conversely, insufficient injection pressure can cause incomplete filling of the mold, resulting in the creation of defective parts. Therefore, determining the correct injection pressure is crucial. The optimum injection pressure should be set to ensure complete mold filling without causing unwanted deformations in the product. This is a critical factor in producing high-quality and flawless parts. [2]

Cooling time is the time it takes for the product to cool after being removed from the mold. The correct cooling time ensures that the product hardens to the desired size and shape. Rapid cooling can lead to stress and cracking, while slow cooling can extend production time. [14]

Packing pressure is the pressure applied to compress the thermoplastic material in the mold after injection. The correct packing pressure is important for compressing the material and ensuring the dimensional stability of the product. [14]

Mold temperature is the temperature of the inner surface of the injection mold. The correct mold temperature affects the fluidity of the material and the filling process. Incorrect mold temperature can affect the surface quality and dimensional tolerances of the product. [14]

Packing time is the time the thermoplastic material is compressed in the injection mold. The correct packing time ensures that the material is compressed to the desired density. [14]

Melt temperature is the temperature of the thermoplastic melt before molding. The correct melt temperature affects the fluidity of the material and filling performance. Incorrect melt temperature can result in filling deficiencies or surface defects. [14]

Each of these parameters is important to control in the injection molding process, and adjusting them correctly can improve product quality and reduce costs.

CHAPTER 3

MODELING AND REGRESSION ANALYSIS

Mathematical modeling is the process of mathematically describing a real-world phenomenon or system. In a more theoretical definition, mathematical modeling is the definition of the relationship between input and output parameters in the data set obtained as a result of physical problems using mathematical equations. In this process, it is very important to determine the experiments that need to be carried out with the appropriate experimental design method in order to define the relationship between input and output parameters with the highest accuracy value. [15]

In this chapter, the definitions of the concepts of mathematical modeling, regression analysis and neuro-regression approach, which are the basis of the thesis, are briefly and concisely discussed. Figure 3.1 shows the design process that ends with finding the most optimal solution for a problem.

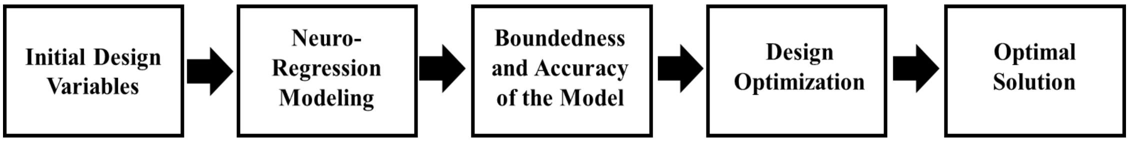

Figure 3.1. Flow diagram for the optimal design

3.1. Regression Analysis

Regression analysis is a statistical technique used to understand how one variable is affected by one or more other variables. It is often used to understand how the dependent variable is explained by the independent variables. In other words, regression analysis is a statistical technique used in creating a mathematical model. In this context, regression analysis can be considered a part of modeling. [16] Regression analysis can be classified as simple linear regression, simple non-linear regression, multiple linear regression and multiple non-linear regression, based on the number of variables of the problem and model type. [17]

3.1.1. Simple Linear Regression

Simple linear regression is a type of regression analysis that examines the effect of a single independent variable on a single dependent variable. The main purpose of this type of regression is to define the linear function that best expresses the relationship between the dependent and independent variables. [18] The simple linear regression model showing the relationship between variables is included in Equation 3.1;

$$y = \beta_0 + \beta_1 X + \varepsilon \tag{3.1}$$

where β_0 is the point where line intersects y-axis and also regression constant. β_1 is the slope of the line / the regression coefficient, lastly ε is the error value.

3.1.2. Simple Non-linear Regression

Simple non-linear regression is a regression analysis that examines situations where the dependent variable does not show a linear relationship with the independent variables. In this case, modeling of the dependent variable cannot be done with a linear function and a non-linear function or model is usually used. Simple nonlinear regression is preferred on complex data sets or when a linear model is not appropriate. For example, non-linear regression can be used in case such as the change of a dependent variable over time. The simple non-linear regression model showing the relationship between variables is included in Equation 3.2;

$$y = \beta_0 + \beta_1 X^2 + \varepsilon \tag{3.2}$$

where β_0 is the point where line intersects y-axis and also regression constant. β_1 is the slope of the line / the regression coefficient, lastly ε is the error value. [18]

3.1.3. Multiple Linear Regression

Multiple linear regression is a method of regression analysis that examines the effect of multiple independent variables on one or more dependent variables. This analysis is used to model situations where the dependent variable is affected by more than one independent variable. [18] The Multiple linear regression model is generally expressed by the following formula;

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{3.3}$$

3.1.4. Multiple Non-Linear Regression

Multiple non-linear regression is a method of regression analysis performed using a non-linear model to examine the effect of multiple independent variables on one or more dependent variables. This type of analysis is used to more accurately model the relationship between the independent variables and the dependent variable. It is also suitable when the data is complex and a linear model is not appropriate. Equation 3.4 is the general form of multiple non-linear regression model. [18]

$$y = \beta_0 + \beta_1 X_1^2 + \beta_2 X_2^2 + \cdots + \beta_n X_n^2 + \varepsilon \tag{3.4}$$

When performing regression analysis, the performance of the model is determined according to the values of the coefficient of determination (R^2). This value shows the percentage of changes in the dependent variable that can be explained by the independent variables. The coefficient of determination value may take a negative value in some special cases. This event means that the model is not suitable for the defined problem. Additionally, R^2 taking the value of zero means that the independent variables cannot explain the dependent variable in any way. R^2 value being 1 or close to 1 means that the reliability of the model is high. In modeling studies in the literature, this value is considered to be around 0.90 for a good model. The mathematical formulation of the R-squared value is given in Equation 3.5, 3.6 and 3.7;

$$R^2 = 1 - \frac{SSE}{SST} \tag{3.5}$$

$$SSE = \sum_i (\hat{y}_i - \bar{y})^2 \tag{3.6}$$

$$SST = \sum_i (y_i - \bar{y})^2 \qquad \textbf{(3.7)}$$

In these equations, SSE is sum of squared regression, SST is total variation in the data, y_i is the y value for observation I, $\bar{y}$ is the mean of y value, $\hat{y}_i$ is the predicted value of y for observation i.

3.2. Artificial Neural Network

Artificial neural network (ANN) is an artificial intelligence model designed based on the functioning of the neural networks of the human brain. Artificial neural networks are used to perform a variety of functions such as identifying, classifying or predicting complex data patterns.

The basic components of artificial neural networks are: [19]

Input Layer: It is the layer that represents the input of the data set. Each input represents a feature or variable.

Hidden Layers: These are the layers consisting of nerve cells located between the input and output layers. They are used to understand complex patterns present in the data set. Additionally, there may be more than one hidden layer in the artificial neural network.

Output Layer: This is the layer where the outputs of the artificial neural network occur. Depending on the type of operation, the output layer may have one or more outputs.

3.3. Neuro-Regression Modeling

Optimum design can be obtained by the following steps as Neuro-regression modelling, boundedness of the model and optimization. [20] Neuro-regression modelling (NRM) is a hybrid method that combines the strengths of regression analysis and artificial neural network to increase the reliability of modeling predictions. Neuro-regression modeling is often used when modeling non-linear relationships. It is also effective when modeling complex relationships with multiple independent variables. In cases where traditional regression models cannot be successful in non-linear structures, neuro-regression models can be preferred due to their performance.

In the NRM approach, the data set; It can be divided into three subheadings: training, testing and validation. During the training phase, data is used to create the mathematical model. The aim here is to enable the model to learn the physical and mathematical nature of the problem by using the data set consisting of inputs and outputs included in the system. Although the data used in the training phase is generally set to be 70-80% of the entire data set, this percentage may change. If successful models can be obtained by keeping the training set percentage at lower levels, lower percentages can be used. The test set is a data set separated from the entire data set to evaluate the performance of the model obtained at the end of the training process. This data set accounts for 10% to 15% of the total data set. It consists of data that the model has not seen before during training and is used to check the generalization ability of the model. The validation set is a data set used to adjust the performance of the model in the training process. This set makes up the remaining part (10-15%) of the total data set. A validation set is used to ensure that the model does not overfit the training data set. [16, 21]

3.4. Cross Validation

Cross-validation is a method used to check the performance and generalization ability of the model in applications such as machine learning. In this validation technique, sample observation sections are obtained from the training set. After the model is set based on the training set, its performance is measured against new validation sets. For example, the model is trained on the first layer and tested on the remaining layers. Then, while the model is trained on the second layer, it is tested on the remaining layers and this process is repeated. In short, cross-validation is used to detect problems such as overfitting and increase generalization ability. Additionally, it enables more reliable model predictions to be made in problems with small numbers of data. Also, the most commonly used cross-validation method is k-fold cross-validation. [22, 23]

CHAPTER 4

OPTIMIZATION

4.1 Introduction

Optimization is the application of processes or methods aimed at maximizing or minimizing the objective functions of a system within certain constraints to make it as efficient as possible. In short, it is the collection of methods applied to solve a problem in the best possible way or to bring a system to the optimal state. Maximizing or minimizing means achieving the greatest success in the shortest time. Optimization is mostly applied to find solutions to existing problems. Optimization studies are developed according to the specific requirements of the problem under consideration. Problems with limited decision variables are referred to as constrained models, while those without such limitations are defined as unconstrained models. [24]

4.2 Definition of an Optimization Problem

The optimization problem is expressed mathematically as follows;

Maximum or minimum : $f_i(x)$ **(4.1)**

$$x = (x_1, x_2, \ldots., x_n) \quad \textbf{(4.2)}$$

Subject to $h_j(x) = 0, \quad (j = 1,2,3, \ldots, J)$ **(4.3)**

$$g_k(x) \leq 0, \quad (k = 1,2,3, \ldots, K) \quad \textbf{(4.4)}$$

here *x* is optimization variables, $f_i(x)$ is objective function, $h_j(x)$, and $g_k(x)$ are equality and inequality constraints of the optimization problem respectively. In short, the purpose of mathematical definition of the optimization problem is to determine the decision variables that obtain the best value.

Optimization classified into two types, single and multi-objective optimizations, according to their purposes. [25-27]

4.2.1 Single Objective Optimization

Single-objective optimization, which can be expressed mathematically, is the determination of the parameters that the model must have in order to find the most appropriate value for a problem. In such problems, there is a single objective such as reducing mass or cost, and increasing efficiency.

Single objective optimization problems can be described mathematically as follows;

Minimum : $$f(x) \tag{4.5}$$

$$x = (x_1, x_2, \dots., x_n) \tag{4.6}$$

Subject to $$h_j(x) = 0, \qquad (j = 1,2,3, \dots, k) \tag{4.7}$$

$$g_i(x) \leq 0, \qquad (i = 1,2,3, \dots, m) \tag{4.8}$$

where $f\,(x)$ is objective function which is parameter to be optimized and the x values are called the design parameters. Additionally, $h_j\,(x)$ and $g_i\,(x)$ functions express the constraint range established for the optimization of the objective function. Figure. 4.1 indicated that maximization and minimization of the objective function. As it can be seen in figure, $-f\,(x)$ can be maximized to minimize $f\,(x)$. [25, 26]

4.2.2 Multi Objective Optimization

Engineering problems encountered in real life involve many objectives that require both durable and cheap, or both durable and light. Since single-objective optimization cannot meet these requirements at the same time, meaningful results cannot be obtained. For this reason, multi-objective optimization algorithms have been developed by researchers.[28] Multi-objective optimization is the simultaneous optimization of multiple objectives. Therefore, such problems have a set of solutions rather than a single optimal solution.

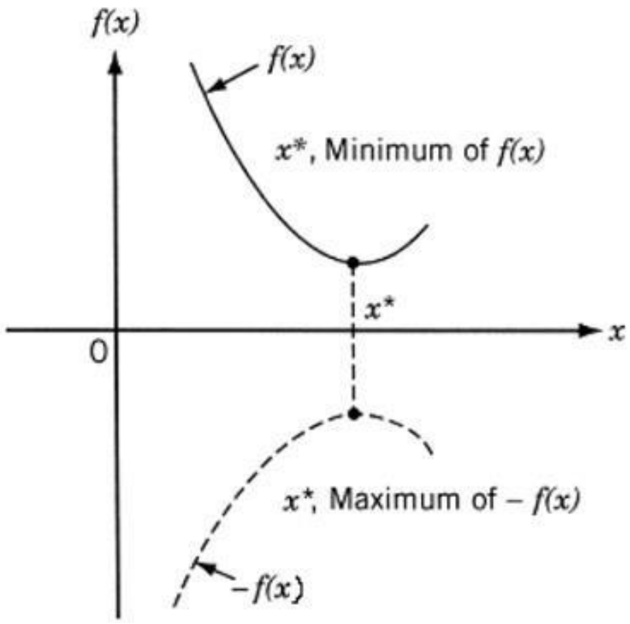

Figure 4.1. The maximum and minimum of the objective function

Multi objective optimization problems can be described mathematically as follows;

Minimum: $f_1(x),\ f_2(x) \ldots\ f_t(x)$ **(4.9)**

$x = (x_1, x_2, \ldots., x_n)$ **(4.10)**

Subject to $h_j(x) = 0,\quad (j = 1,2,3, \ldots, k)$ **(4.11)**

$g_i(x) \leq 0,\quad (i = 1,2,3, \ldots, m)$ **(4.12)**

where $f(x)$ is objective function which is parameter to be optimized, while the x values are called the design parameters. Also, $h_j(x)$ and $g_i(x)$ functions are defined as the constraint range established for the optimization of the objective function. This optimization problem can be written as a maximization or minimization.[26]

4.3 Traditional and Non-Traditional Optimization Methods

Traditional optimization (deterministic methods) aims to solve problems using mathematical formulas or analytical techniques. It is generally effective for problems with continuously differentiable functions. For example, it includes techniques such as Lagrange multipliers and constraint variation [29].

Stochastic systems are also systems in which there is a random relationship between inputs and outputs based on probability distribution. In stochastic optimization, decision variables, constraints or objective functions contain uncertainty. Therefore, problems are described by probability distributions or stochastic processes. Stochastic methods, which operate based on computational simulation of concepts or problems, are used across all disciplines, thanks to their ability to produce discrete solutions and obtain solutions close to global optimum, regardless of the starting point.[30]

Stochastic studies that began with genetic algorithms have been expanded to include other stochastic methods such as Differential Evolution (DE), Simulated Annealing (SA), Random Search (RS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Tabu Search (TS), and Artificial Bee Colony (ABC). Within the scope of the thesis, optimization scenarios were solved with Modified Differential Evolution (MDE), Modified Simulated Annealing (MSA), Modified Nelder-Mead (MNM) and Modified Random Search (MRS) algorithms, which are frequently used in engineering problems. In general, the term modified algorithm refers to a customized or improved version of certain features or functionality of a base algorithm. These modifications are often aimed at providing solutions better suited to a particular application or type of problem.[26, 31]

4.3.1 Modified Differential Evolution Algorithm

Differential Evolution (DE) is a population-based optimization algorithm based on the principles of natural selection and genetic crossover. It is also widely used to solve continuous and multidimensional optimization problems. Differential Evolution (DE) does not directly handle constraints but is effective for optimizing problems where constraints are embedded within the objective function. Among various algorithms, DE stands out as one of the most robust methods for optimizing problems with real-valued parameters.

The Modified Differential Evolution (MDE) algorithm has been developed by introducing adjustments that alter the scale factor and crossover rate. These adaptations facilitate the avoidance of stagnation for all solutions in the original DE algorithm. The primary advantage of the MDE algorithm lies in the scalability and convergence speed of each solution.[30, 32, 33] The flowchart of the algorithm is given in Figure 4.2.[30]

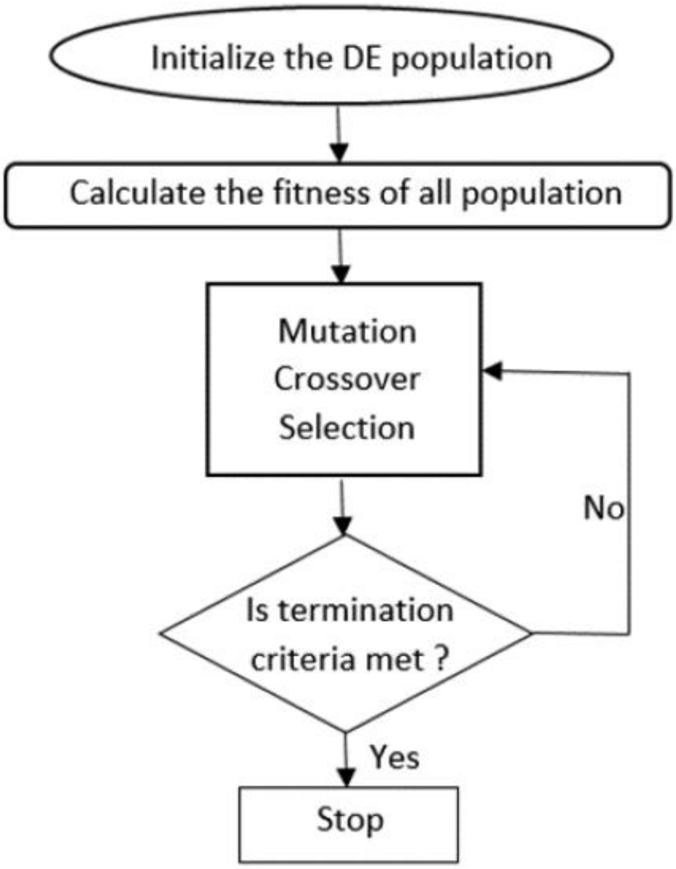

Figure 4.2. Flowchart of Differential Evolution Algorithm [30]

4.3.2 Modified Nelder-Mead Algorithm

The Nelder-Mead optimization algorithm is used for locating the minimum point within a local context in multi-dimensional optimization problems that do not have constraints. Since it is not a global algorithm, it is not suitable for optimization problems with large local minimum. However, it can give effective results in optimization problems involving a small number of local minimum. The NM algorithm, which has four control parameters: reflection, expansion, construction and shrinkage factor, is an iterative method.

NM optimization algorithm cannot solve constrained optimization problems. Therefore, a Modified Nelder-Mead (NNM) algorithm is obtained by adding a "penalty function" to the traditional flow [34-36]. The flowchart of the algorithm is given in Figure 4.3.[37]

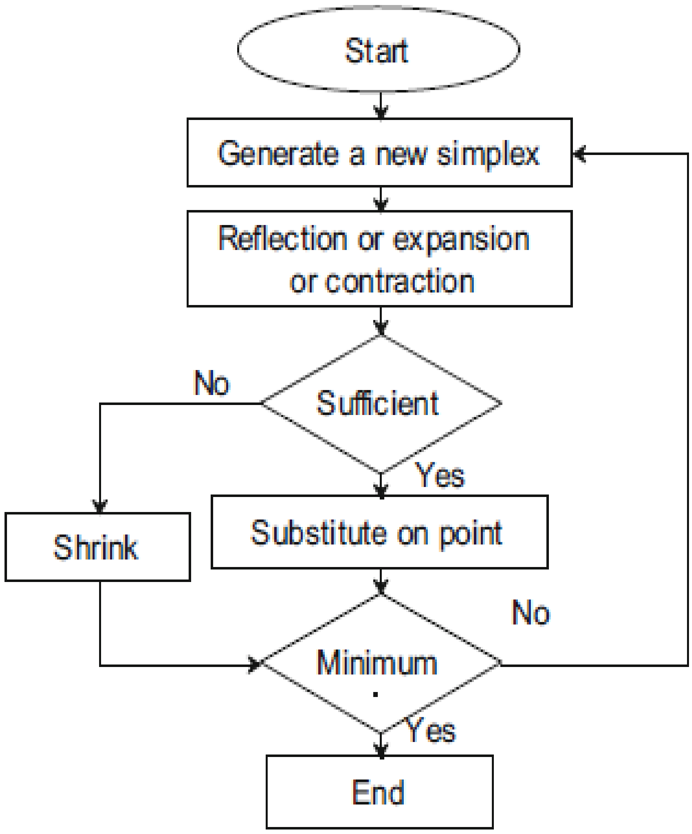

Figure 4.3. Flowchart of Nelder-Mead Algorithm [30]

4.3.3 Modified Simulated Annealing Algorithm

Simulated annealing (SA) is a meta-heuristic local search technique used for discrete and to a lesser extent continuous optimization problems. One of the main features of this method is the attempt to find the global optimum by moving away from local optima by allowing steps that worsen the objective function. In short, it is among the algorithms used to obtain the best solutions.

Modified Simulated Annealing (MSA) is more powerful than the traditional Simulated Annealing method because it increases the ability to find the global optimum using hybrid algorithms and can also quickly identify local minimum.[21, 38, 39] The flowchart of the algorithm is given in Figure 4.4.[30]

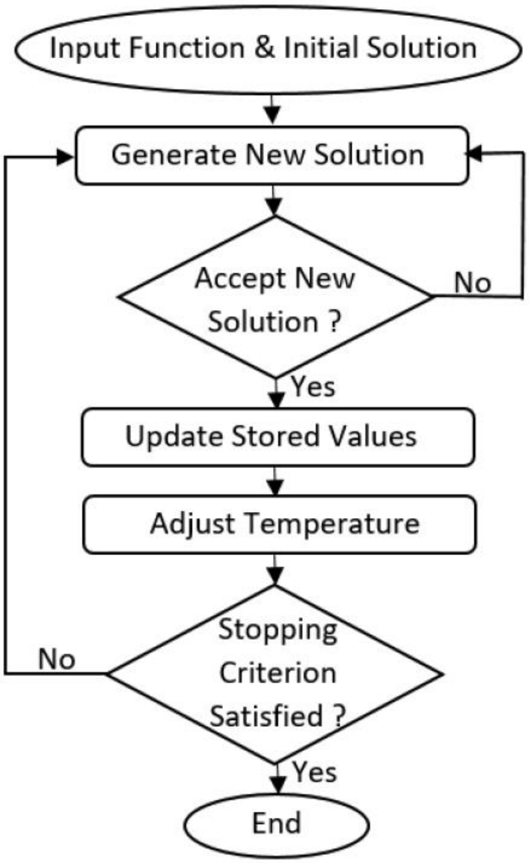

Figure 4.4. Flowchart of Simulated Annealing Algorithm [30]

4.3.4 Modified Random Search Algorithm

The Random Search (RA) method, also known as the Monte-Carlo method, was the earliest optimization algorithm utilizing stochastic processes. The algorithm begins by generating a population with randomly chosen starting points. It then evaluates the local minimum convergence of these starting points using a local search method. The best local minimum point identified through this process is selected as the solution.

Also, Modified Random Search (MRS), methods like conjugate gradient, Quasi-Newton, Newton, Levenberg-Marquardt, and non-linear interior point methods are employed to optimize the placement of all variables within the objective function.[40, 41] The flowchart of the algorithm is given in Figure 4.5.[42]

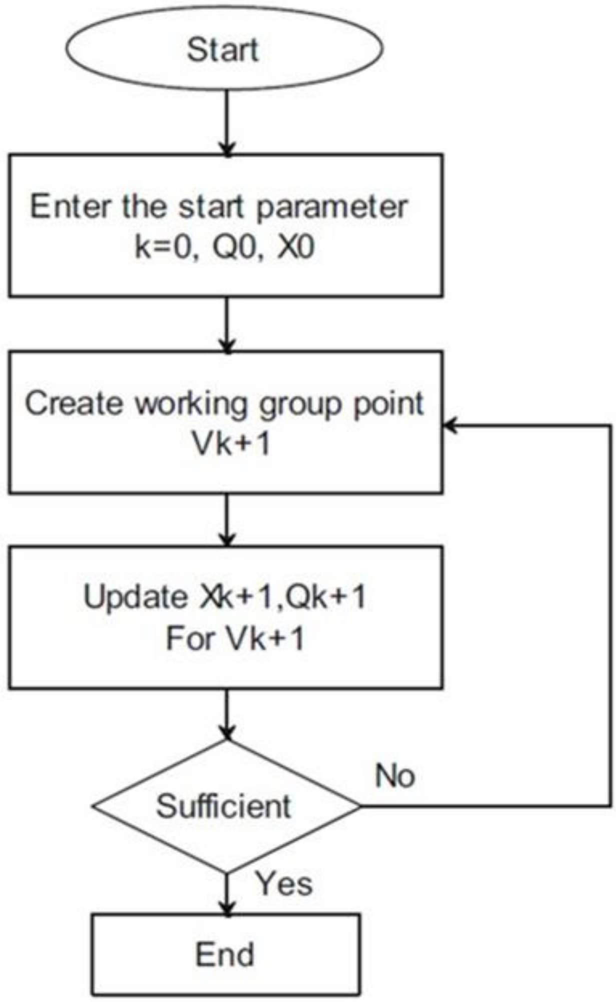

Figure 4.5. Flowchart of Random Search Algorithm [42]

CHAPTER 5

RESULTS AND DISCUSSION

5.1. Problem Statement

In this thesis, an optimization study was conducted to reduce the cycle time of the injection molding process, which is significant for industrial production and used in the manufacturing of plastic parts with low tolerance and complex structures. While performing the optimization study, attention was paid to ensuring that product defects such as shrinkage and warpage remained within acceptable ranges, alongside other process parameters that affect the cycle time.

In the Saad Mukras' study [11], as seen in Table 5.1, seven process parameters (injection speed, injection pressure, cooling time, packing pressure, mold temperature, packing time, and melt temperature) and two product defects (shrinkage and warpage) were identified. From the experimental data, the lower and upper limits of the process parameters and acceptable product defects were determined. The relationships between the process parameters, cycle time, and product defects were examined, interpreted, and compared.

Table 5.1. Process Parameters of injection molding process [11]

Inputs	Outputs
Injection speed (IS) Injection pressure (IP) Cooling time (CT) Packing pressure (PP) Mold temperature (MOT) Packing time (PT) Melt temperature (MT)	Cycle Time (CYCT) Shrinkage (SK) Warpage (WP)

Saad Mukras [11] conducted his experiments using Arburg Allrounder 420C model injection molding unit and a simple mold with product dimensions of 117mm x 93mm and a thickness of 3mm. The most important factor affecting the injection time is the fluidity of the material being molded and its behavior in response to speed. For example, while polyethylene group polymers are suitable for high-speed molding, polypropylene materials yield better results when molded at lower speeds compared to polyethylene materials. In the related study, the experimental work was conducted with polyethylene material (HDPE M80064), and the material properties are shown in Table 5.2.[11]

Table 5.2. Properties of HDPE M80064 [11]

Property of HDPE M80064	Value
Stress at yield	33 MPa
Melt flow rate (at 190°C and 2.16 kg)	8 g/10 min
Density	964 kg/m3

To determine the optimal combination of process parameters for achieving the shortest cycle time, it's necessary to establish and refine a relationship between these parameters and the cycle time and Table 5.4 [11] shows these relationships. This optimization must consider constraints related to acceptable product defects, defined by two additional relationships that link process parameters to product defects, such as warpage and volumetric shrinkage, and these are shown in Table 5.3.[11]

Table 5.3. Acceptable Product Defects [11]

Parameters	Minimum	Maximum
Warpage (mm)	1.97	6.49
Shirinkage (cm^3)	2.9	16

Table 5.4. Relationship between process parameters of injection molding process and cycle time and product defects

Process Parameters	Relationship with outputs
Injection speed (IS)	Increasing the injection speed reduces cycle time while increasing warpage and shrinkage.
Injection pressure (IP)	Increasing the injection pressure shortens the cycle time and reduces warpage and shrinkage.
Cooling time (CT)	Increasing the cooling time reduces warpage and shrinkage and increases cycle time.
Packing pressure (PP)	While increasing the packing pressure reduces warpage and shrinkage, a clear comment cannot be made about the cycle time.
Mold temperature (MOT)	Increasing the mold temperature increases warpage and shrinkage and also increases cycle time.
Packing time (PT)	Increasing packaging time reduces warpage and shrinkage but increases cycle time.
Melt temperature (MT)	Increasing the melt temperature increases warpage and shrinkage and increases cycle time.

Table 5.5. Experimental Results [11]

	INPUT							OUTPUT		
No	**IS mm/s**	**IP bar**	**CT sec**	**PP bar**	**MOT °C**	**PT sec**	**MT °C**	**WP mm**	**SK cm^3**	**CYCT Sec**
1	15	450	10	100	15	9	200	5.8	3.97	31.1
2	15	450	30	100	15	3	200	6.8	5.17	43.9
3	15	450	10	400	15	3	200	6	4.59	24.7
4	15	450	30	400	15	9	200	2.9	2.45	49.8
5	15	800	10	100	15	3	200	4.5	5.26	24.5
6	15	800	30	100	15	9	200	3.4	3.95	49.8
7	15	800	10	400	15	9	200	3.9	2.55	31.4
8	15	800	30	400	15	3	200	6	4.49	43.8
9	60	450	10	100	15	3	200	4.4	5.38	23.6
10	60	450	30	100	15	9	200	3.7	4	48.9
11	60	450	10	400	15	9	200	3.5	2.63	30.3
12	60	450	30	400	15	3	200	7.7	4.62	42.7
13	60	800	10	100	15	9	200	5.8	4.34	29.0
14	60	800	30	100	15	3	200	9.1	5.21	41.9
15	60	800	10	400	15	3	200	7	4.1	22.9
16	60	800	30	400	15	9	200	2.9	1.97	47.9
17	15	450	10	100	45	3	200	4.7	5.33	25.6
18	15	450	30	100	45	9	200	9	4.05	49.9
19	15	450	10	400	45	9	200	5.1	3.24	31.2
20	15	450	30	400	45	3	200	6.8	5.09	43.8
21	15	800	10	100	45	9	200	4	4.1	30.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
23	15	800	10	400	45	3	200	9.6	5.17	24.8
24	15	800	30	400	45	9	200	4	3.15	49.8
25	60	450	10	100	45	9	200	4.5	4.19	29.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
27	60	450	10	400	45	3	200	8.6	5.31	23.3
28	60	450	30	400	45	9	200	4.5	3.25	48.7
29	60	800	10	100	45	3	200	11	5.53	22.4
30	60	800	30	100	45	9	200	3.8	4.14	47.9
31	60	800	10	400	45	9	200	6	2.28	29.4
32	60	800	30	400	45	3	200	7.9	4.27	41.9
33	15	450	10	100	15	3	250	8.4	5.92	24.4
34	15	450	30	100	15	9	250	5.2	3.85	49.7
35	15	450	10	400	15	9	250	4.5	3.12	31.4
36	15	450	30	400	15	3	250	8	5.35	43.7
37	15	800	10	100	15	9	250	5	3.95	31.2
38	15	800	30	100	15	3	250	7.6	5.85	43.7
39	15	800	10	400	15	3	250	6.7	5.48	24.6
40	15	800	30	400	15	9	250	6.4	3.02	49.7
41	60	450	10	100	15	9	250	4.8	4.15	29.5
42	60	450	30	100	15	3	250	6	6.06	42.1
43	60	450	10	400	15	3	250	7.7	5.83	22.9
44	60	450	30	400	15	9	250	5.2	3.2	48.1
45	60	800	10	100	15	3	250	16	6.16	22.6
46	60	800	30	100	15	9	250	7.1	4.07	47.8
47	60	800	10	400	15	9	250	6	3.29	29.5
48	60	800	30	400	15	3	250	9.1	5.48	41.9

(cont. on next page)

Table 5.5. (cont.)

	INPUT							OUTPUT		
No	**IS mm/s**	**IP bar**	**CT sec**	**PP bar**	**MOT °C**	**PT sec**	**MT °C**	**WP mm**	**SK cm^3**	**CYCT Sec**
49	15	450	10	100	45	9	250	5.8	4.54	30.8
50	15	450	30	100	45	3	250	7.9	6.21	43.8
51	15	450	10	400	45	3	250	9.9	5.95	24.3
52	15	450	30	400	45	9	250	8.4	3.84	49.8
53	15	800	10	100	45	3	250	13.6	6.25	24.3
54	15	800	30	100	45	9	250	8.8	4.43	49.7
55	15	800	10	400	45	9	250	7	3.94	31.0
56	15	800	30	400	45	3	250	8.6	5.87	43.9
57	60	450	10	100	45	3	250	8.1	6.49	22.6
58	60	450	30	100	45	9	250	7.6	4.63	48.2
59	60	450	10	400	45	9	250	9.3	4.13	29.4
60	60	450	30	400	45	3	250	8.3	6.11	42.2
61	37,5	625	20	250	30	6	200	6.2	4.2	35.4
62	37,5	625	20	250	30	6	250	8	4.84	35.3
63	37,5	625	20	250	15	6	225	9	4.26	35.3
64	37,5	625	20	250	45	6	225	3.6	4.87	35.4
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
67	37,5	450	20	250	30	6	225	6.5	4.44	35.6
68	37,5	800	20	250	30	6	225	7.6	4.45	35.3
69	37,5	625	20	100	30	6	225	4.8	4.97	35.4
70	37,5	625	20	400	30	6	225	7.5	4.27	35.4
71	37,5	625	10	250	30	6	225	6.3	4.61	26.1
72	37,5	625	30	250	30	6	225	5.7	4.5	45.4
73	37,5	625	20	250	30	3	225	7.4	5.61	32.4
74	37,5	625	20	250	30	9	225	5.6	3.63	38.3
75	37,5	625	20	250	30	6	225	7.2	4.54	35.3
76	60	800	10	100	45	9	250	7.65	4.31	28.2
77	60	800	30	100	45	3	250	8.01	5.66	42.2
78	60	800	10	400	45	3	250	11.2	4.53	21.9
79	60	800	30	400	45	9	250	4.88	2.51	47.4

5.2. Neuro-Regression Modeling Results

Neuro-regression modeling (NRM) is a hybrid approach that merges the benefits of regression analysis with those of artificial neural networks to enhance the accuracy of predictive models. This technique is particularly useful for capturing non-linear relationships and effectively handling complex interactions involving multiple independent variables as detailed in Section 3.2.

In this thesis, the initial step in optimizing cycle time involves mathematical modeling. Before starting the optimization process, Neuro-Regression analysis, which combines Artificial Neural Network (ANN) techniques with traditional regression analysis was employed to enhance the accuracy, robustness, and reliability of the model predictions. Neuro-Regression analysis was used to model three output variables. The dataset, shown in Table 5.5, was randomly divided into three parts. Each segment consisted of 80% training data, 20% testing data, with an additional 10% of the training data used as validation data. This division resulted in 79 original data sets being categorized into five sub-groups, including training, testing, and validation groups, utilizing different k-fold cross-validation methods (described in Section 3.4) to assess the quality, reliability, robustness, and potential overfitting of the empirical model. These k-fold cross-validation groups are detailed in Appendix A.

At this phase, the aim was to utilize 12 different regression models sourced from the literature, listed in Table 5.6. The coefficients (IS, IP, CT, PP, MOT, PT, MT, CYT, SK, WP) in these models were defined using the data provided in Appendix A. Subsequently, $R^2_{training}$ $R^2_{adjusted}$, $R^2_{testing}$, and $R^2_{validation}$ values were calculated using "Wolfram Mathematica 10" to evaluate the reliability and robustness of the models.

After identifying suitable models based on the coefficient of determination (R^2), it is crucial during model selection to consider the lower and upper limits of the output within the desired physical range. This approach ensures that the mathematical models developed for the optimization process can accurately predict cycle time, warpage, and shrinkage parameters, along with the optimal process parameters to achieve the desired outcomes. To provide a detailed explanation of the k-fold cross-validation process, only the Neuro-Regression results for cycle time across 60 models are presented in Table 5.7. The results for other outputs are available in Appendix B. For a model to be selected from the 60 Neuro-Regression results generated by 12 different models, the coefficient of determination values for all data groups should exceed 0.90, and the maximum-minimum values must be within an acceptable range according to the problem's physical requirements. Each data group is color coded in Table 5.7. The first-order logarithmic multiple non-linear (FOLN) model group was chosen for the cycle time output because it had better coefficient of determination and lower upper limit values for all data groups compared to others. Additionally, the values in all groups are significant and acceptable for the FOLN model, making it the preferred choice. Consequently, the fourth group data and model (FOLN4) were selected for cycle time optimization analysis (Eq.5.1). The R^2 values for training, testing, and validation, along with the maximum-minimum values for this model, are 0.998257, 0.963582, 0.959767, 50.0832, and 21.2556, respectively.

$$\begin{aligned} Cycle\ Time = {} & 6.7498 + 16.804\mathrm{xLog[CT]} - 0.7732\mathrm{xLog[IP]} - 1.583\mathrm{xLog[IS]} \\ & - 0.4012\mathrm{xLog[MOT]} - 2.6471\mathrm{xLog[MT]} - 0.4180\mathrm{x[Log[PP]} \\ & + 5.565\mathrm{xLog[PT]} \end{aligned} \tag{5.1}$$

The analysis results for the shrinkage parameter, the second output, are provided in Appendix C. For a model to be chosen from the 60 Neuro-Regression results generated by 12 different models, the coefficient of determination values for all data groups must be greater than 0.90, and the maximum-minimum values should fall within an acceptable range according to the problem's physical requirements. Based on these criteria, the model group with the highest correlation value and the simplest form (a linear equation) was selected for the shrinkage output. Table 5.8 shows the chosen model group for this output. As shown in the table, the first group and model (L) were selected at random for the optimization analysis of shrinkage (Eq.5.2). The R^2 values for training, testing, and validation, along with the maximum-minimum values for this model, are 0.994287, 0.9465, 0.972329, 6.52953, and 2.48942, respectively.

The analysis results for the warpage parameter are provided in Appendix D. For a model to be chosen from the 60 Neuro-Regression results generated by 12 different models, the coefficient of determination values for all data groups must be greater than 0.90 and the maximum-minimum values should fall within an acceptable range according to the problems.

Table 5.6. Multiple regression model types including linear, quadratic, trigonometric, logarithmic, and their rational forms [31]

Model Name	Nomenclature	Formula
Multiple linear	L	$Y = \sum_{i=1}^{2}(a_i x_i) + c$
Multiple linear rational	LR	$Y = \frac{\sum_{i=1}^{2}(a_i x_i) + c_1}{\sum_{j=1}^{2}(\beta_j x_j)} + c_2$
Second order multiple non-linear	SON	$Y = \sum_{k=1}^{2}\sum_{j=1}^{2}(a_j x_j x_k) + \sum_{i=1}^{2}(a_i x_i) + c$
Second order multiple non-linear rational	SONR	$Y = \frac{\sum_{k=1}^{2}\sum_{j=1}^{2}(a_j x_j x_k) + \sum_{i=1}^{2}(a_i x_i) + c_1}{\sum_{l=1}^{2}\sum_{m=1}^{2}(\beta_m x_m x_l) + \sum_{n=1}^{2}(\beta_n x_n)} + c_2$
First order trigonometric multiple non-linear	FOTN	$Y = \sum_{i=1}^{2}(a_i Sin[x_i] + a_i Cos[x_i]) + c$
First order trigonometric multiple non-linear rational	FOTNR	$Y = \frac{\sum_{i=1}^{2}(a_i Sin[x_i] + a_i Cos[x_i]) + c_1}{\sum_{j=1}^{2}(\beta_j Sin[x_j] + \gamma_j Cos[x_j])} + c_2$

(cont. on next page)

Table 5.6 (cont.)

Model Name	Nomenclature	Formula
Second order trigonometric multiple non-linear	SOTN	$Y = \sum_{i=1}^{2}(a_i Sin[x_i] + a_i Cos[x_i]) + \sum_{j=1}^{2}\left(\beta_j Sin^2[x_j] + \gamma_j Cos^2[x_j]\right) + c$
Second order trigonometric multiple non-linear rational	SOTNR	$Y = \frac{\sum_{i=1}^{2}(a_i Sin[x_i] + a_i Cos[x_i]) + \sum_{j=1}^{2}\left(\beta_j Sin^2[x_j] + \gamma_j Cos^2[x_j]\right) + c_1}{\sum_{k=1}^{2}(\theta_i Sin[x_k] + \theta_i Cos[x_k]) + \sum_{l=1}^{2}\left(\delta_j Sin^2[x_l] + \delta_j Cos^2[x_l]\right)}$
First order logarithmic multiple non-linear	FOLN	$Y = \sum_{i=1}^{2}(a_i Log[x_i]) + c$
First order logarithmic multiple non-linear rational	FOLNR	$Y = \frac{\sum_{i=1}^{2}(a_i Log[x_i]) + c_1}{\sum_{j=1}^{2}\left(\beta_j Log[x_j]\right)} + c_2$
Second order logarithmic multiple non-linear	SOLN	$Y = \sum_{k=1}^{2}\sum_{j=1}^{2}\left(a_j Log[x_j x_k]\right) + \sum_{i=1}^{2}(a_i Log[x_i]) + c$
Second order logarithmic multiple non-linear rational	SOLNR	$Y = \frac{\sum_{k=1}^{2}\sum_{j=1}^{2}\left(a_j Log[x_j x_k]\right) + \sum_{i=1}^{2}(a_i Log[x_i]) + c_1}{\sum_{m=1}^{2}\sum_{l=1}^{2}(a_l Log[x_l x_m]) + \sum_{n=1}^{2}(a_n Log[x_n])} + c_2$

Table 5.7 K-folds cross validation results of the Neuro-regression model for Cycle time

Models	R^2 training	R^2 testing	R^2 validation	Maximum	Minimum
L1	0.999568	0.989042	0.987301	50.3377	22.5436
L2	0.999533	0.99705	0.927734	50.393	22.3843
L3	0.999543	0.991708	0.993982	50.3594	22.2136
L4	0.999804	0.980056	0.99602	50.1389	22.3399
L5	0.99952	0.996868	0.987905	50.332	22.4008
LR1	0.999741	0.99476	0.997102	50.5389	21.8247
LR2	0.999717	0.998953	0.95494	50.5024	21.9626
LR3	0.999755	0.991632	0.99787	50.7963	22.1029
LR4	~~0.972732~~	~~0.115168~~	~~0.413481~~	~~∞~~	~~∞~~
LR5	0.999759	0.994537	0.998007	51.1599	22.0895
SON1	0.999875	0.993801	0.996669	48.8516	21.8279
SON2	0.999872	0.99588	0.985072	50.9829	21.7642
SON3	0.999885	0.989309	0.999925	50.8447	21.7175
SON4	0.99998	0.987566	0.999306	50.0223	22.0589
SON5	0.999874	0.993887	0.998478	52.0226	21.7601
SONR1	0.996219	0.77602	0.942262	58.3891	21.2811
SONR2	0.995881	0.393605	0.882625	76.9801	23.706
SONR3	0.995599	~~-0.34415~~	0.954694	77.7397	22.7213
SONR4	0.995991	0.72239	0.915258	57.554	23.6485
SONR5	0.75662	~~-3.29838~~	-1.73009	72.9159	11.6262
FOTN1	0.999677	0.996216	0.998336	77.8571	~~-47.1218~~
FOTN2	0.999605	0.996455	0.965956	50.2909	22.2598
FOTN3	0.999693	0.99417	0.999545	98.9265	~~-5.3652~~
FOTN4	0.999937	0.982755	0.998163	89.9144	~~-5.81346~~
FOTN5	0.999676	0.997797	0.993351	103.127	~~-5.86926~~
FOTNR1	0.999757	~~-0.582858~~	~~0.996865~~	~~1.06844 x 10^9~~	~~-1.45309 x 10^9~~
FOTNR2	0.999752	~~0.998484~~	~~0.96197~~	~~826600~~	~~-1.98678 x 10^6~~
FOTNR3	0.972815	~~0.0725967~~	~~0.790992~~	~~1.73847 x 10^6~~	~~-2.29909 x 10^{13}~~
FOTNR4	0.999957	~~0.982521~~	~~0.998432~~	~~983320~~	~~-48604.3~~
FOTNR5	0.980183	~~-0.16534~~	~~0.125922~~	~~3.53352 x 10^8~~	~~-1.18453 x 10^7~~
SOTN1	0.999875	0.353848	0.996708	70.1185	~~-6.09993~~
SOTN2	0.999878	0.946824	0.985565	79.0751	~~-0.988886~~
SOTN3	0.999892	0.988765	0.999933	71.286	~~-0.0127627~~
SOTN4	0.999985	0.979677	0.999379	75.9441	4.32376
SOTN5	0.999881	0.84386	0.99841	71.9273	0.508661
SOTNR1	~~0.458857~~	~~-12.8106~~	~~-11.6458~~	~~8.12399x 10^7~~	~~-5.09671 x 10^7~~
SOTNR2	~~0.372791~~	~~-9.04555~~	~~-21.0832~~	~~399621~~	~~-5.2744 x 10^{12}~~
SOTNR3	~~0.599091~~	~~-10.5251~~	~~-5.67089~~	~~1.35105 x 10^6~~	~~-3.4348 x 10^{13}~~
SOTNR4	~~0.257363~~	~~-12.6865~~	~~-12.1428~~	~~6.97267 x 10^{12}~~	~~-1.41959 x 10^6~~
SOTNR5	~~0.541811~~	~~-21.6127~~	~~-12.2732~~	~~292144~~	~~-252737~~
FOLN1	0.998618	0.88536	0.861618	50.1565	22.1698
FOLN2	0.998206	0.974149	0.884906	50.121	21.7683
FOLN3	0.997984	0.970407	0.935697	50.2424	21.3245
FOLN4	0.998257	0.963582	0.959767	50.0832	21.2556
FOLN5	0.998066	0.975132	0.970573	49.8732	21.8725

(cont. on next page)

Table 5.7. (cont.)

FOLNR1	0.999648	0.986341	0.987663	50.286	22.0668
FOLNR2	0.999605	0.996455	0.965956	50.2909	22.2598
FOLNR3	0.999716	0.975281	0.998123	50.4644	22.1223
FOLNR4	0.999743	0.985427	0.995217	49.5562	22.4833
FOLNR5	0.999634	0.993944	0.994978	50.4909	22.2014
SOLN1	0.999875	0.993351	0.996628	48.8076	21.916
SOLN2	0.999871	0.996188	0.984921	49.7479	21.7399
SOLN3	0.999884	0.989244	0.999872	50.8473	21.7229
SOLN4	0.999979	0.987535	0.999248	49.7293	22.0352
SOLN5	0.999873	0.994175	0.998306	51.9714	21.8016
SOLNR1	0.999842	0.986945	0.994771	49.4431	22.6943
SOLNR2	0.99984	0.994611	0.995554	48.5876	22.7393
SOLNR3	0.999813	0.987163	0.998419	49.4558	22.3296
SOLNR4	0.9999	0.988489	0.998882	49.5541	22.6402
SOLNR5	0.999843	0.977038	0.988928	48.9121	22.4958

Table 5.8. K-folds cross validation results of the Neuro-regression model for Shrinkage

Models	R^2 training	R^2 testing	R^2 validation	Maximum	Minimum
L1	0.994287	0.9465	0.972329	6.52953	2.48942
L2	0.996026	0.890347	0.908814	6.33944	2.70892
L3	0.995597	0.901156	0.588459	6.61099	2.46753
L4	0.995748	0.802034	0.819835	6.47921	2.58088
L5	0.995708	0.529528	0.867713	6.63747	2.34224

$$\text{Shrinkage} = 4.4907 - 0.0036 \text{ x CT} - 0.00068 \text{ x IP} - 0.0016 \text{ x IS} + 0.01090 \text{ x MOT} + 0.0125 \text{ x MT} - 0.0028 \text{ x PP} - 0.3098 \text{ x PT} \quad \textbf{(5.2)}$$

While choosing the model for the cycle time and shrinkage parameters, values within the reliable range could not be obtained for the warpage parameter with the 12 models used as detailed in the table 5.6. Therefore, in addition to these models, a hybrid model that is a combination of fourth-order multiple nonlinear and third-order logarithmic non-linear model was proposed as shown in the equation 5.3. Table 5.9. shows the chosen model for this output. As shown in the table, the second group and model (Hybrid 2) were selected at random for the optimization analysis of warpage (Eq.5.4). The R^2 values for training, testing, and validation, along with the maximum-minimum values for this model, are 0.90201, 0.85898, 0.94362, 16.3952, 0.94176, respectively.

$$Y = \sum_{r=1}^{8}\sum_{s=1}^{8}\sum_{t=1}^{8}\sum_{v=1}^{8}(\alpha_r x_r x_s x_t x_v) + \sum_{l=1}^{8}\sum_{m=1}^{8}\sum_{p=1}^{8}(\beta_l x_l x_m x_p) + \sum_{k=1}^{8}\sum_{j=1}^{8}(\alpha_j x_j x_k) + \sum_{i=1}^{8}(\alpha_i x_i) + \frac{\sum_{r=1}^{8}\sum_{s=1}^{8}\sum_{t=1}^{8}(\alpha_t \operatorname{Log}[x_r x_s x_t]) + \sum_{k=1}^{8}\sum_{j=1}^{8}(\alpha_j \operatorname{Log}[x_j x_k] + \sum_{i=1}^{8}(\alpha_i \operatorname{Log}[x_i]) + d}{\sum_{a=1}^{8}\sum_{b=1}^{8}\sum_{c=1}^{8}(\alpha_c \operatorname{Log}[x_a x_b x_c]) + \sum_{e=1}^{8}\sum_{d=1}^{8}(\alpha_d \operatorname{Log}[x_e x_d] + \sum_{f=1}^{8}(\alpha_f \operatorname{Log}[x_f]) + d} \quad \textbf{(5.3)}$$

Table 5.9. K-folds cross validation results of the Neuro-regression model for Warpage

Models	R^2 training	R^2 testing	R^2 validation	Maximum	Minimum
Hybrid 2	0.90201	0.85898	0.94362	16.3952	0.94176

$$\begin{aligned}
\boldsymbol{Warpage} = {} & 24.3694 - 0.105x\mathrm{IS} - 0.042x\mathrm{IP} + 0.0005x\mathrm{IS\ IP} + 2.118x\mathrm{CT} + 0.0035x\mathrm{IS\ CT} \\
& - 0.00002x\mathrm{IP\ CT} - 0.0910x\mathrm{PP} - 0.0001x\mathrm{IS\ \ PP} + 0.0001x\mathrm{IP\ PP} \\
& - 0.0018x\mathrm{CT\ PP} + 7.16x10^{-9}x\mathrm{IS\ IP\ CT\ PP} - 0.691x\mathrm{MOT} + 0.0031x\mathrm{IS\ MOT} \\
& + 0.0007x\mathrm{IP\ MOT} + 0.004x\mathrm{CT\ MOT} - 1.03x10^{-7}\mathrm{xIS\ IP\ CT\ MOT} \\
& - 0.0001x\mathrm{PP\ MOT} + 5.22x10^{-9}\ x\mathrm{IS\ IP\ PP\ MOT} \\
& - 1.754x10^{-8}\ x\ \mathrm{IP\ CT\ PP\ MOT} + 5.708x\mathrm{PT} - 0.038x\mathrm{IS\ PT} - 0.0013x\mathrm{IP\ PT} \\
& - 0.114x\mathrm{CT\ PT} + 2.016x10^{-8}x\mathrm{IS\ IP\ CT\ PT} - 0.0065x\mathrm{PP\ PT} \\
& + 1.122x10^{-8}x\mathrm{IS\ IP\ PP\ PT} - 1.066x10^{-7}x\mathrm{IP\ CT\ PP\ PT} + 0.0057x\mathrm{MOT\ PT} \\
& - 1.157x10^{-7}x\mathrm{IS\ IP\ MOT\ PT} + 1.519x10^{-6}x\mathrm{CT\ \ PP\ MOT\ \ PT} + 0.0863x\mathrm{MT} \\
& - 0.0001x\mathrm{IS\ MT} + 0.0002x\mathrm{IP\ MT} - 0.0001x\mathrm{CT\ MT} - 0.00001x\mathrm{IS\ CT\ MT} \\
& - 9.47x10^{-7}x\mathrm{IP\ CT\ MT} - 1.079x10^{-8}x\mathrm{IS\ IP\ CT\ MT} - 0.0001x\mathrm{CT}^2\ \mathrm{MT} \\
& - 0.0005x\mathrm{PP\ MT} + 2.353x10^{-6}x\mathrm{IS\ PP\ MT} - 6.269x10^{-7}x\mathrm{IP\ PP\ MT} \\
& - 4.074x10^{-9}x\mathrm{IS\ IP\ PP\ MT} + 5.952x10^{-6}x\mathrm{CT\ PP\ MT} \\
& + 7.99x10^{-9}x\mathrm{IP\ CT\ PP\ MT} + 1.029x10^{-6}x\mathrm{PP}^2\ \mathrm{MT} + 0.0012x\mathrm{MOT\ MT} \\
& + 3.99x10^{-6}x\mathrm{IS\ MOT\ MT} - 1.723x10^{-6}x\mathrm{IP\ MOT\ MT} \\
& - 2.744x10^{-8}x\mathrm{IS\ \ IP\ MOT\ MT} + 5.923x10^{-6}x\mathrm{CT\ MOT\ MT} \\
& + 2.778x10^{-6}x\mathrm{PP\ MOT\ MT} - 6.118x10^{-8}x\mathrm{CT\ PP\ MOT\ MT} \\
& - 0.0237x\mathrm{PT\ MT} + 0.0001x\mathrm{IS\ PT\ MT} - 4.584x10^{-8}x\mathrm{IS\ IP\ PT\ MT} \\
& + 0.0005x\mathrm{CT\ PT\ MT} + 0.00001x\mathrm{PP\ PT\ MT} + 2.456x10^{-8}x\mathrm{IP\ PP\ PT\ MT} \\
& - 1.483x10^{-7}x\mathrm{PP\ MOT\ PT\ MT} - 17.22x\mathrm{Log[IS\ IP\ CT]} \\
& + 12.79x\mathrm{Log[IS\ IP\ PP]} + 4.433x\mathrm{Log[IP\ CT\ PP]} + 2.513x\mathrm{Log[IS\ IP\ MOT]} \\
& - 3.536x\mathrm{Log[IP\ CT\ MOT]} + 4.917x\mathrm{Log[CT\ PP\ MOT]} - 0.622x\mathrm{Log[IS\ IP\ PT]} \\
& - 3.502x\mathrm{Log[IP\ CT\ PT]} + 3.547x\mathrm{Log[CT\ PP\ PT]} - 2.056x\mathrm{Log[IS\ IP\ MT]} \\
& -5.345x\mathrm{Log[IP\ CT\ MT]} - 0.154x\mathrm{Log[CT\ PP\ MT]}; \quad \textbf{(5.4)}
\end{aligned}$$

5.3. Optimization Results

Regression analysis is used to predict future values, while optimization is used to find the optimal solution. Both make significant contributions to data analysis and decision-making processes using statistical and mathematical techniques. In this context, while performing the optimization study, models that most reliably expressed the physical problem for the three outputs were selected as a result of the regression analysis.

In this context, an optimization study was carried out to determine the optimal values of the process parameters in order to minimize the cycle time of the injection molding process. In order to minimize the cycle time of the injection molding process, which is the objective function, an optimization study was carried out by determining six scenarios, as presented in detail in Table 5.10. In addition, warpage and shrinkage parameters, which are very critical for injection molding, were determined as a limitation for the scenarios. In addition, the optimization studies were carried out with stochastic optimization methods using the "Simulated Annealing", "Random Search", "Nelder-Mead" and "Differential Evolution" algorithms in the "Wolfram MATHEMATICA 10" program with the help of the "NMinimize" tool.

Table 5.10. Optimization scenarios for cycle time

Scenario	**Optimization Problem (Cycle Time)**
1	15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250
2	**6.8 ≤ Warpage ≤16**, 15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250
3	**2.9 ≤ Warpage ≤6.8,** 15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250
4	**Shrinkage ≤4.52,** 15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250
5	**4.52 ≤ shrinkage ≤6.49,** 15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250
6	**4.52 ≤ shrinkage ≤6.49** **6.8 ≤ warpage ≤16** 15 ≤ IS ≤ 60, 450 ≤ IP≤ 800, 10 ≤ CT ≤30, 100≤ PP ≤ 400, 15 ≤ MOT ≤ 45, 3≤ PT ≤9, 200 ≤ MT ≤ 250

Scenario 1 was created by determining the theoretical boundaries of the phenomenon discussed. In this context, the optimization study was carried out without any additional constraints by determining the upper and lower limits of each input value within the physical limits. The purpose of this scenario is to investigate cycle time values only in the input parameter ranges, without warpage and shrinkage constraints. In addition to scenario 1, in the second scenario, the warpage parameter is limited to the range of 2.6 and 15 according to the limits of the physical phenomenon, while in third scenario, the shrinkage value is limited to 1.97 and 6.49.

In the fourth scenario, the hybrid effects of warpage and shrinkage parameters, which are a combination of scenarios 2 and 3, on the objective function were investigated. The purpose of creating this scenario is to see how much the optimum result will be affected when the variables are constrained.

In the first scenario, the cycle time which is objective function, is calculated to be 21.2557 seconds for all optimization algorithms and also the suggested design parameters were found as shown in the last column. Additionally, shrinkage and warpage values (that is other corresponding outputs) were calculated as 5.37425 mm^3 and 10.7621 mm, respectively for all algorithms. That is, the minimum cycle time value is 21.2557 seconds within the given physical constraints.

According to the results in Scenario 1, the next scenarios were created by restricting output values other than cycle time. For the second scenario, an average value was found for the warpage output in the data set, and then it was limited to maximum and minimum ranges of the warpage value. It was decided that the warpage parameter in this range was inactive for second scenario in the range of $6.8 \leq$ Warpage ≤ 16. For this reason, scenario 3 was proposed.

In the third scenario, the warpage value is kept between the minimum and average value ($2.9 \leq$ Warpage ≤ 6.8) as a constraint. Although this interval is an active constraint for the optimization problem, it did not give better results than the previous two scenarios for cycle time minimization.

After the scenarios in which the warpage output value was considered a constraint, the fourth scenario was created by determining the ranges of the shrinkage value, which is another output. For this scenario, after calculating the average of the shrinkage parameter from the data set to determine the range in which the shrinkage value is active, shrinkage values that were smaller than the average were taken as constraints. As seen in the 4th scenario in Table 5.11, all algorithms gave values of 22.0984, 4.52, 9.35984 for cycle time, shrinkage and warpage parameters, respectively. On the other hand, the MOT value is calculated as 24.0095 as a design parameter. Since this value does not comply with the operating principle of the device, the fourth scenario does not give physically meaningful results.

Since no meaningful design parameter could be obtained in the fourth scenario, a second physically meaningful range was determined for the shrinkage value in the fifth scenario, and a new constraint was created in the range of 4.52 ≤ Shrinkage ≤6.49. Considering the cycle time values calculated by all algorithms in this scenario, although the shrinkage constraint added to the first scenario and within the range specified in the table is inactive, the result and design parameters are within a significant range.

The sixth scenario includes the combination of the second and fifth scenarios described previously. But this hybrid effect did not produce better results than previous scenarios. In conclusion, it can be said that simultaneously constraining both shrinkage and warpage values within the determined limits does not provide any benefit for the optimization study. In such cases, instead of investigating hybrid effects, the priority is to decide which constraint is more important for a different optimization scenario. It is found that the best results can be achieved by allowing some flexibility with the constraints.

As a result, unlike the referenced article, the optimization method applied using reliable equations as a result of the regression analysis was suggested, resulting in a lower cycle time (21.2557 seconds) than the time presented in the reference study (21.56 seconds).

Table 5.11. Results of the optimization problem for cycle time model

Scenario No	**Optimization Algorithms**	**Cycle time**	**Shrinkage**	**Warpage**	**Suggested Design**
1	MNM	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MDE	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MSA	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MRS	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250

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Table 5.11 (cont.)

2	MNM	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MDE	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MSA	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
	MRS	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400,MOT=45, PT= 3, MT=250
3	MNM	22.1382	5.22518	6.80	IS=52.82, IP=624.52, CT=10, PP=374.52, MOT=45, PT= 3, MT=248.023
	MDE	22.1382	5.22518	6.80	IS=52.82, IP=624.52, CT=10, PP=374.52, MOT=45, PT= 3, MT=248.023
	MSA	22.1382	5.22518	6.80	IS=52.82, IP=624.52, CT=10, PP=374.52, MOT=45, PT= 3, MT=248.023
	MRS	22.1382	5.22518	6.80	IS=52.82, IP=624.52, CT=10, PP=374.52, MOT=45, PT= 3, MT=248.023
4	MNM	22.0984	4.52	9.35984	IS=60, IP=800, CT=10, PP=400,MOT=24.0095, PT= 3, MT=200
	MDE	22.0984	4.52	9.35984	IS=60, IP=800, CT=10, PP=400,MOT=24.0095, PT= 3, MT=200
	MSA	22.0984	4.52	9.35984	IS=60, IP=800, CT=10, PP=400,MOT=24.0095, PT= 3, MT=200
	MRS	22.0984	4.52	9.35984	IS=60, IP=800, CT=10, PP=400,MOT=24.0095, PT= 3, MT=200
5	MNM	21.2557	5.37425	10.7621	IS=60, IP=799.9, CT=10, PP=399.9, MOT=44.9, PT= 3, MT=250
	MDE	21.2557	5.37425	10.7621	IS=60, IP=799.9, CT=10, PP=399.9, MOT=44.9, PT= 3, MT=250
	MSA	21.2557	5.37425	10.7621	IS=60, IP=799.9, CT=10, PP=399.9, MOT=44.9, PT= 3, MT=250
	MRS	21.2557	5.37425	10.7621	IS=60, IP=799.9, CT=10, PP=399.9, MOT=44.9, PT= 3, MT=250
6	MNM	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400, MOT=45, PT= 3, MT=250
	MDE	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400, MOT=45, PT= 3, MT=250
	MSA	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400, MOT=45, PT= 3, MT=250
	MRS	21.2557	5.37425	10.7621	IS=60, IP=800, CT=10, PP=400, MOT=45, PT= 3, MT=250

Figures 5.1 shows convergence graphs of the minimization results obtained with four different search algorithms for cycle time as objective function. The number of iterations indicates when to stop the algorithms and also it gives different values for each design. It can be seen that when MDE optimization algorithms gives stable value after 30 iterations, MNM gives stable results after about 70 iterations. The reason why there are fluctuations in MSA and MRS optimization algorithms is that there is no improvement in successive iterations.

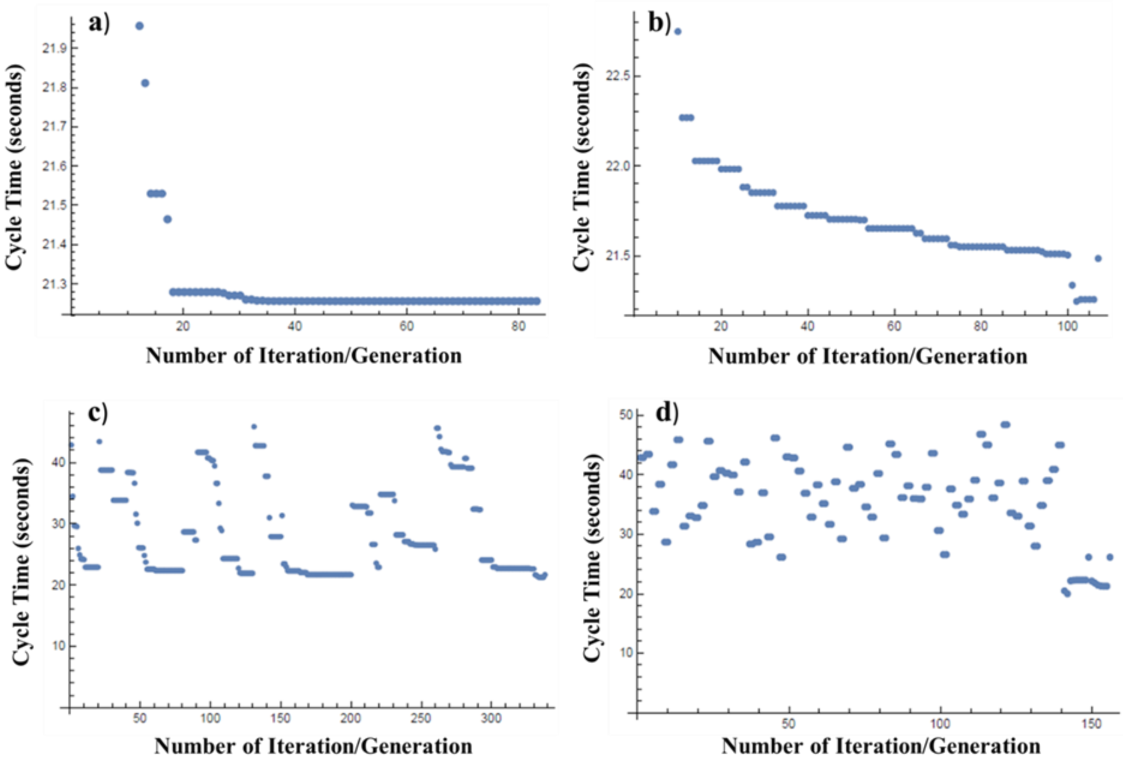

Figure 5.1. Convergence graphic representations of the stochastic algorithms for Cycle time (a) MDE, (b) MNM, (c) MSA, and (d) MRS

The results obtained for the cycle time model developed in this thesis(Equation 5.1) using the optimum design parameters of the reference study is shown in Table 5.12 for comparison with the results of reference study[11]. It is seen from the table that there are small differences between the model results and the results obtained in the reference study in the vast majority of the groups. It can be said that the model is appropriate for such a problem interms of optimization.

Table 5.12. Comparison of cycle time optimization results

Reference Study [11]	Thesis Study	Difference (%)	Reference Study [11]	Thesis Study	Difference (%)
47.63	46.73	1.90	43.23	44.18	-2.19
47.12	46.25	1.85	27.77	27.49	1.02
47.12	46.25	1.85	25.71	26.08	-1.42
47.12	46.25	1.85	23.99	24.44	-1.86
47.12	46.25	1.85	22.50	22.37	0.57
47.12	46.25	1.85	21.97	21.77	0.92
47.12	46.25	1.85	21.83	21.83	0.00
47.12	46.25	1.85	21.83	21.83	0.00
47.12	46.25	1.85	21.83	21.83	0.00
47.12	46.25	1.85	21.83	21.83	0.00
43.23	44.18	-2.19	43.23	44.18	-2.19
29.06	28.19	3.01	27.77	27.49	1.02
29.06	28.19	3.01	25.71	26.08	-1.42
29.06	28.19	3.01	23.99	24.44	-1.86
29.06	28.19	3.01	22.50	22.37	0.57
29.06	28.19	3.01	21.97	21.77	0.92
29.06	28.19	3.01	21.62	21.60	0.11
29.06	28.19	3.01	21.62	21.63	-0.07
29.06	28.19	3.01	21.62	21.63	-0.07
29.06	28.19	3.01	21.62	21.63	-0.07
43.23	44.18	-2.19	43.23	44.18	-2.19
27.77	27.49	1.02	27.77	27.49	1.02
26.45	26.63	-0.67	25.71	26.08	-1.42
26.45	26.63	-0.67	23.99	24.44	-1.86
26.45	26.63	-0.67	22.50	22.37	0.57
26.45	26.63	-0.67	21.97	21.77	0.92
26.45	26.63	-0.67	21.59	21.54	0.21
26.45	26.63	-0.67	21.56	21.64	-0.37
26.45	26.63	-0.67	21.56	21.64	-0.37
26.45	26.63	-0.67	21.56	21.64	-0.37
43.23	44.18	-2.19	43.23	44.18	-2.19
27.77	27.49	1.02	27.77	27.49	1.02
25.71	26.08	-1.42	25.71	26.08	-1.42
24.33	24.80	-1.94	23.99	24.44	-1.86
24.33	24.80	-1.94	22.50	22.37	0.57
24.33	24.80	-1.94	21.97	21.77	0.92

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Table 5.12 (cont.)

24.33	24.80	-1.94	21.59	21.54	0.21
24.33	24.80	-1.94	21.56	21.64	-0.37
24.33	24.80	-1.94	21.56	21.64	-0.37
24.33	24.80	-1.94	21.56	21.64	-0.37
43.23	44.18	-2.19	43.23	44.18	-2.19
27.77	27.49	1.02	27.77	27.49	1.02
25.71	26.08	-1.42	25.71	26.08	-1.42
23.99	24.44	-1.86	23.99	24.44	-1.86
22.55	22.44	0.47	22.50	22.37	0.57
22.55	22.44	0.47	21.97	21.77	0.92
22.55	22.44	0.47	21.59	21.54	0.21
22.55	22.44	0.47	21.56	21.64	-0.37
22.55	22.44	0.47	21.56	21.64	-0.37
22.55	22.44	0.47	21.56	21.64	-0.37

CHAPTER 6

CONCLUSION

In this thesis, optimization studies were carried out to obtain a short cycle time of the injection molding method, taking into account the shrinkage and warpage effects of the process parameters. First of all, using the experimental data given in the literature, the Neuro-Regression approach and k-fold cross-validation techniques, which combines the strengths of artificial neural network and traditional regression, were used to obtain the mathematical model of the process. Among the models proposed and analyzed for seven input parameters (mold temperature, melt temperature, packing pressure, packing time, cooling time, injection speed, and injection pressure) and three output parameters (cycle time, warpage and shrinkage), training, according to the determination coefficient of test and validation, model selection for each output was made with the Wolfram Mathematica program. When the values given by the optimization algorithms used are compared, it is seen that the optimization algorithms used give approximately the same results for the objective function. Additionally, optimization studies show that plastic injection molding cycle time can be reduced with appropriate process parameters and constraints.

Briefly, this study reveals that the cycle time of the plastic injection molding method can be improved by considering the effects of process parameters. In addition, shrinkage and warpage parameters have a significant impact on the process. Therefore, in addition to the process parameters, the ranges of shrinkage and warpage parameters must be precisely determined to obtain the desired cycle times. This thesis study includes determining the expected cycle time and plastic injection mold process parameters using regression models and optimization scenarios. In the Saad Mukras' study, the current problem has been addressed with different optimization methods. The difference of this thesis study from previous studies is the use of different regression models and optimization scenarios to shorten the plastic injection cycle time.

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APPENDIX A

REGRESSION AND CROSS VALIDATION GROUPS

Table A.1. Testing Data Of Cross Validation Group 1

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
8	15	800	30	400	15	3	200	6	4.49	43.8
14	60	800	30	100	15	3	200	9.1	5.21	41.9
21	15	800	10	100	45	9	200	4	4.1	30.9
25	60	450	10	100	45	9	200	4.5	4.19	29.8
33	15	450	10	100	15	3	250	8.4	5.92	24.4
36	15	450	30	400	15	3	250	8	5.35	43.7
45	60	800	10	100	15	3	250	16	6.16	22.6
53	15	800	10	100	45	3	250	13.6	6.25	24.3
61	37.5	625	20	250	30	6	200	6.2	4.2	35.4
62	37.5	625	20	250	30	6	250	8	4.84	35.3
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3
70	37.5	625	20	400	30	6	225	7.5	4.27	35.4
72	37.5	625	30	250	30	6	225	5.7	4.5	45.4

Table A.2. Traning Data Of Cross Validation Group 1

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
2	15	450	30	100	15	3	200	6.8	5.17	43.9
3	15	450	10	400	15	3	200	6	4.59	24.7
4	15	450	30	400	15	9	200	2.9	2.45	49.8
5	15	800	10	100	15	3	200	4.5	5.26	24.5
6	15	800	30	100	15	9	200	3.4	3.95	49.8
7	15	800	10	400	15	9	200	3.9	2.55	31.4
9	60	450	10	100	15	3	200	4.4	5.38	23.6
10	60	450	30	100	15	9	200	3.7	4	48.9
11	60	450	10	400	15	9	200	3.5	2.63	30.3
12	60	450	30	400	15	3	200	7.7	4.62	42.7
13	60	800	10	100	15	9	200	5.8	4.34	29.0
15	60	800	10	400	15	3	200	7	4.1	22.9
16	60	800	30	400	15	9	200	2.9	1.97	47.9
17	15	450	10	100	45	3	200	4.7	5.33	25.6
18	15	450	30	100	45	9	200	9	4.05	49.9

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Table A.2. (cont.)

19	15	450	10	400	45	9	200	5.1	3.24	31.2
20	15	450	30	400	45	3	200	6.8	5.09	43.8
22	15	800	30	100	45	3	200	7.9	5.55	48.8
23	15	800	10	400	45	3	200	9.6	5.17	24.8
24	15	800	30	400	45	9	200	4	3.15	49.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
27	60	450	10	400	45	3	200	8.6	5.31	23.3
28	60	450	30	400	45	9	200	4.5	3.25	48.7
29	60	800	10	100	45	3	200	11	5.53	22.4
30	60	800	30	100	45	9	200	3.8	4.14	47.9
31	60	800	10	400	45	9	200	6	2.28	29.4
32	60	800	30	400	45	3	200	7.9	4.27	41.9
34	15	450	30	100	15	9	250	5.2	3.85	49.7
35	15	450	10	400	15	9	250	4.5	3.12	31.4
37	15	800	10	100	15	9	250	5	3.95	31.2
38	15	800	30	100	15	3	250	7.6	5.85	43.7
39	15	800	10	400	15	3	250	6.7	5.48	24.6
40	15	800	30	400	15	9	250	6.4	3.02	49.7
41	60	450	10	100	15	9	250	4.8	4.15	29.5
42	60	450	30	100	15	3	250	6	6.06	42.1
43	60	450	10	400	15	3	250	7.7	5.83	22.9
44	60	450	30	400	15	9	250	5.2	3.2	48.1
46	60	800	30	100	15	9	250	7.1	4.07	47.8
47	60	800	10	400	15	9	250	6	3.29	29.5
48	60	800	30	400	15	3	250	9.1	5.48	41.9
49	15	450	10	100	45	9	250	5.8	4.54	30.8
50	15	450	30	100	45	3	250	7.9	6.21	43.8
51	15	450	10	400	45	3	250	9.9	5.95	24.3
52	15	450	30	400	45	9	250	8.4	3.84	49.8
54	15	800	30	100	45	9	250	8.8	4.43	49.7
55	15	800	10	400	45	9	250	7	3.94	31.0
56	15	800	30	400	45	3	250	8.6	5.87	43.9
57	60	450	10	100	45	3	250	8.1	6.49	22.6
58	60	450	30	100	45	9	250	7.6	4.63	48.2
59	60	450	10	400	45	9	250	9.3	4.13	29.4
60	60	450	30	400	45	3	250	8.3	6.11	42.2
63	37.5	625	20	250	15	6	225	9	4.26	35.3
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6
69	37.5	625	20	100	30	6	225	4.8	4.97	35.4
71	37.5	625	10	250	30	6	225	6.3	4.61	26.1
73	37.5	625	20	250	30	3	225	7.4	5.61	32.4
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
75	37.5	625	20	250	30	6	225	7.2	4.54	35.3
76	60	800	10	100	45	9	250	7.65	4.31	28.2
77	60	800	30	100	45	3	250	8.01	5.66	42.2
78	60	800	10	400	45	3	250	11.2	4.53	21.9
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.3. Validation Data Of Cross Validation Group 1

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
7	15	800	10	400	15	9	200	3.9	2.55	31.4
16	60	800	30	400	15	9	200	2.9	1.97	47.9
26	60	450	30	100	45	3	200	7.2	5.68	42.7
50	15	450	30	100	45	3	250	7.9	6.21	43.8
63	37.5	625	20	250	15	6	225	9	4.26	35.3
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6

Table A.4. Testing Data Of Cross Validation Group 2

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
4	15	450	30	400	15	9	200	2.9	2.45	49.8
9	60	450	10	100	15	3	200	4.4	5.38	23.6
16	60	800	30	400	15	9	200	2.9	1.97	47.9
19	15	450	10	400	45	9	200	5.1	3.24	31.2
23	15	800	10	400	45	3	200	9.6	5.17	24.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
29	60	800	10	100	45	3	200	11	5.53	22.4
40	15	800	30	400	15	9	250	6.4	3.02	49.7
43	60	450	10	400	15	3	250	7.7	5.83	22.9
48	60	800	30	400	15	3	250	9.1	5.48	41.9
51	15	450	10	400	45	3	250	9.9	5.95	24.3
57	60	450	10	100	45	3	250	8.1	6.49	22.6
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
69	37.5	625	20	100	30	6	225	4.8	4.97	35.4
75	37.5	625	20	250	30	6	225	7.2	4.54	35.3
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.5. Training Data Of Cross Validation Group 2

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
2	15	450	30	100	15	3	200	6.8	5.17	43.9
3	15	450	10	400	15	3	200	6	4.59	24.7
5	15	800	10	100	15	3	200	4.5	5.26	24.5
6	15	800	30	100	15	9	200	3.4	3.95	49.8
7	15	800	10	400	15	9	200	3.9	2.55	31.4
8	15	800	30	400	15	3	200	6	4.49	43.8
10	60	450	30	100	15	9	200	3.7	4	48.9

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Table A.5. (cont.)

11	60	450	10	400	15	9	200	3.5	2.63	30.3
12	60	450	30	400	15	3	200	7.7	4.62	42.7
13	60	800	10	100	15	9	200	5.8	4.34	29.0
14	60	800	30	100	15	3	200	9.1	5.21	41.9
15	60	800	10	400	15	3	200	7	4.1	22.9
17	15	450	10	100	45	3	200	4.7	5.33	25.6
18	15	450	30	100	45	9	200	9	4.05	49.9
20	15	450	30	400	45	3	200	6.8	5.09	43.8
21	15	800	10	100	45	9	200	4	4.1	30.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
24	15	800	30	400	45	9	200	4	3.15	49.8
25	60	450	10	100	45	9	200	4.5	4.19	29.8
27	60	450	10	400	45	3	200	8.6	5.31	23.3
28	60	450	30	400	45	9	200	4.5	3.25	48.7
30	60	800	30	100	45	9	200	3.8	4.14	47.9
31	60	800	10	400	45	9	200	6	2.28	29.4
32	60	800	30	400	45	3	200	7.9	4.27	41.9
33	15	450	10	100	15	3	250	8.4	5.92	24.4
34	15	450	30	100	15	9	250	5.2	3.85	49.7
35	15	450	10	400	15	9	250	4.5	3.12	31.4
36	15	450	30	400	15	3	250	8	5.35	43.7
37	15	800	10	100	15	9	250	5	3.95	31.2
38	15	800	30	100	15	3	250	7.6	5.85	43.7
39	15	800	10	400	15	3	250	6.7	5.48	24.6
41	60	450	10	100	15	9	250	4.8	4.15	29.5
42	60	450	30	100	15	3	250	6	6.06	42.1
44	60	450	30	400	15	9	250	5.2	3.2	48.1
45	60	800	10	100	15	3	250	16	6.16	22.6
46	60	800	30	100	15	9	250	7.1	4.07	47.8
47	60	800	10	400	15	9	250	6	3.29	29.5
49	15	450	10	100	45	9	250	5.8	4.54	30.8
50	15	450	30	100	45	3	250	7.9	6.21	43.8
52	15	450	30	400	45	9	250	8.4	3.84	49.8
53	15	800	10	100	45	3	250	13.6	6.25	24.3
54	15	800	30	100	45	9	250	8.8	4.43	49.7
55	15	800	10	400	45	9	250	7	3.94	31.0
56	15	800	30	400	45	3	250	8.6	5.87	43.9
58	60	450	30	100	45	9	250	7.6	4.63	48.2
59	60	450	10	400	45	9	250	9.3	4.13	29.4
60	60	450	30	400	45	3	250	8.3	6.11	42.2
61	37.5	625	20	250	30	6	200	6.2	4.2	35.4
62	37.5	625	20	250	30	6	250	8	4.84	35.3
63	37.5	625	20	250	15	6	225	9	4.26	35.3
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3

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Table A.5. (cont.)

70	37.5	625	20	400	30	6	225	7.5	4.27	35.4
71	37.5	625	10	250	30	6	225	6.3	4.61	26.1
72	37.5	625	30	250	30	6	225	5.7	4.5	45.4
73	37.5	625	20	250	30	3	225	7.4	5.61	32.4
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
76	60	800	10	100	45	9	250	7.65	4.31	28.2
77	60	800	30	100	45	3	250	8.01	5.66	42.2
78	60	800	10	400	45	3	250	11.2	4.53	21.9

Table A.6. Validation Data Of Cross Validation Group 2

No	**IS**	**IP**	**CT**	**PP**	**MOT**	**PT**	**MT**	**WP**	**SK**	**CYCT**
2	15	450	30	100	15	3	200	6.8	5.17	43.9
10	60	450	30	100	15	9	200	3.7	4	48.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
41	60	450	10	100	15	9	250	4.8	4.15	29.5
58	60	450	30	100	45	9	250	7.6	4.63	48.2
61	37.5	625	20	250	30	6	200	6.2	4.2	35.4

Table A.7. Testing Data Of Cross Validation Group 3

No	**IS**	**IP**	**CT**	**PP**	**MOT**	**PT**	**MT**	**WP**	**SK**	**CYCT**
2	15	450	30	100	15	3	200	6.8	5.17	43.9
6	15	800	30	100	15	9	200	3.4	3.95	49.8
11	60	450	10	400	15	9	200	3.5	2.63	30.3
17	15	450	10	100	45	3	200	4.7	5.33	25.6
20	15	450	30	400	45	3	200	6.8	5.09	43.8
27	60	450	10	400	45	3	200	8.6	5.31	23.3
31	60	800	10	400	45	9	200	6	2.28	29.4
35	15	450	10	400	15	9	250	4.5	3.12	31.4
38	15	800	30	100	15	3	250	7.6	5.85	43.7
42	60	450	30	100	15	3	250	6	6.06	42.1
46	60	800	30	100	15	9	250	7.1	4.07	47.8
50	15	450	30	100	45	3	250	7.9	6.21	43.8
55	15	800	10	400	45	9	250	7	3.94	31.0
59	60	450	10	400	45	9	250	9.3	4.13	29.4
73	37.5	625	20	250	30	3	225	7.4	5.61	32.4
77	60	800	30	100	45	3	250	8.01	5.66	42.2

Table A.8. Training Data Of Cross Validation Group 3

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
3	15	450	10	400	15	3	200	6	4.59	24.7
4	15	450	30	400	15	9	200	2.9	2.45	49.8
5	15	800	10	100	15	3	200	4.5	5.26	24.5
7	15	800	10	400	15	9	200	3.9	2.55	31.4
8	15	800	30	400	15	3	200	6	4.49	43.8
9	60	450	10	100	15	3	200	4.4	5.38	23.6
10	60	450	30	100	15	9	200	3.7	4	48.9
12	60	450	30	400	15	3	200	7.7	4.62	42.7
13	60	800	10	100	15	9	200	5.8	4.34	29.0
14	60	800	30	100	15	3	200	9.1	5.21	41.9
15	60	800	10	400	15	3	200	7	4.1	22.9
16	60	800	30	400	15	9	200	2.9	1.97	47.9
18	15	450	30	100	45	9	200	9	4.05	49.9
19	15	450	10	400	45	9	200	5.1	3.24	31.2
21	15	800	10	100	45	9	200	4	4.1	30.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
23	15	800	10	400	45	3	200	9.6	5.17	24.8
24	15	800	30	400	45	9	200	4	3.15	49.8
25	60	450	10	100	45	9	200	4.5	4.19	29.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
28	60	450	30	400	45	9	200	4.5	3.25	48.7
29	60	800	10	100	45	3	200	11	5.53	22.4
30	60	800	30	100	45	9	200	3.8	4.14	47.9
32	60	800	30	400	45	3	200	7.9	4.27	41.9
33	15	450	10	100	15	3	250	8.4	5.92	24.4
34	15	450	30	100	15	9	250	5.2	3.85	49.7
36	15	450	30	400	15	3	250	8	5.35	43.7
37	15	800	10	100	15	9	250	5	3.95	31.2
39	15	800	10	400	15	3	250	6.7	5.48	24.6
40	15	800	30	400	15	9	250	6.4	3.02	49.7
41	60	450	10	100	15	9	250	4.8	4.15	29.5
43	60	450	10	400	15	3	250	7.7	5.83	22.9
44	60	450	30	400	15	9	250	5.2	3.2	48.1
45	60	800	10	100	15	3	250	16	6.16	22.6
47	60	800	10	400	15	9	250	6	3.29	29.5
48	60	800	30	400	15	3	250	9.1	5.48	41.9
49	15	450	10	100	45	9	250	5.8	4.54	30.8
51	15	450	10	400	45	3	250	9.9	5.95	24.3
52	15	450	30	400	45	9	250	8.4	3.84	49.8
53	15	800	10	100	45	3	250	13.6	6.25	24.3
54	15	800	30	100	45	9	250	8.8	4.43	49.7
56	15	800	30	400	45	3	250	8.6	5.87	43.9
57	60	450	10	100	45	3	250	8.1	6.49	22.6
58	60	450	30	100	45	9	250	7.6	4.63	48.2
60	60	450	30	400	45	3	250	8.3	6.11	42.2

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Table A.8. (cont.)

61	37.5	625	20	250	30	6	200	6.2	4.2	35.4
62	37.5	625	20	250	30	6	250	8	4.84	35.3
63	37.5	625	20	250	15	6	225	9	4.26	35.3
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3
69	37.5	625	20	100	30	6	225	4.8	4.97	35.4
70	37.5	625	20	400	30	6	225	7.5	4.27	35.4
71	37.5	625	10	250	30	6	225	6.3	4.61	26.1
72	37.5	625	30	250	30	6	225	5.7	4.5	45.4
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
75	37.5	625	20	250	30	6	225	7.2	4.54	35.3
76	60	800	10	100	45	9	250	7.65	4.31	28.2
78	60	800	10	400	45	3	250	11.2	4.53	21.9
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.9. Validation Data Of Cross Validation Group 3

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
13	60	800	10	100	15	9	200	5.8	4.34	29.0
23	15	800	10	400	45	3	200	9.6	5.17	24.8
28	60	450	30	400	45	9	200	4.5	3.25	48.7
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3

Table A.10. Testing Data Of Cross Validation Group 4

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
5	15	800	10	100	15	3	200	4.5	5.26	24.5
12	60	450	30	400	15	3	200	7.7	4.62	42.7
15	60	800	10	400	15	3	200	7	4.1	22.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
32	60	800	30	400	45	3	200	7.9	4.27	41.9
34	15	450	30	100	15	9	250	5.2	3.85	49.7
39	15	800	10	400	15	3	250	6.7	5.48	24.6
41	60	450	10	100	15	9	250	4.8	4.15	29.5
44	60	450	30	400	15	9	250	5.2	3.2	48.1
47	60	800	10	400	15	9	250	6	3.29	29.5
52	15	450	30	400	45	9	250	8.4	3.84	49.8
56	15	800	30	400	45	3	250	8.6	5.87	43.9

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Table A.10. (cont.)

58	60	450	30	100	45	9	250	7.6	4.63	48.2
60	60	450	30	400	45	3	250	8.3	6.11	42.2
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
78	60	800	10	400	45	3	250	11.2	4.53	21.9

Table A.11. Training Data Of Cross Validation Group 4

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
2	15	450	30	100	15	3	200	6.8	5.17	43.9
3	15	450	10	400	15	3	200	6	4.59	24.7
4	15	450	30	400	15	9	200	2.9	2.45	49.8
6	15	800	30	100	15	9	200	3.4	3.95	49.8
7	15	800	10	400	15	9	200	3.9	2.55	31.4
8	15	800	30	400	15	3	200	6	4.49	43.8
9	60	450	10	100	15	3	200	4.4	5.38	23.6
10	60	450	30	100	15	9	200	3.7	4	48.9
11	60	450	10	400	15	9	200	3.5	2.63	30.3
13	60	800	10	100	15	9	200	5.8	4.34	29.0
14	60	800	30	100	15	3	200	9.1	5.21	41.9
16	60	800	30	400	15	9	200	2.9	1.97	47.9
17	15	450	10	100	45	3	200	4.7	5.33	25.6
18	15	450	30	100	45	9	200	9	4.05	49.9
19	15	450	10	400	45	9	200	5.1	3.24	31.2
20	15	450	30	400	45	3	200	6.8	5.09	43.8
21	15	800	10	100	45	9	200	4	4.1	30.9
23	15	800	10	400	45	3	200	9.6	5.17	24.8
24	15	800	30	400	45	9	200	4	3.15	49.8
25	60	450	10	100	45	9	200	4.5	4.19	29.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
27	60	450	10	400	45	3	200	8.6	5.31	23.3
28	60	450	30	400	45	9	200	4.5	3.25	48.7
29	60	800	10	100	45	3	200	11	5.53	22.4
30	60	800	30	100	45	9	200	3.8	4.14	47.9
31	60	800	10	400	45	9	200	6	2.28	29.4
33	15	450	10	100	15	3	250	8.4	5.92	24.4
35	15	450	10	400	15	9	250	4.5	3.12	31.4
36	15	450	30	400	15	3	250	8	5.35	43.7
37	15	800	10	100	15	9	250	5	3.95	31.2
38	15	800	30	100	15	3	250	7.6	5.85	43.7
40	15	800	30	400	15	9	250	6.4	3.02	49.7
42	60	450	30	100	15	3	250	6	6.06	42.1
43	60	450	10	400	15	3	250	7.7	5.83	22.9
45	60	800	10	100	15	3	250	16	6.16	22.6
46	60	800	30	100	15	9	250	7.1	4.07	47.8
48	60	800	30	400	15	3	250	9.1	5.48	41.9
49	15	450	10	100	45	9	250	5.8	4.54	30.8
50	15	450	30	100	45	3	250	7.9	6.21	43.8
51	15	450	10	400	45	3	250	9.9	5.95	24.3
53	15	800	10	100	45	3	250	13.6	6.25	24.3
54	15	800	30	100	45	9	250	8.8	4.43	49.7
55	15	800	10	400	45	9	250	7	3.94	31.0
57	60	450	10	100	45	3	250	8.1	6.49	22.6
59	60	450	10	400	45	9	250	9.3	4.13	29.4

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Table A.11. (cont.)

61	37.5	625	20	250	30	6	200	6.2	4.2	35.4
62	37.5	625	20	250	30	6	250	8	4.84	35.3
63	37.5	625	20	250	15	6	225	9	4.26	35.3
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3
69	37.5	625	20	100	30	6	225	4.8	4.97	35.4
70	37.5	625	20	400	30	6	225	7.5	4.27	35.4
71	37.5	625	10	250	30	6	225	6.3	4.61	26.1
72	37.5	625	30	250	30	6	225	5.7	4.5	45.4
73	37.5	625	20	250	30	3	225	7.4	5.61	32.4
75	37.5	625	20	250	30	6	225	7.2	4.54	35.3
76	60	800	10	100	45	9	250	7.65	4.31	28.2
77	60	800	30	100	45	3	250	8.01	5.66	42.2
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.12. Validation Data Of Cross Validation Group 4

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
19	15	450	10	400	45	9	200	5.1	3.24	31.2
31	60	800	10	400	45	9	200	6	2.28	29.4
37	15	800	10	100	15	9	250	5	3.95	31.2
43	60	450	10	400	15	3	250	7.7	5.83	22.9
62	37.5	625	20	250	30	6	250	8	4.84	35.3
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.13. Testing Data Of Cross Validation Group 5

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
3	15	450	10	400	15	3	200	6	4.59	24.7
7	15	800	10	400	15	9	200	3.9	2.55	31.4
10	60	450	30	100	15	9	200	3.7	4	48.9
13	60	800	10	100	15	9	200	5.8	4.34	29.0
18	15	450	30	100	45	9	200	9	4.05	49.9
24	15	800	30	400	45	9	200	4	3.15	49.8
28	60	450	30	400	45	9	200	4.5	3.25	48.7
30	60	800	30	100	45	9	200	3.8	4.14	47.9
37	15	800	10	100	15	9	250	5	3.95	31.2
49	15	450	10	100	45	9	250	5.8	4.54	30.8
54	15	800	30	100	45	9	250	8.8	4.43	49.7
63	37.5	625	20	250	15	6	225	9	4.26	35.3
67	37.5	450	20	250	30	6	225	6.5	4.44	35.6
71	37.5	625	10	250	30	6	225	6.3	4.61	26.1
76	60	800	10	100	45	9	250	7.65	4.31	28.2

Table A.14. Training Data Of Cross Validation Group 5

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
1	15	450	10	100	15	9	200	5.8	3.97	31.1
2	15	450	30	100	15	3	200	6.8	5.17	43.9
4	15	450	30	400	15	9	200	2.9	2.45	49.8
5	15	800	10	100	15	3	200	4.5	5.26	24.5
6	15	800	30	100	15	9	200	3.4	3.95	49.8
8	15	800	30	400	15	3	200	6	4.49	43.8
9	60	450	10	100	15	3	200	4.4	5.38	23.6
11	60	450	10	400	15	9	200	3.5	2.63	30.3
12	60	450	30	400	15	3	200	7.7	4.62	42.7
14	60	800	30	100	15	3	200	9.1	5.21	41.9
15	60	800	10	400	15	3	200	7	4.1	22.9
16	60	800	30	400	15	9	200	2.9	1.97	47.9
17	15	450	10	100	45	3	200	4.7	5.33	25.6
19	15	450	10	400	45	9	200	5.1	3.24	31.2
20	15	450	30	400	45	3	200	6.8	5.09	43.8
21	15	800	10	100	45	9	200	4	4.1	30.9
22	15	800	30	100	45	3	200	7.9	5.55	48.8
23	15	800	10	400	45	3	200	9.6	5.17	24.8
25	60	450	10	100	45	9	200	4.5	4.19	29.8
26	60	450	30	100	45	3	200	7.2	5.68	42.7
27	60	450	10	400	45	3	200	8.6	5.31	23.3
29	60	800	10	100	45	3	200	11	5.53	22.4
31	60	800	10	400	45	9	200	6	2.28	29.4
32	60	800	30	400	45	3	200	7.9	4.27	41.9
33	15	450	10	100	15	3	250	8.4	5.92	24.4
34	15	450	30	100	15	9	250	5.2	3.85	49.7
35	15	450	10	400	15	9	250	4.5	3.12	31.4
36	15	450	30	400	15	3	250	8	5.35	43.7
38	15	800	30	100	15	3	250	7.6	5.85	43.7
39	15	800	10	400	15	3	250	6.7	5.48	24.6
40	15	800	30	400	15	9	250	6.4	3.02	49.7
41	60	450	10	100	15	9	250	4.8	4.15	29.5
42	60	450	30	100	15	3	250	6	6.06	42.1
43	60	450	10	400	15	3	250	7.7	5.83	22.9
44	60	450	30	400	15	9	250	5.2	3.2	48.1
45	60	800	10	100	15	3	250	16	6.16	22.6
46	60	800	30	100	15	9	250	7.1	4.07	47.8
47	60	800	10	400	15	9	250	6	3.29	29.5
48	60	800	30	400	15	3	250	9.1	5.48	41.9
50	15	450	30	100	45	3	250	7.9	6.21	43.8
51	15	450	10	400	45	3	250	9.9	5.95	24.3
52	15	450	30	400	45	9	250	8.4	3.84	49.8
53	15	800	10	100	45	3	250	13.6	6.25	24.3
55	15	800	10	400	45	9	250	7	3.94	31.0
56	15	800	30	400	45	3	250	8.6	5.87	43.9
57	60	450	10	100	45	3	250	8.1	6.49	22.6
58	60	450	30	100	45	9	250	7.6	4.63	48.2

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Table A.14. (cont.)

59	60	450	10	400	45	9	250	9.3	4.13	29.4
60	60	450	30	400	45	3	250	8.3	6.11	42.2
61	37.5	625	20	250	30	6	200	6.2	4.2	35.4
62	37.5	625	20	250	30	6	250	8	4.84	35.3
64	37.5	625	20	250	45	6	225	3.6	4.87	35.4
65	15	625	20	250	30	6	225	7.3	4.31	35.9
66	60	625	20	250	30	6	225	7.6	4.51	35.0
68	37.5	800	20	250	30	6	225	7.6	4.45	35.3
69	37.5	625	20	100	30	6	225	4.8	4.97	35.4
70	37.5	625	20	400	30	6	225	7.5	4.27	35.4
72	37.5	625	30	250	30	6	225	5.7	4.5	45.4
73	37.5	625	20	250	30	3	225	7.4	5.61	32.4
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
75	37.5	625	20	250	30	6	225	7.2	4.54	35.3
77	60	800	30	100	45	3	250	8.01	5.66	42.2
79	60	800	30	400	45	9	250	4.88	2.51	47.4

Table A.15. Validation Data Of Cross Validation Group 5

No	IS	IP	CT	PP	MOT	PT	MT	WP	SK	CYCT
9	60	450	10	100	15	3	200	4.4	5.38	23.6
35	15	450	10	400	15	9	250	4.5	3.12	31.4
45	60	800	10	100	15	3	250	16	6.16	22.6
53	15	800	10	100	45	3	250	13.6	6.25	24.3
74	37.5	625	20	250	30	9	225	5.6	3.63	38.3
78	60	800	10	400	45	3	250	11.2	4.53	21.9

APPENDIX B

K-FOLD CROSS VALIDATION RESULTS OF THE NEURO-REGRESSION MODEL FOR CYCLE TIME

Table B.1. K-Fold Cross Validation Results Of The Neuro-Regressıon Model For Cycle Time

Models	**R^2 training**	**R^2 training Adjusted**	**R^2 testing**	**R^2 validation**	**Maximum**	**Minimum**
L1	0,999568	0,999422	0,989042	0,987301	50,3377	22,5436
L2	0,999533	0,999374	0,99705	0,927734	50,393	22,3843
L3	0,999543	0,999388	0,991708	0,993982	50,3594	22,2136
L4	0,999804	0,999737	0,980056	0,99602	50,1389	22,3399
L5	0,99952	0,99936	0,996868	0,987905	50,332	22,4008
LR1	0,999741	0,999652	0,99476	0,997102	50,5389	21,8247
LR2	0,999717	0,99962	0,998953	0,95494	50,5024	21,9626
LR3	0,999755	0,999672	0,991632	0,99787	50,7963	22,1029
LR4	0,972732	0,963449	0,115168	0,413481	∞	∞
LR5	0,999759	0,999679	0,994537	0,998007	51,1599	0,999759
SON1	0,999875	1,00088	0,993801	0,996669	48,8516	21,8279
SON2	0,999872	1,00089	0,99588	0,985072	50,9829	21,7642
SON3	0,999885	1,00081	0,989309	0,999925	50,8447	21,7175
SON4	0,99998	1,00014	0,987566	0,999306	50,0223	22,0589
SON5	0,999874	1,00101	0,993887	0,998478	52,0226	21,7601
SONR1	0,996219	1,02647	0,77602	0,942262	58,3891	21,2811
SONR2	0,995881	1,02884	0,393605	0,882625	76,9801	23,706
SONR3	0,995599	1,0308	-0,34415	0,954694	77,7397	22,7213
SONR4	0,995991	1,02806	0,72239	0,915258	57,554	23,6485
SONR5	0,75662	2,94704	-3,29838	-1,73009	72,9159	11,6262
FOTN1	0,999677	0,999384	0,996216	0,998336	77,8571	-47,1218
FOTN2	0,999605	0,99947	0,996455	0,965956	50,2909	22,2598
FOTN3	0,999693	0,999413	0,99417	0,999545	98,9265	-5,3652
FOTN4	0,999937	0,99988	0,982755	0,998163	89,9144	-5,81346
FOTN5	0,999676	0,999391	0,997797	0,993351	103,127	-5,86926
FOTNR1	0,999757	0,999535	-0,582858	0,996865	1,06844 x 10^9	-1,4530 x 10^9
FOTNR2	0,999752	0,999527	0,998484	0,96197	826600	-1,9867 x 10^6
~~FOTNR3~~	0,972815	0,9481	0,0725967	0,790992	1,73847 x 10^6	-2,299 x 10^{13}
FOTNR4	0,999957	0,999917	0,982521	0,998432	983320	-48604,3
FOTNR5	0,980183	0,962698	-0,16534	0,125922	3,53352 x 10^8	-1,1845 x 10^7
SOTN1	0,999875	1,00004	0,353848	0,996708	70,1185	-6,09993
SOTN2	0,999878	1,00004	0,946824	0,985565	79,0751	-0,988886

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Table B.1. (cont.)

SOTN3	0,999892	1,00004	0,988765	0,999933	71,286	-0,0127627
SOTN4	0,999985	1,00001	0,979677	0,999379	75,9441	4,32376
SOTN5	0,999881	1,00004	0,84386	0,99841	71,9273	0,508661
SOTNR1	0,458857	1,19261	-12,8106	-11,6458	$8{,}12399 \times 10^{7}$	$-5{,}0967 \times 10^{7}$
SOTNR2	0,372791	1,22324	-9,04555	-21,0832	399621	$-5{,}274 \times 10^{12}$
SOTNR3	0,599091	1,1427	-10,5251	-5,67089	$1{,}35105 \times 10^{6}$	$-3{,}434 \times 10^{13}$
SOTNR4	0,257363	1,26433	-12,6865	-12,1428	$6{,}97267 \times 10^{12}$	$-1{,}4195 \times 10^{6}$
SOTNR5	0,541811	1,16661	-21,6127	-12,2732	292144	-252737
FOLN1	0,998618	0,998148	0,88536	0,861618	50,1565	22,1698
FOLN2	0,998206	0,997596	0,974149	0,884906	50,121	21,7683
FOLN3	0,997984	0,997298	0,970407	0,935697	50,2424	21,3245
FOLN4	0,998257	0,997663	0,963582	0,959767	50,0832	21,2556
FOLN5	0,998066	0,997421	0,975132	0,970573	49,8732	21,8725
FOLNR1	0,999648	0,999528	0,986341	0,987663	50,286	22,0668
FOLNR2	0,999605	0,99947	0,996455	0,965956	50,2909	22,2598
FOLNR3	0,999716	0,99962	0,975281	0,998123	50,4644	22,1223
FOLNR4	0,999743	0,999656	0,985427	0,995217	49,5562	22,4833
FOLNR5	0,999634	0,999511	0,993944	0,994978	50,4909	22,2014
SOLN1	0,999875	1,00088	0,993351	0,996628	48,8076	21,916
SOLN2	0,999871	1,00091	0,996188	0,984921	49,7479	21,7399
SOLN3	0,999884	1,00081	0,989244	0,999872	50,8473	21,7229
SOLN4	0,999979	1,00015	0,987535	0,999248	49,7293	22,0352
SOLN5	0,999873	1,00102	0,994175	0,998306	51,9714	21,8016
SOLNR1	0,999842	1,00111	0,986945	0,994771	49,4431	22,6943
SOLNR2	0,99984	1,00112	0,994611	0,995554	48,5876	22,7393
SOLNR3	0,999813	1,00131	0,987163	0,998419	49,4558	22,3296
SOLNR4	0,9999	1,0007	0,988489	0,998882	49,5541	22,6402
SOLNR5	0,999843	1,00125	0,977038	0,988928	48,9121	22,4958

APPENDIX C

K-FOLD CROSS VALIDATION RESULTS OF THE NEURO-REGRESSION MODEL FOR SHRINKAGE

Table C.1. K-Fold Cross Validation Results Of The Neuro-Regressıon Model For Shrinkage

Models	**R^2 training**	**R^2 training Adjusted**	**R^2 testing**	**R^2 validation**	**Maximum**	**Minimum**
L1	0,994287	0,992342	0,9465	0,972329	652,953	248,942
L2	0,996026	0,994673	0,890347	0,908814	633,944	270,892
L3	0,995597	0,994098	0,901156	0,588459	661,099	246,753
L4	0,995748	0,994301	0,802034	0,819835	647,921	258,088
L5	0,995708	0,994278	0,529528	0,867713	663,747	234,224
LR1	0,996461	0,995256	0,836693	0,997256	615,063	198,203
LR2	0,996955	0,995918	0,930663	0,928382	61,409	247,541
LR3	0,996982	0,995955	0,90055	0,732434	649,453	217,876
LR4	0,998034	0,997365	0,565501	0,939326	642,849	194,014
LR5	0,997067	0,996089	0,570768	0,807517	628,463	178,961
SON1	0,998871	100,791	0,701653	0,994193	625,846	207,847
SON2	0,998964	100,725	0,925439	0,957904	640,257	23,315
SON3	0,998828	10,082	0,870433	0,880853	664,069	226,269
SON4	0,999005	100,697	0,818809	0,963464	647,038	205,729
SON5	0,998757	100,994	0,665092	0,943016	652,651	189,541
SONR1	0,997518	101,737	0,584673	0,985843	581,958	191,361
SONR2	0,997876	101,487	0,894011	0,935967	687,608	247,256
SONR3	0,997555	101,712	0,925348	0,842284	639,557	1,199,108
SONR4	0,997842	10,151	0,690422	0,867589	614,004	191,262
SONR5	0,997266	102,187	0,754911	0,860553	640,714	198,618
FOTN1	0,994344	0,989201	0,933182	0,974586	133,605	-914,125
FOTN2	0,996099	0,992553	0,888147	0,907871	141,511	-48,214
FOTN3	0,995648	0,991692	0,900731	0,588634	144,307	-637,199
FOTN4	0,995814	0,992008	0,800913	0,818802	131,092	-988,863
FOTN5	0,995822	0,992136	0,472305	0,873529	132,055	-206,878
FOTNR1	0,996606	0,993521	-210,208	0,99845	6,53127 x 10^{7}	-2,385 x 10^{14}
FOTNR2	0,996943	0,994163	0,909116	0,904534	2,20756 x 10^{14}	-4,7765 x 10^{7}
~~FOTNR3~~	0,980367	0,962519	-109,537	0,472236	8,54025 x 10^{13}	-3,3920 x 10^{7}
FOTNR4	0,998214	0,996591	0,251933	0,941985	16153,2	-998416
FOTNR5	0,99723	0,994787	0,272634	0,810426	1,81033 x 10^{13}	-2,9654 x 10^{6}
SOTN1	0,998904	100,039	0,0607194	0,995041	140,398	-128,439
SOTN2	0,998964	100,725	0,925439	0,957904	640,257	23,315

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Table C.1. (cont.)

SOTN3	0,998932	100,038	0,754669	0,896517	195,847	-117,606
SOTN4	0,99907	100,033	0,640653	0,965788	184,166	-886,682
SOTN5	0,998809	100,043	0,0673541	0,944804	128,838	-970,888
SOTNR1	0,964208	101,274	-0,316913	0,443116	$4{,}02844 \times 10^{7}$	$-4{,}6580 \times 10^{7}$
SOTNR2	0,997876	101,487	0,894011	0,935967	687,608	247,256
SOTNR3	0,817874	106,482	-196,549	-871,468	$1{,}1969 \times 10^{7}$	$-8{,}4812 \times 10^{7}$
SOTNR4	-0,858195	105,047	-426,478	-260,807	$4{,}30968 \times 10^{14}$	$-1{,}4716 \times 10^{6}$
SOTNR5	0,59817	114,612	-465,172	-630,228	$2{,}10699 \times 10^{6}$	-937642
FOLN1	0,993715	0,991576	0,880337	0,963267	654,349	25,432
FOLN2	0,995605	0,994108	0,869835	0,889426	635,436	279,252
FOLN3	0,994805	0,993037	0,89294	0,544334	66,296	258,703
FOLN4	0,994982	0,993274	0,787308	0,759085	654,009	266,387
FOLN5	0,994722	0,992962	0,616001	0,851619	662,188	247,463
FOLNR1	0,995847	0,994433	0,790382	0,992535	614,752	198,122
FOLNR2	0,99645	0,995241	0,913018	0,910732	618,037	252,624
FOLNR3	0,996134	0,994818	0,90811	0,707937	651,188	227,814
FOLNR4	0,997927	0,997222	0,472941	0,954831	641,284	195,859
FOLNR5	0,996521	0,995361	0,483257	0,785375	628,406	190,348
SOLN1	0,998865	100,794	0,629624	0,993577	667,842	19,741
SOLN2	0,998917	100,758	0,923298	0,958237	640,009	256,309
SOLN3	0,9987	10,091	0,883934	0,869095	669,944	2,254
SOLN4	0,998933	100,747	0,809045	0,958057	650,836	207,273
SOLN5	0,998715	101,028	0,633231	0,943016	66,812	21,364
SOLNR1	0,997568	101,703	0,828948	0,984944	59,847	199,864
SOLNR2	0,998642	10,095	0,785586	0,933226	60,885	246,129
SOLNR3	0,99818	101,274	0,826796	0,872497	629,664	20,897
SOLNR4	0,997939	101,443	0,763983	0,888807	637,197	19,538
SOLNR5	0,998211	101,431	0,0314994	0,913186	657,769	149,456

APPENDIX D

K-FOLD CROSS VALIDATION RESULTS OF THE NEURO-REGRESSION MODEL FOR WARPAGE

Table D.1. K-Fold Cross Validation Results Of The Neuro-Regressıon Model For Warpage

Models	**R^2 training**	**R^2 training Adjusted**	**R^2 testing**	**R^2 validation**	**Maximum**	**Minimum**
L1	0,958926	0,944944	0,235182	0,529389	963,885	342,254
L2	0,9513774	0,93482	0,467102	0,68513	107,721	308,567
L3	0,948534	0,931014	-0,118204	0,0352003	108,634	298,486
L4	0,945285	0,926659	0,0999092	0,0915001	109,098	274,845
L5	0,952694	0,936925	0,0809636	0,551954	107,676	26,919
LR1	0,964903	0,952955	0,261134	0,544286	197,854	370,765
LR2	0,972346	0,962932	-0,205378	0,513128	∞	∞
LR3	0,968557	0,957854	-225,576	-0,00142651	195,953	113,435
LR4	0,966058	0,954503	-304,714	0,255312	203,296	35,106
LR5	0,973238	0,964318	-0,425343	0,976478	161,514	-0,0639384
SON1	0,979028	11,468	-0,485974	0,536851	122,662	-186,034
SON2	0,976583	116,392	-0,115598	0,515703	137,703	369,547
SON3	0,972803	119,038	-240,022	0,251666	128,223	244,426
SON4	0,976088	116,739	-279,845	0,361544	136,472	206,615
SON5	0,976357	118,915	-110,946	0,879726	14,81	-0,694468
SONR1	0,977239	115,933	-0,233745	0,429327	112,313	346,141
SONR2	0,98248	112,264	-0,219801	0,568396	305,558	374,155
SONR3	0,979049	114,666	-304,141	0,198805	$5,65567 \times 10^6$	329,265
SONR4	0,97543	117,199	-201,943	0,347455	395,883	336,704
SONR5	0,98344	113,248	-10,966	0,984069	34975,3	-320133
FOTN1	0,960071	0,923772	-0,0470769	0,473211	270,338	-259,159
FOTN2	0,954543	0,913218	0,145279	0,706416	223,577	-798,344
FOTN3	0,949843	0,904246	-0,165507	0,234208	108,849	-105,558
FOTN4	0,946678	0,898203	0,0645017	0,0599025	150,452	-923,527
FOTN5	0,957204	0,919442	-0,54116	0,552896	239,585	-798,499
FOTNR1	0,973303	0,949032	-265,44	0,952712	$6,80593 \times 10^6$	$-1,639 \times 10^{13}$
FOTNR2	0,976085	0,954344	-0,264565	0,514429	$1,19275 \times 10^6$	$-1,7734 \times 10^6$
~~FOTNR3~~	-0,977206	0,956485	-0,538231	0,487786	$1,56526 \times 10^6$	$-4,6926 \times 10^6$
FOTNR4	0,940882	0,887138	-0,743046	0,570448	$7,59114 \times 10^7$	$-2,7493 \times 10^8$
FOTNR5	0,93954	0,886193	-124,688	0,41942	$2,59067 \times 10^8$	$-6,9618 \times 10^7$
SOTN1	0,987677	100,439	-0,353635	0,962897	353,186	-412,456
SOTN2	0,976752	100,827	0,359297	0,516841	493,917	-345,314

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Table D.1. (cont.)

SOTN3	0,98181	100,647	-281,536	0,695345	412,616	-446,159
SOTN4	0,983304	100,594	-26,503	0,442634	363,242	-195,889
SOTN5	0,978297	100,789	-0,78679	0,886771	204,313	-402,138
SOTNR1	0,932588	102,399	-0,260311	-0,889261	676380	$-9,8609 \times 10^{6}$
SOTNR2	0,83888	105,735	0,0252322	-22,759	$1,63988 \times 10^{8}$	$-1,0031 \times 10^{7}$
SOTNR3	0,689166	111,064	-628,768	0,556463	$1,36491 \times 10^{12}$	-277526
SOTNR4	0,750534	108,879	-488,014	-391,384	$4,59624 \times 10^{12}$	$-2,6072 \times 10^{6}$
SOTNR5	0,810224	106,901	-720,538	0,627188	$2,22612 \times 10^{7}$	$-1,689 \times 10^{13}$
FOLN1	0,958855	0,944848	0,236239	0,500062	961,407	343,263
FOLN2	0,950672	0,933879	0,478239	0,676976	107,163	315,374
FOLN3	0,948645	0,931162	-0,157262	0,156097	109,043	306,556
FOLN4	0,945018	0,926301	0,112366	0,0142752	109,374	28,382
FOLN5	0,952843	0,937124	0,057237	0,554257	107,834	271,416
FOLNR1	0,964968	0,953042	0,258171	0,527377	110,364	371,657
FOLNR2	0,972445	0,963064	-0,145237	0,50538	941,668	286,749
FOLNR3	0,968374	0,957608	-208,373	0,0200497	187,592	319,728
FOLNR4	0,96558	0,953862	-268,929	0,201171	196,228	354,807
FOLNR5	0,973398	0,964531	-0,484978	0,976369	162,153	-0,290539
SOLN1	0,980044	113,969	-0,728693	0,597001	141,605	-250,013
SOLN2	0,976484	116,461	-0,12512	0,514183	139,802	317,716
SOLN3	0,973489	118,558	-257,195	0,328712	149,335	237,645
SOLN4	0,975699	117,011	-264,534	0,364935	134,209	203,496
SOLN5	0,97652	118,784	-11,549	0,883115	149,578	207,556
SOLNR1	0,977239	115,933	-0,233745	0,429327	112,313	346,141
SOLNR2	0,98248	112,264	-0,219801	0,568396	305,558	374,155
SOLNR3	0,979049	114,666	-304,141	0,198805	$5,65567 \times 10^{6}$	329,265
SOLNR4	0,97543	117,199	-201,943	0,347455	395,883	336,704
SOLNR5	0,98344	113,248	-10,966	0,984069	34975,3	-320133