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Process Parameters Optimization in Plastic Manufacturing Industry using Machine Learning

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Abstract: This research is aimed at optimizing the process parameters in plastic manufacturing industry using machine learning. Taguchi L27 orthogonal array was employed in the design of experiments and small-the-better signal to noise ratio was used in the analysis of volumetric shrinkage variation (VSV) of the plastic tray. The analysis of variance (ANOVA) was used to determine the significant parameters affecting VSV of the product. Artificial neural network (ANN) was employed in optimization of the machine process parameters settings and prediction of the quality characteristic. The results showed that the optimal VSV occurred at mould temperature of 44^0C, melt temperature of 210^0C, holding pressure of 41MPa, injection time of 6 seconds, and packing time of 8 seconds. The ANOVA results showed that the mould temperature was the dominant factor influencing VSV of the plastic product. The optimization of the machine process parameters and quality characteristic using ANN model reduced the shrinkage value of the product by 29.9%. This study concludes that the optimal process parameters settings determined using ANN are better than the settings being used in the industry.

Key words: Plastics Injection moulding, Process parameters, Volumetric shrinkage variation, Optimization, Machine learning, Artificial neural network

INTRODUCTION

Plastic injection moulding is one of the well-known shape forming manufacturing process that is able to produce large quantities of plastic parts of complex shapes and sizes requiring precise dimensions in short time at low cost. The several processes involved in plastics injection moulding includes: plasticizing, injection, packing, cooling and ejection. The desired shape of the molten plastic product is formed by the mould upon solidification. The dimensional and the physical characteristics of the plastic product are affected by the mould temperature, melt temperature, injection speed, packing pressure and inhomogeneous cooling under packing process (Behrooz et al., 2011). Also, the plastic injection moulding requires adequate knowledge of the mould design, the polymer types and the requirements of the process parameters for producing a low cost product. Inappropriate material selection, wrong process parameters settings, poor part and mould designs can affect the quality of plastic products.

Several defects that frequently occur in the plastic injection moulding process include warpage, shrinkage, sink marks, and weld lines (Mohammad et al., 2013). To avoid the high costs and time delays associated with the above problems, it is necessary to consider the combined effects of part geometry, material characteristics, mould design and processing conditions on the manufacturability of a part. The manufacturing process parameters of the plastic injection moulding machine predominantly affect the quality of the plastic product during the production (Fei et al., 2011; Cirak, 2014). Final optimal process parameter setting of the machine is recognized as one of the most important steps in injection moulding for improving the quality of moulded products (Jaafar et al., 2020).

The process parameters of the plastic injection moulding machine such as the mould temperature melt temperature, injection pressure, cooling temperature, cooling time, screw speed, packing pressure or holding pressure, packing time, cycle time, filling time or injection time and injection speed have been found to have effects on the quality characteristics of the plastic products (Behrooz et al., 2011). Product and process quality is playing an increasingly important role in the competitive success of manufacturing companies. As a consequence, this trend forces manufacturing companies to further improve their production (Wuest et al., 2014). If an industrial process is more precise, less scrap is produced or even a higher tolerance class can be achieved and the produced components can generate more profit for the company. The appropriate and prompt selection of process parameters in manufacturing processes plays a significant role in ensuring the quality of the product, reducing the machining cost and in increasing the productivity of the process (Mohammad et al., 2013). In practice, the adjustment of process parameters to get dimensions of a produced part in predefined tolerances can be a difficult task. Often times, it requires of machine learning techniques to be able to successfully determine the optimum process parameters settings that can optimize the quality characteristics of products.

In this study, machine learning was employed to minimize volumetric shrinkage of plastic try produced through injection moulding process. This study aimed at optimizing process parameters in plastic manufacturing industry using machine learning. The following objectives were pursued: (a) to determine optimum process parameters for the production of plastic tray; (b) to assess the relationship between the quality characteristic and each of the process parameters; and (3) to optimize and predict the volumetric shrinkage using artificial neural network. The modelling of the plastic injection machine was done with SOLIDWORKS computer aided design (CAD) software. ANSYS finite element analysis (FEA) software was employed in simulation of the plastic injection moulding process. Artificial neural network was employed in optimization of the quality characteristic of the product. This study is significant as the outcome would enhance the quality of the product, increase productivity and reduce the cost of production in the selected industry.

2. Review of Related Literature

A continuously increasing number of commercial plastic products are produced by plastic injection moulding process using plastic injection moulding machine, which is among the most widely used equipment in the plastic manufacturing industry. As plastic parts with more stringent quality specifications are produced for more applications, intelligent methods of increasing the volume of produced plastic products while improving product quality are needed. Many studies have been carried out on the optimization of process parameters and quality characteristics of injected plastic products using many optimization tools. For instance, Martina et al. (2021) applied machine learning technique for optimization of energy and plastic material consumption in the production of thermoplastic parts in small and medium scale (SME) industries. The essence was to investigate the extent machine learning can contribute to energy and material optimization in plastic parts processing in SMEs. The results revealed that machine learning can successfully aid in optimization of energy and material consumption.

Bekir (2017) studied the effects of process parameters on plastic made of polyvinyl chloride material using artificial neural network. The quality characteristic to be optimized was the shrinkage of the moulded parts. An ANN model was developed to map the complex nonlinear relationship between process parameters and volumetric shrinkage variation of the moulded parts using a Levenberg Marquardt algorithm. The results showed that the shrinkage ratios obtained from ANN model was in agreement with those obtained using inline processes. ANN model was able to improve the volumetric shrinkage variation of the parts produced. The study concluded that ANN model is an effective tool for the process optimization of injection moulding. Anand and Sunil (2015) applied Taguchi method in optimization of process parameters of an injection moulding machine for polypropylene material. The purpose of the study was to determine the optimal process parameters settings that can increase productivity, improve the quality and reduce the cost of production in plastic injection moulding industry. The study utilized Taguchi robust design method to design and carry out experiments. The results showed that the optimal process parameter settings for the polypropylene material were obtained using Taguchi method.

Ashwani and Deepak (2018) reviewed recent works on various methods of optimization of process parameters in plastic injection. The following approaches or optimization techniques were reviewed: mathematical modelling, Taguchi method, Artificial Neural Networks (ANN), Fuzzy logic, genetic algorithms (GA), finite element method (FEM), nonlinear modelling, Response surface methodology, linear regression analysis, grey relational analysis and principle component analysis (PCA). The study discussed the strength and the weakness of each approach in determining the optimal process parameters in injection moulding process. Olga and Kristian (2018) reviewed monitoring and control system for thermoplastics injection moulding and application of artificial intelligence (AI) in the system. The study, having reviewed recent works on monitoring and control in injection moulding using AI, observed and explained that application of AI methods can be very beneficial in increasing controllability of the process.

Ihueze et al. (2023a) utilized Taguchi robust design method to determine the optimal process and material parameters for an electrical cable insulation company. The quality characteristics of interest in the cable insulation extrusion process were relative density and tensile strength. The study applied L18 and L9 orthogonal arrays to conduct production experiments for optimal materials parameters and machine process parameters settings respectively. The results showed that the optimum control factors levels that minimized variability in the cable insulation manufacturing process were determined using Taguchi robust design method. The study concluded from its findings that Taguchi robust design is a powerful tool that can improve the product quality, reduce product costs and achieve significant economic benefits in the manufacturing sector. Ayokunle et al. (2020) utilized the artificial neural network in determining the extrusion process parameters settings in another Nigerian cable manufacturing industry. The study concluded that the use of ANN to predict the extrusion process parameters is better than the conventional techniques which is expensive and time-consuming.

Jaafar et al. (2020) studied volumetric shrinkage of plastic food container made from an injection moulding process. The study integrated Moldflow and statistical technique to minimize the volumetric shrinkage of the butter tub. Moldflow was used to simulate the plastic filling of the single cavity mould of butter tub based on the Taguchi's L9 orthogonal array. In addition, ANOVA was applied to investigate significant impact of the process parameters on the quality of the butter tub. The results showed that the optimal process parameters that minimized the volumetric shrinkage were obtained. The melt temperature and the mould temperature were found from the ANOVA result to be the most significant parameters.

Chihun et al. (2020) combined an artificial neural network and a random search to develop a system to recommend process conditions for injection moulding process. To develop a recommender system, random search was conducted using the trained ANN model. A user interface system was also developed, which can be used directly with the injection-moulding machine. The method enabled the setting of process conditions that yielded parts whose weights were close to the target, considering only the geometry and target weight. Wen-Chin et al. (2018) proposed an intelligent manufacturing system (IMS) for injection moulding process. The IMS composed of three subsystems: a multiple response optimization systems of plastic injection moulding (PIM), a database management system of process parameters, and a PIM real-time monitoring and control system. The study concluded that the proposed PIM intelligent manufacturing systems enabled the functions of real-time monitoring, process parameter optimization and database management. The system can assure better PIM product quality, yield rate, effectively reduce the manufacturing cost, and promote healthy competition among the PIM industries in the future.

Párizs et al. (2022) utilized four machine learning algorithms – k-nearest neighbour, naïve Bayes, linear discriminant analysis and decision trees in predicting the quality of multi-cavity injection molding. Their results showed that all the machine learning algorithms examined adequately predicted the quality characteristics even with a very little training data. The decision tree was found to be the most accurate among the examined algorithms. Wang et al. (2023) established a machine learning based process window for injection molding product quality assessment. The study utilized a random forest and regression to predict the product quality with 100% prediction accuracy. Ma et al. (2023) utilized CAE simulation, process window and machine learning to design an intelligent recommendation system for optimizing the injection molding process parameters. Mould temperature, melt temperature, injection speed, packing time and packing pressure were the injection process parameters considered and the weight of the product was the quality characteristic optimized. The result showed that the model achieved 99.7% prediction accuracy when validated with the real production. The study concluded that their recommendation system has a significant application value in reducing production costs and cycle time, as it can provide initial injection process parameter suggestions solely through the mould's data.

Reddy et al. (2017) applied Taguchi method and ANOVA in selection of the optimal process parameter settings that would optimize the tensile strength and hardness of injection moulded fly ash reinforced linear low density polyethylene. The process parameters considered were melt temperature, cooling time, injection speed and injection pressure. The ANOVA result showed that the melt temperature was the most significant parameter affecting the tensile strength of the cylindrical rod while injection speed was insignificant. Mohammed et al. (2023) presented a hybrid optimization approach for intelligent manufacturing in plastic injection moulding. The study focused on global optimization of process parameters to ensure high-quality products while reducing cycle time, material waste and energy consumption. The process parameters considered were melt temperature, injection velocity, injection pressure, holding time and cooling time. The hybrid approach combines artificial neural network and genetic algorithm, and employed a multi-objective optimization model based on the design of experiments. The results showed that hybrid approach efficiently adjusted process parameters to meet quality standards, significantly reducing raw material consumption (2%), cycle time (12%) and energy consumption (16%).

Kapoor and Kumar (2016) studied optimization of the shrinkage in injection molding of 40% glass filled nylon 66 using response surface methodology and genetic algorithm. The process parameters optimized were mould temperature, packing pressure, packing time and cooling. The results showed that the optimal process parameters settings, which reduced the shrinkage by 34.783% were established. From the existing literature, many works have been carried out in the determination of optimum process parameters settings and optimization of quality characteristics of injection moulding process using machine learning. The process parameters levels obtained are usually unique, not generic. The optimum process parameter settings obtained for product A may not be useful for product B. The optimum settings that worked for one machine/material may not work effectively in another machine/material or for another quality characteristic. Hence, this study intends to optimize the process parameters for the production of polyvinyl chloride plastic tray using machine learning.

3. Materials and Methods

3.1 Material

In this study, the polyvinyl chloride material was considered. The relevant data of the appropriate process parameters settings as well as the datasheet of the PVC plastic material was obtained from the plastic manufacturing industry (Oasis Preform Synergy Limited). The company was selected based on their capability to produce high-quality plastic products and its easy accessibility. Figure 1 shows the plastic injection moulding machine (Nissei NEX1000) used in the production in Oasis Preform Synergy Ltd.

Figure 1: Plastic Injection Moulding Machine (Nissei NEX1000).

3.2 Taguchi Design of Experiments

Taguchi's robust design provides a powerful and efficient method for designing products and process that operate consistently and optimally over a variety of conditions. The primary goal is to find factor settings that minimize response variation. The product quality of injection molding is significantly affected by various process parameters, such as melt temperature, mould temperature, packing pressure and packing time (Xu et al., 2022; Wang et al., 2022). In order to select the process parameters used in this study, the operating manual of the machine was consulted after reviewing related literature. According to Ihueze et al. (2023a), a thorough understanding of the process parameters including the minimum, the maximum and the current values of the process parameter levels should be ensured before selection of process parameters to be used in Taguchi robust design. Having understood the likely process parameters that can affect the product from the machine manual, and their minimum, maximum and current values, some parameters were initially selected. The screening of the process parameters and their levels and few experimental trials were made before the final selection of the process parameters and their levels. In order to properly reveal a nonlinear effect of the process parameters on the quality characteristics, three levels of each of the process parameters were chosen (Hamzaçebi, 2020). The mould temperature, melt temperature, holding pressure, packing time and injection time were selected as the input parameters in this study. Table 1 shows the process parameters and their levels selected for this study.

Table 1: Input Process Parameters with their Various Levels

Process Parameters	Symbol	Unit	Level 1	Level 2	Level 3
Melt temperature	ME	^{0}C	170	190	210
Mould temperature	MD	^{0}C	44	54	64
Injection time	IT	seconds	5	6	7
Holding pressure	HP	MPa	38	41	44
Packing time	PT	seconds	8	11	15

In the use of Taguchi robust design method for the design of experiments, two vital tools utilized are: (1) orthogonal array (OA), which accommodates many design factors simultaneously; and (2) signal to noise ratio (SNR), which measures quality with emphasis on variation (Taguchi et al., 2004). L27 orthogonal array, as shown in Table 2, was employed in the design of experiments based on the number of selected process parameters and their levels.

Table 2: L27 Orthogonal Array in Coded Unit

Experiment No.	Process Parameters				
	ME	MD	IT	HP	PT
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	2	3	1
11	2	1	2	3	2
12	2	1	2	3	3
13	2	2	3	1	1
14	2	2	3	1	2
15	2	2	3	1	3
16	2	3	1	2	1
17	2	3	1	2	2
18	2	3	1	2	3
19	3	1	3	2	1
20	3	1	3	2	2
21	3	1	3	2	3
22	3	2	1	3	1
23	3	2	1	3	2
24	3	2	1	3	3
25	3	3	2	1	1
26	3	3	2	1	2
27	3	3	2	1	3

The Taguchi method uses the SNR to measure the quality characteristic deviating from the desired value. The SNR acts as the objective function for optimization (Ihueze et al., 2023b). The most common Taguchi SNR are smaller-the-better, larger-the-better and nominal-the-best (Chen & Kurniawan, 2014; Ihueze et al., 2023a). The SNRs are expressed as (Dieter 2000).

Nominal is the best:

$$SNR_n = 10\ log\left(\frac{\bar{y}^2}{s^2}\right) \quad (1)$$

Smaller the better:

$$SNR_s = -10\ log\left(\frac{1}{n}\sum y_i{}^2\right) \quad (2)$$

Larger the better:

$$SNR_l = -10log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i{}^2}\right) \quad (3)$$

Where: y is the response observed; $\bar{y}$ is the mean response; n is the number of experimental trials and S is the standard deviation.

For proper analysis of the data and arriving at the optimal results, the appropriate SNR ratio must be chosen (Madu et al., 2024). In this study, the critical response of interest to be minimized is the volumetric shrinkage. The volumetric shrinkage of plastic product is a defect which needs to be eliminated or be as minimal as possible in plastic manufacturing. Hence, the smaller the better SNR, required to make the system response as small as possible, shown in equation (2) was selected for the analysis of the data.

3.5 Data Collection and Analysis

The purpose of this study is to model and optimize the process parameters in plastic injection moulding machine using artificial neural network (ANN) for quality and productivity improvement of plastic products. Data of the process condition, injection moulding machine specifications as well as properties of the plastic material including the density, molar mass, boiling point, melting point, thermal conductivity and heat capacity were obtained from secondary data sources (extant literatures, journal and publications reviewed) and encoded into a computer aided design (CAD) software known as Solidworks to model the process and simulated using ANSYS Finite element modelling (FEM) software. Figure 2 shows the flow chart for ANSYS finite element simulation. After modelling and simulating the plastic process, the model was combined with the artificial neural network (ANN) and analyzed. Experimentally, volumetric shrinkage variation output parameters were measured for different processing conditions. An empirical model was used decide the shrinkages of plastic polymers in the injection process.

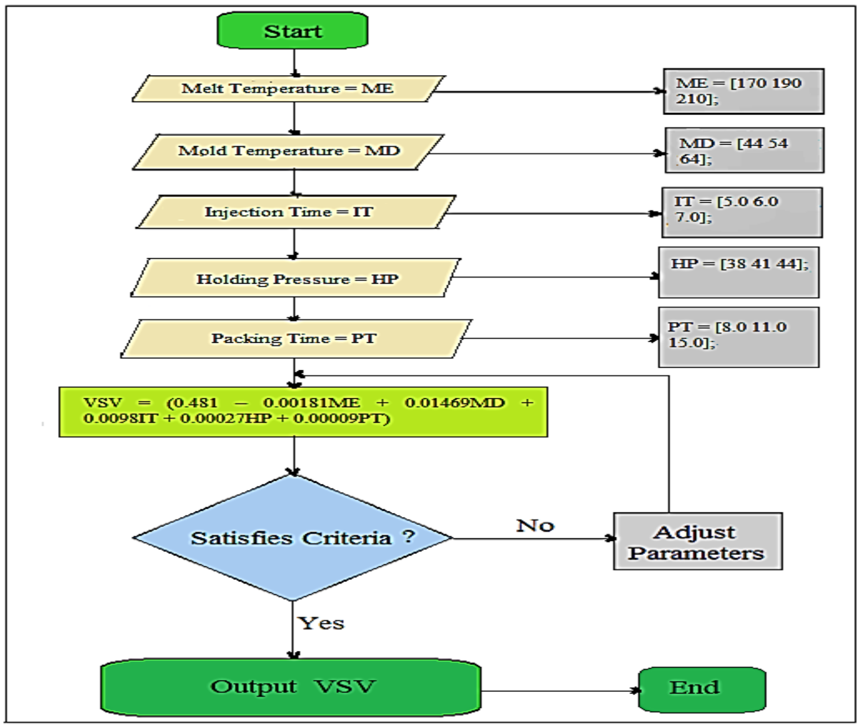

Figure 2: Flow chart for ANSYS Finite Element Modelling (FEM) of the Volumetric Shrinkage Variation (VSV) of Plastic Tray Specimen

3.5.1 Artificial Neural Network (ANN)

In this study, the ANN model was developed in MATLAB environment. Figure 3 shows the schematic diagram of the artificial neural network model. The neural network consisted of five (5) input layers, seven (7) hidden layers, and one (1) output layer. The input parameters consisted of the process parameter training datasets and the testing dataset as obtained from Indorama Plastic Company's PVC material datasheet. These parameters are the mould temperature (T_{mould}), melt temperature (T_{melt}), holding pressure (p_{hold}), packing time (t_{pack}) and injection time ($t_{injection}$). The output parameters of the model consist of the volumetric shrinkage variation (VSV). The training algorithm utilized in this study was the Levenberg Marquardt algorithm.

ANN method, a Levenberg Marquardt algorithm neural network model, was applied to map the complex nonlinear relationship between process conditions of the injection moulded parts and ANN model. This method was used in the process optimization for an industrial part in order to improve the volumetric shrinkage variation in the part. The simulations and calculations of the algorithms were done in MATLAB Packaged Program Environment which is especially suitable for controlling these types of systems.

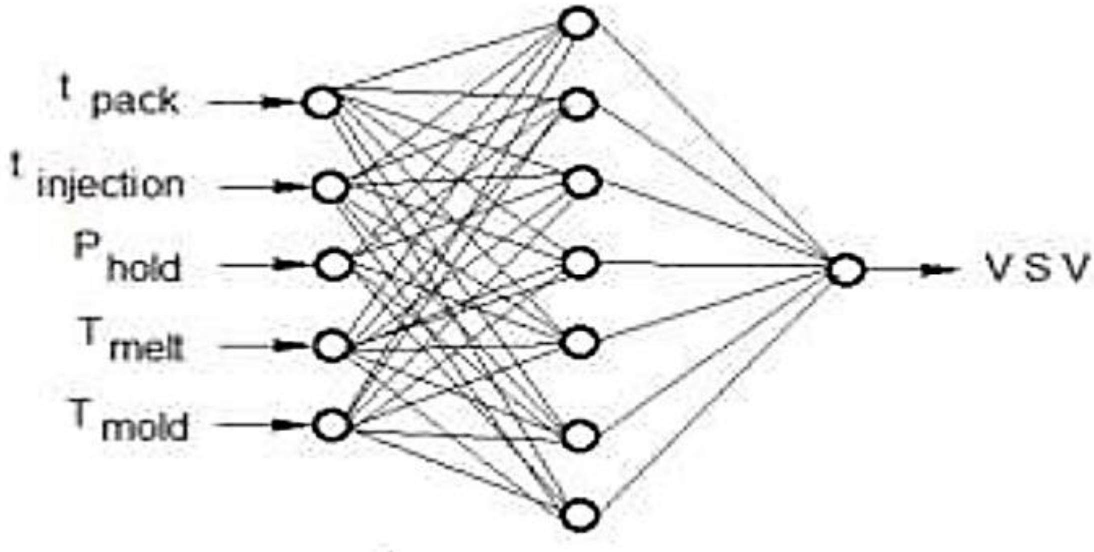

Figure 3: Schematic Diagram of the Neural Network Model

4. Results and Discussion

The small plastic tray was used for this research which has the problem of shrinkage of material at the corner of the part. The problem of shrinkage occurred due to uneven packing of the part. The small plastic tray was made of Polyvinyl Chloride (PVC). The volumetric shrinkage variation was influenced by the process parameters: mould temperature, melt temperature, holding pressure, packing time and injection time. Those parameters that had significant influences on the volumetric shrinkage variation were identified by the Taguchi DOE technique. In this work, simulation based on the Taguchi robust design method was performed by utilizing the ANSYS and MATLAB software to estimate the influence of the process parameters on the volumetric shrinkage variation (VSV) of the PVC tray. The objective was a minimum VSV. Artificial Neural Network (ANN) was used to determine the optimal process parameters that minimized volumetric shrinkage defects for productivity and quality product.

4.1 Volumetric Shrinkage Variation (VSV) Analysis

Twenty-seven (27) 3D simulation models were performed using the selected input plastic moulding process parameters based on Taguchi L27 orthogonal array. Following the L27 orthogonal array, twenty-seven (27) experimental runs were conducted and the corresponding VSV output was evaluated by Taguchi robust design method. Table 3 shows the modelling and simulation results of the volumetric shrinkage variation (VSV) on the plastic tray specimens.

Table 3: Results of L27 Orthogonal Array Experiments for Volumetric Shrinkage Variation of the Plastic Tray

Experiment No.	ME	MD	IT	HP	PT	Volumetric Shrinkage Variation (VSV)
1	170	44	5	38	8	0.87964
2	170	44	5	38	11	0.87991
3	170	44	5	38	15	0.88027
4	170	54	6	41	8	1.03715
5	170	54	6	41	11	1.03742
6	170	54	6	41	15	1.03778
7	170	64	6	44	8	1.18486
8	170	64	7	44	11	1.19493
9	170	64	7	44	15	1.19511
10	190	44	7	38	8	0.86385
11	190	44	7	38	11	0.86412
12	190	44	7	38	15	0.86448
13	190	54	5	41	8	0.99196
14	190	54	5	41	11	0.99223
15	190	54	5	41	15	0.99259
16	190	64	6	38	8	1.14704
17	190	64	6	38	11	1.14731
18	190	64	6	38	15	1.14749
19	210	44	6	41	8	0.81866
20	210	44	6	41	11	0.81893
21	210	44	6	41	15	0.81929
22	210	54	7	38	8	0.97374
23	210	54	7	38	11	0.97401
24	210	54	7	38	15	0.97437
25	210	64	5	41	8	1.10185
26	210	64	5	41	11	1.10212
27	210	64	5	41	15	1.10248

Figure 4 reveals the results of the volumetric shrinkage variations on the plastic tray specimens for the twenty-seven (27) runs of experiments. The figure shows that the 9^{th} experiment (melt temperature 170°C, mould temperature 64°C, injection time 7 seconds, holding pressure 44MPa and Packing time 15 seconds) produced the greatest volumetric shrinkage variations at 1.19511. While the 19^{th} experiment had the lowest volumetric shrinkage variations at 0.81866 with process parameters (melt temperature 210°C, mould temperature 44°C, injection time 6 seconds, holding pressure 41MPa and Packing time 8 seconds) on plastic part. This result is in agreement with results gotten from previous studies (Ayokunle et al., 2020; Jaafar et al., 2020).

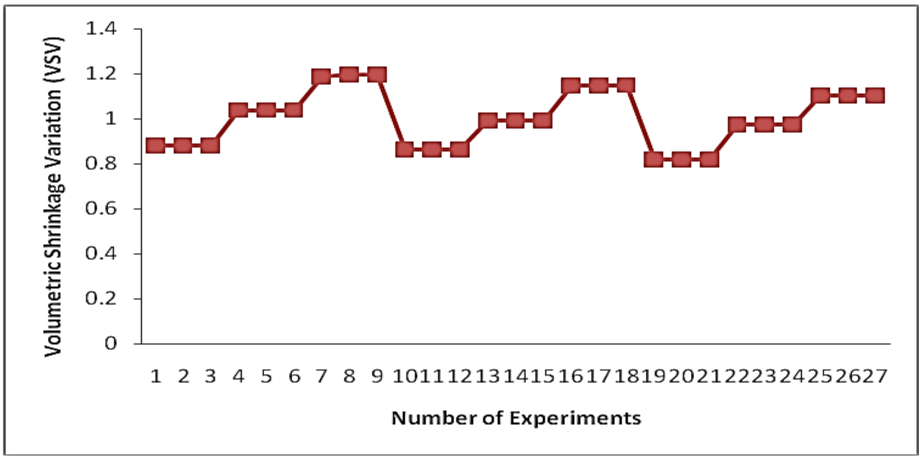

Figure 4: Volumetric Shrinkage Variation (VSV) at different Experiment Runs

Figure 5 depicts the main effect plot for smaller-the-better S/N ratio of the volumetric shrinkage variation (VSV). Based on the results observed from the graphical plots for S/N ratio on the volumetric shrinkage variation, the optimal machining parameters that produce minimum value of volumetric shrinkage variation are ME3MD1IT1HP3PT1. That is: melt temperature 210ºC, mould temperature 44ºC, injection time 6 seconds, holding pressure 44MPa and Packing time 8 seconds.

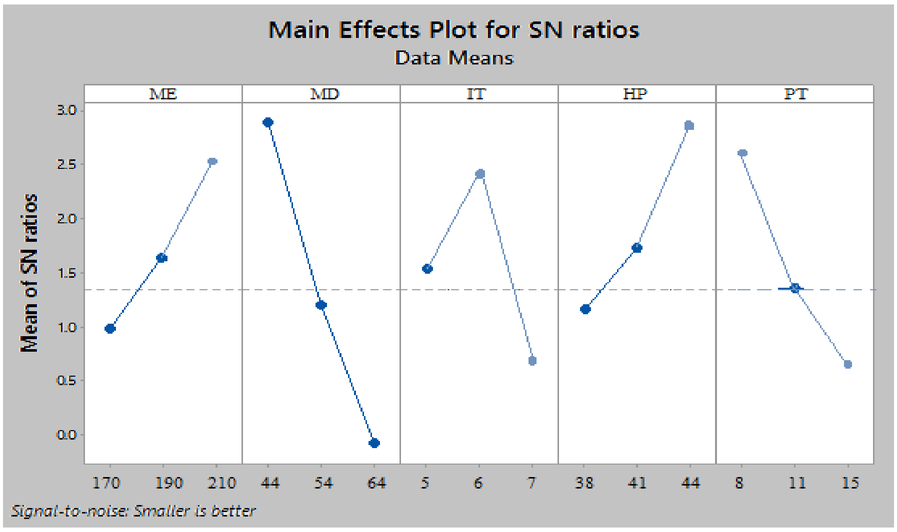

Figure 5: The S/N ratio for Volumetric Shrinkage Variation (VSV)

Table 4 shows the response table for the means of VSV for each level of the process parameters for the smaller the better quality characteristics. The delta (max-min) was computed for each parameter by finding the difference between the maximum and minimum mean values for that parameter. The higher the delta value for a parameter, the higher the effect of that parameter on the quality characteristics (Ihueze et al., 2023a). Figure 6 depicts the response plots of the volumetric shrinkage of the product. From the table and the figure, mould temperature, melt temperature, injection time, holding pressure and packing time were ranked 1st, 2nd, 3rd, 4th and 5th respectively. This shows that the mould temperature of the plastic specimen is the process parameter with the greatest contribution to VSV followed by the melt temperature, injection time and holding pressure while the packing time process parameter contributes the least to VSV.

Table 4: Response Table of Volumetric Shrinkage Variation (VSV)

Plastic Injection Process Parameters	Level 1	Level 2	Level 3	Delta (Max-Min)	Rank
ME	0.98342	1.63864	1.39499	0.65522	2
MD	2.89436	1.20513	-0.08244	2.97680	1
IT	1.16286	1.73707	1.11712	0.61996	3
HP	1.54295	1.03296	1.44114	0.51000	4
PT	1.34325	1.35548	1.21832	0.03716	5

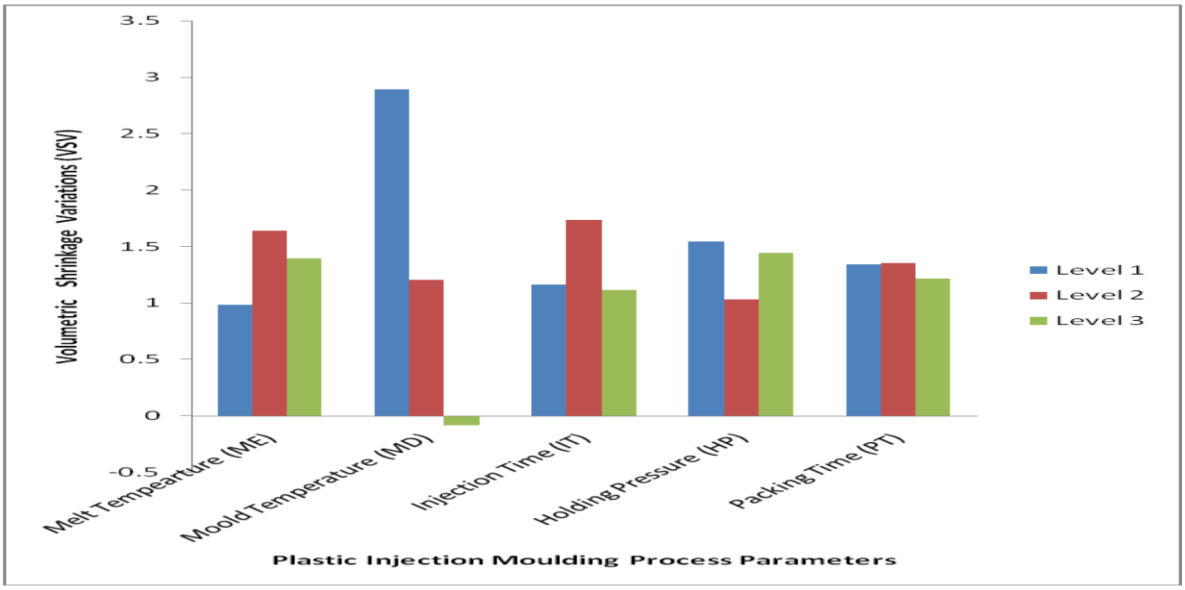

Figure 6: Response Plots of Volumetric Shrinkage Variations

Figure 7 shows the normal probability plots used to assess the normal distribution of the fitted data. It can be seen from figure 7 that the data points fitted lie on the straight line or are closer to the straight line which validates the normality distribution of the simulated data. The mean volumetric shrinkage variation (VSV) at each level of machining parameters was computed by taking arithmetic mean average of VSV at the selected level.

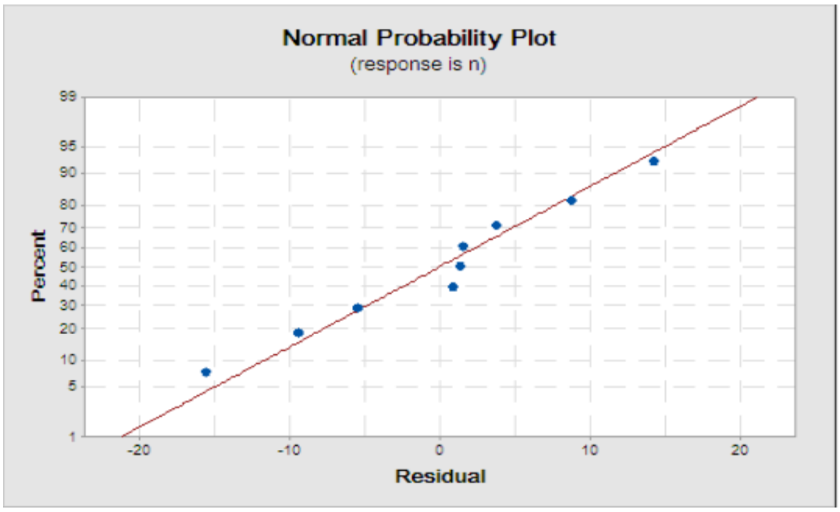

Figure 7: Normal Probability Plot of Volumetric Shrinkage Variation (VSV)

4.2 Relationship between Process Parameters and Volumetric Shrinkage Variation

The relationship between the volumetric shrinkage variation and the various process parameters used in this study was examined to ascertain the effect of each input parameter on the output response.

4.2.1 Relationship between Melt Temperature and Volumetric Shrinkage Variation (VSV)

Figure 8 reveals the results of the relationship between the melt temperature and the volumetric shrinkage variations in the moulded plastic part for the twenty-seven (27) experimental runs. The figure showed that there is a very weak relationship ($R^2 = 0.055$) between melt temperature and the volumetric shrinkage variations in the moulded plastic part for the 27 experimental runs. The figure shows a decreasing trend in the volumetric shrinkage of the moulded plastic part as a result of the increase in melt temperature. The trend model in the figure shows that increase in the melt temperature decreased the volumetric shrinkage of the product. The higher the melt temperature, the lesser the volumetric shrinkage variations induced on the moulded plastic part and vice versa. A weak R^2 value of 0.055 shows that the model did not explain a significant proportion of the variation in the dependent variable. Only 5.5% variation in the volumetric shrinkage was explained by the melt temperature.

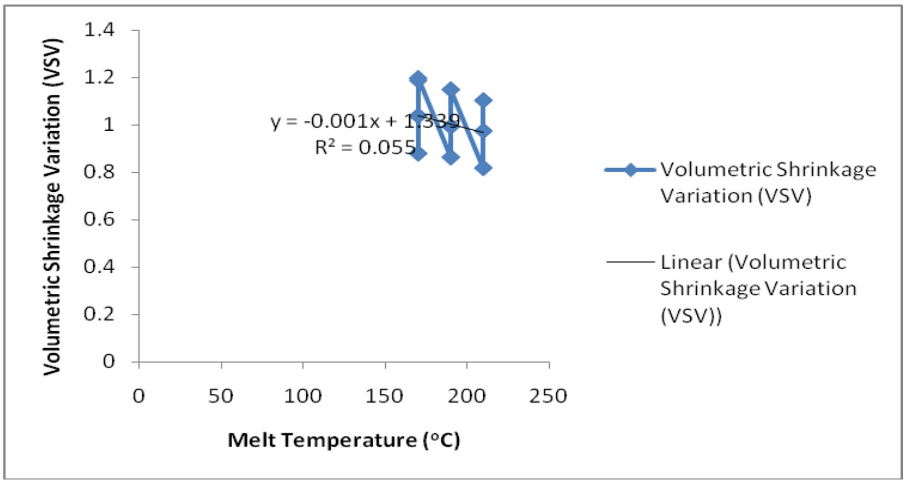

Figure 8: Melt Temperature and Volumetric Shrinkage Variation (VSV) at different Experimental Runs

4.2.2 Relationship between Mould Temperature and Volumetric Shrinkage Variation (VSV)

Figure 9 reveals the results of the relationship between the mould temperature and the volumetric shrinkage variations in the moulded plastic part for the twenty-seven experimental runs. The figure shows that there is a very strong relationship ($R^2 = 0.940$) between mould temperature and the volumetric shrinkage variations in the moulded plastic part for the 27 experimental runs. The figure shows an increasing trend in the volumetric shrinkage of the moulded plastic part as a result of the increase in the mould temperature. The trend model in the figure shows that increase in the mould temperature increased the volumetric shrinkage of the product. The higher the mould temperature, the higher the volumetric shrinkage variations induced on the moulded plastic part and vice versa. A strong positive R^2 value of 0.94 shows that the model explained a large proportion of the variation in the dependent variable. More than 94% of the variation in the volumetric shrinkage was explained by the mould temperature.

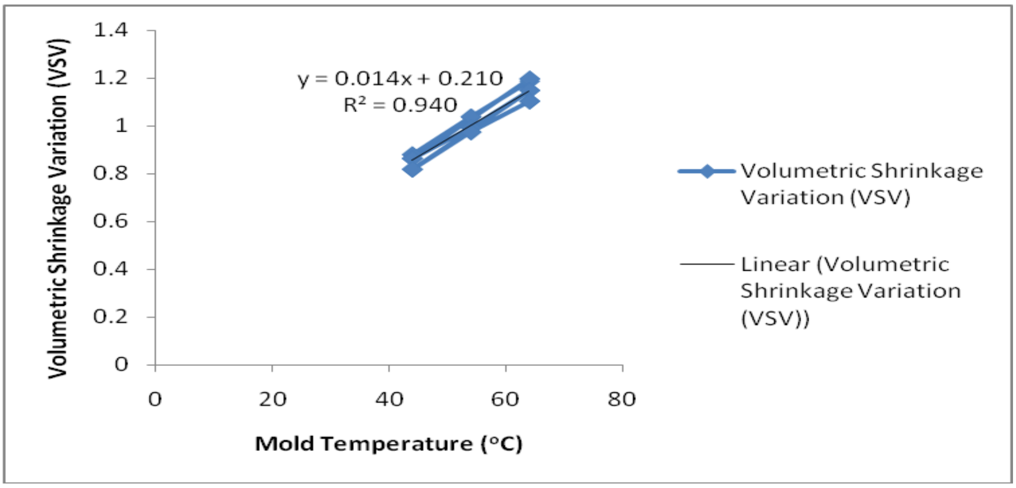

Figure 9: Mould Temperature and Volumetric Shrinkage Variation (VSV) at different Experimental Runs

4.2.3 Relationship between Injection Time and Volumetric Shrinkage Variation (VSV)

Figure 10 reveals the results of the relationship between the injection time and the volumetric shrinkage variations in the moulded plastic part for the twenty-seven experimental runs. The figure shows that there is a very weak relationship ($R^2 = 0.00004$) between injection time and the volumetric shrinkage variations in the moulded plastic part for the 27 experimental runs. The figure shows a decreasing trend in the volumetric shrinkage of the moulded plastic part as a result of the increase in the injection time. The trend model in the figure shows that increase in the injection time decreased the volumetric shrinkage of the product. The higher the injection time, the lesser the volumetric shrinkage variations induced on the moulded plastic part and vice versa. A weak R^2 value of 0.00004 shows that the model did not explain any significant proportion of the variation in the dependent variable. Only an insignificant 0.004% variation in the volumetric shrinkage was explained by the injection time.

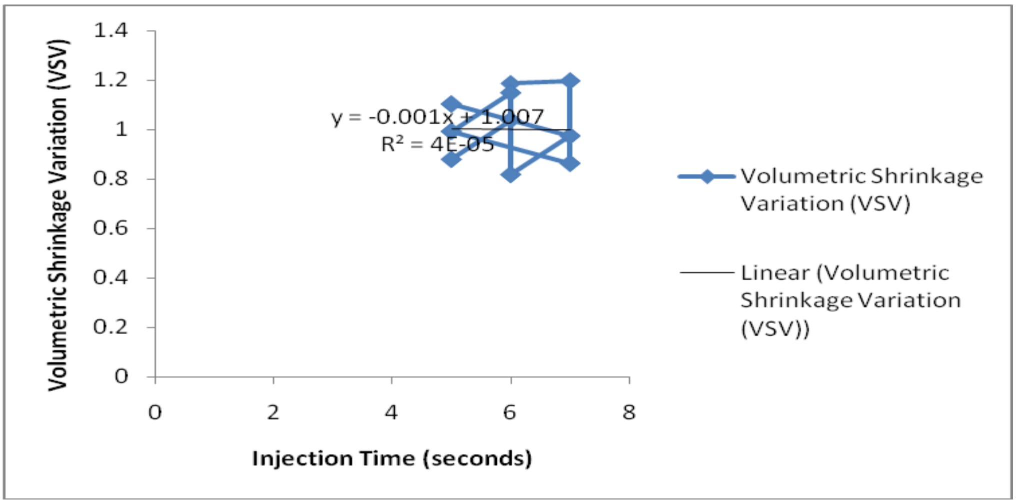

Figure 10: Injection Time and Volumetric Shrinkage Variation (VSV) at different Experimental Runs

4.2.4 Relationship between Holding Pressure and Volumetric Shrinkage Variation (VSV)

Figure 11 reveals the results of the relationship between the holding pressure and the volumetric shrinkage variations in the moulded plastic part for the twenty-seven experimental runs. The figure shows that there is a positive relationship ($R^2 = 0.197$) between holding pressure and the volumetric shrinkage variations in the moulded plastic part for the 27 experimental trials. The figure shows an increasing trend in the volumetric shrinkage of the moulded plastic part as a result of the increase in the holding pressure. The trend model in the figure shows that increase in the holding pressure increased the volumetric shrinkage of the product. The lesser the holding pressure, the lesser the volumetric shrinkage variations induced on the moulded plastic part and vice versa. A positive R^2 value of 0.196 shows that the model explained a small proportion of the variation in the dependent variable. More than 19.6% of the variation in the volumetric shrinkage was explained by the holding pressure.

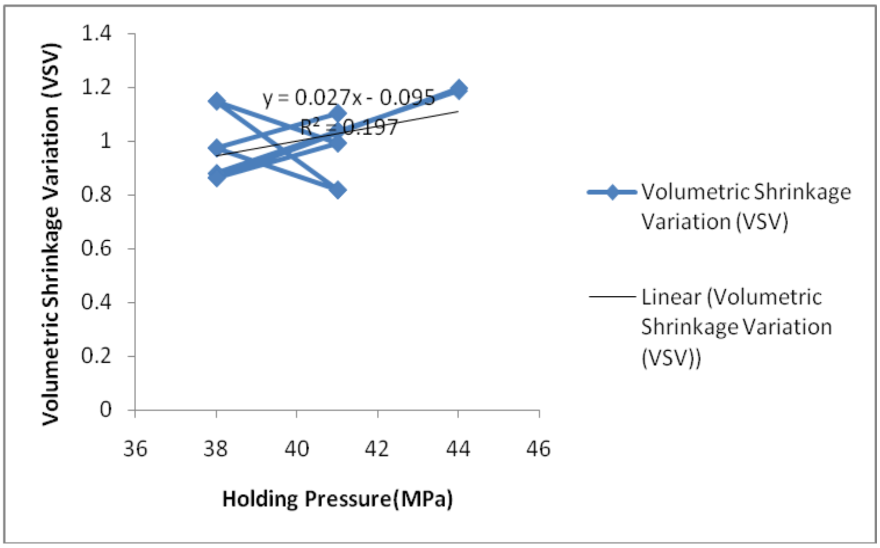

Figure 11: Holding Pressure and Volumetric Shrinkage Variation (VSV) at different Experiment Runs

4.2.5 Relationship between Packing Time (PT) and Volumetric Shrinkage Variation (VSV)

Figure 12 reveals the results of the relationship between the packing time and the volumetric shrinkage variations in the moulded plastic part for the twenty-seven (27) experimental runs. The figure shows that there is a very weak relationship (R^2 = 0.00003) between the packing time and the volumetric shrinkage variations in the moulded plastic part for the 27 runs of experiment. The figure shows a very poor increasing trend in the volumetric shrinkage of the moulded plastic part as a result of the increase in packing time. The trend model in the figure shows that decrease in the packing time decreased the volumetric shrinkage of the product. The lesser the packing time, the lesser the volumetric shrinkage variations induced on the moulded plastic part and vice versa. An insignificant value of R^2 (R^2 = 0.00003) shows that the model did not explain a significant proportion of the variation in the dependent variable. Only 0.003% variation in the volumetric shrinkage was explained by the packing time.

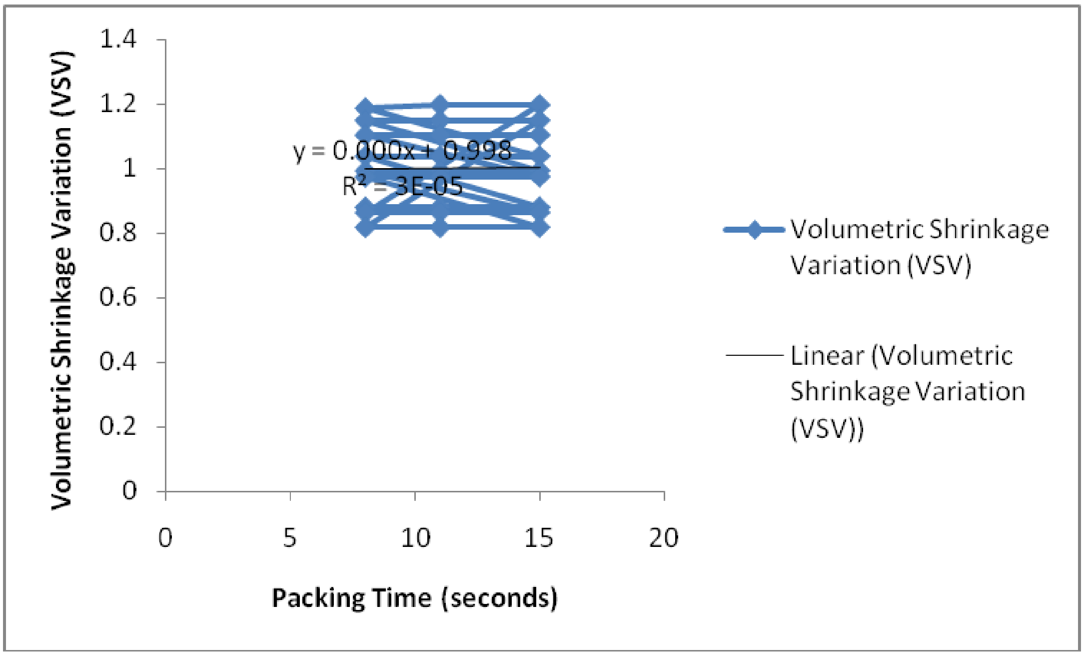

Figure 12: Packing Time and Volumetric Shrinkage Variation (VSV) at different Experiment Runs

4.3 Analysis of Variance (ANOVA) for Volumetric Shrinkage Variation (VSV)

Table 5 shows the ANOVA results for volumetric shrinkage variation with the contribution of each process parameter. The analysis was conducted at 95% confidence level. The p-value shows that melt temperature, mould temperature and holding pressure are the significant factors contributing to VSV of the product as their p-values are less than 0.05. The injection time with p-value of 0.061 and the packing time with p-value of 0.994 did not contribute significantly to the VSV of the product as their p-values are greater than 0.05. The percentage contribution of each parameter was also assessed for proper decision making. According to Ihueze et al. (2023b), percentage contribution is the ratio of pure sum of squares to the total sum of squares of each factor. Mould temperature is the most significant control factor with 80.5% contribution to the volumetric shrinkage of the product, followed by melt temperature with 4.89% contribution and holding pressure with 4.73% contribution. Injection time and packing time have very little influence 2.9% and 0.005% respectively on VSV of plastic tray. This shows that the mould temperature should be given utmost attention during the production of the product as the greater proportion of the volumetric shrinkage on the product was caused by the mould temperature. The optimum value of the mould temperature should be used in order to minimized the VSV of plastic tray. The percentage of the pooled error is 6.9%, showing that no significant factor was left out in the experiment. According to Jou et al. (2014) and Ihueze et al. (2023b), when the pooled error is less than or equal to 15%, no significant factor was left in the experiment and the factors in the pooled error terms could be neglected. F-value shows that all the variables (except packing time) are important, and their relationship with the response did not occur by chance.

Table 5: ANOVA Results for Volumetric Shrinkage Variation (VSV)

Factor	Df	SS	MS	F-Value	P-Value	% Contribution
Melt Temperature	**2**	0.023602	0.011801	5.61	0.014	4.89
Mold Temperature	2	0.388632	0.194316	92.40	0.000	80.5
Injection Time	2	0.014097	0.007049	3.35	0.061	2.9
Holding Pressure	2	0.022860	0.011430	5.44	0.016	4.73
Packing Time	2	0.000025	0.000012	0.01	0.994	0.005
Error	16	0.33646	0.002103			6.9
Total	26	0.482863				100.0

4.4 Optimization of Process Parameters Settings with Artificial Neural Network (ANN)

Artificial Neural network system was used to predict the shrinkage value for two sets of process parameters. One was the recommended setting provided by the Indorama Company and the other was the optimized process parameter setting from this study. Levenberg-Marquardt algorithm was used in this study because it is one of the most efficient training algorithms used in ANN. Levenberg-Marquardt is a robust, efficient and flexible algorithm, which can handle large datasets and a wide range of non-linear models (Ayokunle, 2020). The ANN training and the simulation of the process were done using MATLAB. The five input parameters - melt temperature, mould temperature, injection time, holding pressure and packing time, and one output parameter – volumetric shrinkage variation were used to simulate the ANN model in MATLAB package environment. The volumetric shrinkage from the experimental data was the target (expected) value while the output was the predicted value. Figures 13 and 14 show the artificial neural network training and simulation respectively done using MATLAB tool function. During the training and simulation, the ANN model converged to a stable solution after 500 epochs. 500 epochs were enough for training the ANN model, avoiding overfitting and underfitting of the model.

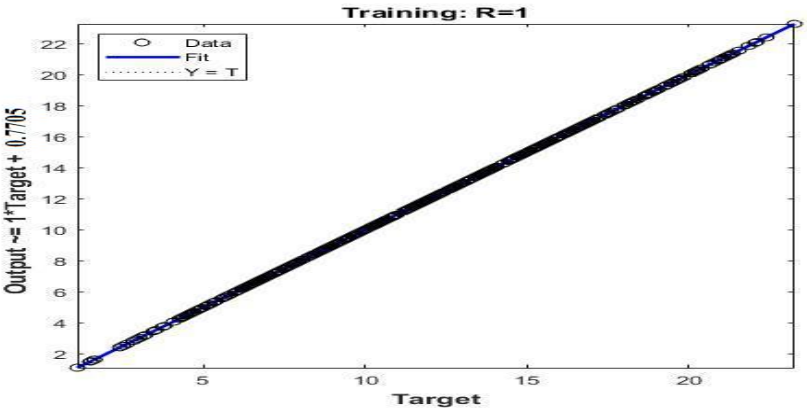

Figure 13: Artificial Neural Network Training

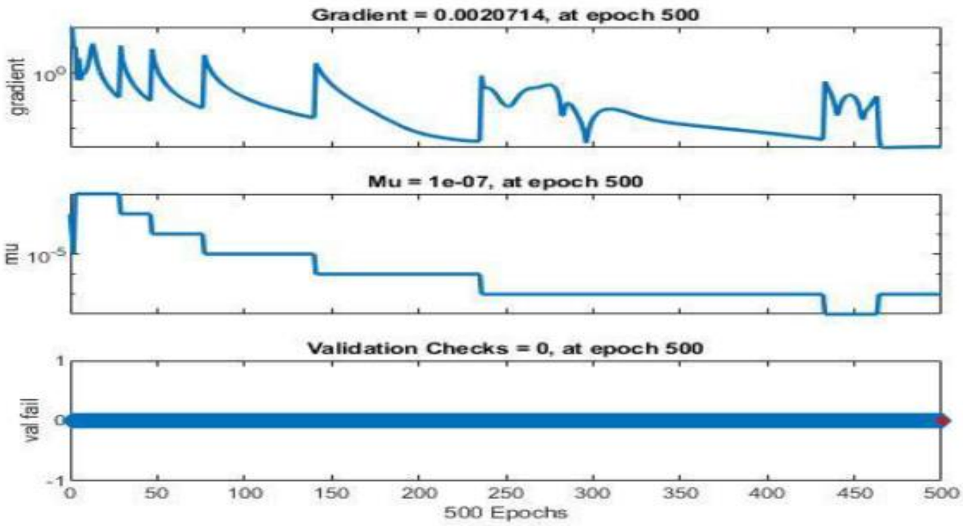

Figure 14: Artificial Neural Network Simulation

Table 6 compares the values of volumetric shrinkage obtained using the Indorama recommended settings and that of Taguchi design of experiments (DOE)' optimized process parameters settings for both simulated and ANN predictions. It was found that the predicted shrinkage values from both simulation and ANN for the DOE optimized process parameters setting are less than that for Indorama recommended process parameters setting. Using ANN method, the shrinkage value obtained in Oasis Preform Synergy Ltd recommended setting was reduced by 29.9% after optimization with mean square error (MSE) of 4.5196 x 10^{-8}. This shows that using DOE's optimized process parameters setting improved the quality characteristics of the product compared to the company recommended setting.

Table 6 Comparison of shrinkage values for design of experiment by Taguchi method

	ME	MD	IT	HP	PT	Simulated VSV	Artificial Neural Network
Indorama recommended settings	230	65	6	42	9	1.17019	1.17019
Optimized process settings	230	45	5	42	9	0.7546	0.7705

For Taguchi method, the shrinkage value obtained in Oasis Preform Synergy Ltd recommended setting is reduced by 29.9% after optimization with mean square error (MSE) of 4.5196 x 10^{-8}.

To be able to validate and evaluate the performance of the artificial neural network model developed, the mean square error (MSE) technique was utilized in this study. The values of the performance criteria must be as close to zero (0) as possible to indicate the high quality of the neural network model developed (Ayokunle et al., 2020). Figure 15 shows the ANN mean square error (MSE). From the figure, it can be confirmed that the ANN model developed is adequate and of a high quality.

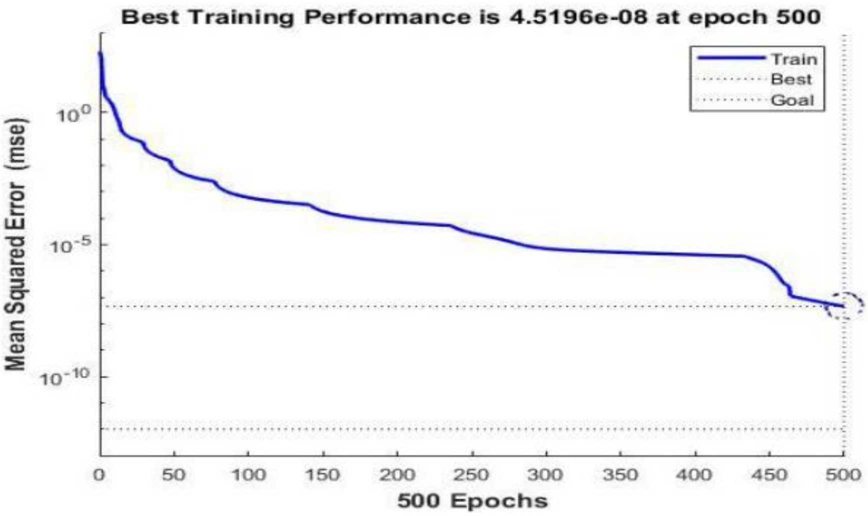

Figure 15: Artificial Neural Network Mean Square Error (MSE)

5. Conclusion

This study optimized the plastic injection moulding process parameters in Oasis Preform Synergy Ltd using machine learning. From the results and outcome of this study, the following conclusions were made:

i. A very strong positive relationship ($R^2 = 0.940$) exists between mould temperature and the volumetric shrinkage variations in the moulded plastic part as increase in the mould temperature increases the volumetric shrinkage variations induced on the moulded plastic part and vice versa.

ii. A weak positive relationship ($R^2 = 0.055$) exists between melt temperature and volumetric shrinkage variations in the moulded plastic part as with lesser melt temperature, lesser volumetric shrinkage variations induced on the moulded plastic part and vice versa. Similar weak positive relationship was also found for holding pressure ($R^2 = 0.197$), injection time ($R^2 = 0.00004$) and packing time ($R^2 = 0.00003$).

iii. The Taguchi design of experiments and the artificial neural network were used successfully to determine the optimal plastic production process parameters that minimized volumetric shrinkage defects.

iv. The optimal machine process parameters that optimized the volumetric shrinkage of the product were ME3MD1IT1HP3PT1 (melt temperature 210ºC, mould temperature 44ºC, injection time 6 seconds, holding pressure 44MPa and Packing time 8 seconds).

v. The ANOVA showed that mould temperature was more effective process parameter with effect of 80.5% followed by melt temperature and holding pressure with effect of 4.89% and 4.73% respectively

vi. The volumetric shrinkage variation was reduced by 29.9% after optimization when compared with the shrinkage value obtained in Oasis Preform Synergy Ltd recommended setting.

vii. The shrinkage value predicted by artificial neural network model for optimized process parameter setting is less than that obtained using recommended process parameters setting by Indorama company.

References

Anand, K.R.D. & Sunil, K. (2015). Practical application of Taguchi method for optimization of process parameters in Injection Moulding Machine for PP material. International Research Journal of Engineering and Technology, 2(4), 264-268.

Ashwani, K. & Deepak, K (2018). Optimization of Process Parameters in Injection-Moulding by Recent Methods for Optimization – Literature Review. International Journal of Management, Technology and Engineering, 8(5), 141-151.

Ayokunle, A., Ademola, A. & Lambe M. A. (2020). Predicting Extrusion Process Parameters in Nigeria Cable Manufacturing Industry using Artificial Neural Network. Advanced Materials Research, 2(2), 1-6.

Behrooz, F., Siavash, G. & Elyar, M. (2011). Optimization of Injection Moulding Process Parameters using Sequential Simplex Algorithm. Journal of Materials and Design, 32(2), 414-423.

Bekir, C. (2017). Determination of effecting process parameters with artificial neural network. Scholars Journal of Engineering and Technology, 5(9), 502-507.

Chen, W. C. & Kurniawan, D. (2014). Process Parameters Optimization for Multiple Quality Characteristics in Plastic Injection Moulding Using Taguchi Method, BPNN, GA, and Hybrid PSO-GA, Int. J. Precis. Eng. Manuf., 15(8), 1583–1593.

Chihun, L., Juwon, N., Kyongho, P., Hyeonjae, Y., Jongsun, K., Kwonil, C., Dongyong, P., Seongjin, P., Junsuk, R. & Seungchul, L. (2020). Development of Artificial Neural Network System to Recommend Process Conditions of Injection Moulding for Various Geometries.

Cirak, B. (2014). Analysis of Empirical Viscosity Models of Polymer Flow in PVC İnjection Process. Advances in Industrial Engineering and Management, 3(4), 19-24.

Dieter, G.E. (2000) Materials and Processing Approach Engineering Design, 3rd Edition. Mc Graw-Hill Informational, Singapore.

Fei, Y., Huajie, M., Lin, H., Wei, G. & Maosheng, S. (2011). Back Propagation Neural Network Modeling for Warpage Prediction and Optimization of Plastic Products during Injection Moulding. Materials and Design, 32, 1844–1850.

Hamzaçebi, C. (2020) Taguchi method as a robust design tool [Online]. Accessed on 8 August 2022, from https://www.researchgate.net/publication/347858318.

Ihueze, C.C., Onwurah, U.O., Okafor, C.E., Obuka, N.S., Okpala, C.C., Okoli, C.O., Nwankwo, C.O. & Kingsley-Omoyibo, Q.A. (2023a). Robust design and setting process and material parameters for electrical cable insulation. The International Journal of Advanced Manufacturing Technology, 126, 3887-3904. https://doi.org/10.1007/s00170-023-11359-4

Ihueze, C.C., Okoli, N.C., Onwurah, U.O., Okafor, C.E. & Kingsley-Omoyibo, Q.A. (2023b). Intelligent assessment of quality characteristics of miscanthus fiber reinforced polypropylene for sustainable products development Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering. http://doi.org.org/10.1177/09544089231167761.

Jaafar, R., Arep, H., Mohamad, E., Razak, J.A., Rahman, M.A.A. & Yuniarti, R. (2020). Analysis on Volumetric Shrinkage of Plastic Food Container Made from an Injection Moulding Process. J. Mater. Process. Technol., 12(3), 1–8.

Jou, W.T., Lin, Y.T., Lee, W.C. & Yeh, T.M. (2014). Integrating the Taguchi Method and Response Surface Methodology for Process Parameter Optimization of Injection Molding. Applied Mathematics and Information Sciences, 8, 3, 1277-1285.

Kapoor, A. & Kumar, D. (2016). Optimization of shrinkage in injection-molding of 40% glass filled nylon 66 using response surface methodology (RSM) and genetic algorithm (GA). International Journal of Engineering Development and Research, 4, 4, 188-193.

Ma, Y., Dang, K., Wang, X., Zhou, Y., Yan, W. & Xie, P. (2023). Intelligent recommendation system of injection molding process parameters based on CAE simulation, process window and machine learning. The International Journal of Advanced Manufacturing Technology. https://doi.org/10.1007/s00170-023-12264-6.

Madu, P.C., Onwurah, U.O**.** & Ihueze, C.C. (2024). Effect of sodium hydroxide treatment on the wear resistance of palm kernel shell particles reinforced polypropylene composite for piping applications. UNIZIK Journal of Engineering and Applied Sciences, 3(1), 430-445.

Martina, W., Jonas, S. & Volker, W. (2021). Machine Learning for Optimization of Energy and Plastic Consumption in the Production of Thermoplastic Parts in SME. Sustainability, 13, 6800. https://doi.org/10.3390/su13126800

Mohammad, S., Meiabadia, A. & Vafaeesefatb, F. S. (2013). Optimization of Plastic Injection Moulding Process by Combination of Artificial Neural Network and Genetic Algorithm. Journal of Optimization in Industrial Engineering 13(5), 49-54

Mohamed, E.G., Ahmed, M. & Redouane, M. (2023). A hybrid optimization approach for intelligent manufacturing in plastic injection molding by using artificial neural network and genetic algorithm Scientific Reports 13, 21817. https://doi.org/10.1038/s41598-023-48679-0

Olga, O. & Kristian, M. (2018). Monitoring and Control for Thermoplastics Injection Moulding- A Review. Materials and Design. 44(12), 414-423.

Pawar, P.J. & Rao, R.V. (2013). Parameter optimization of machining processes using teaching–learning-based optimization algorithm.” The International Journal of Advanced Manufacturing Technology, 67(5): 995– 1006. doi:10.1007/s00170-012-4524-2.

Párizs, R.D., Török, D., Ageyeva, T. & Kovács, J.G. (2022). Machine learning in injection molding: An industry 4.0 method of quality prediction. Sensors, 22, 2704, 1-18. https://doi.org/10.3390/s22072704.

Reddy, B.S., Arun, K. & Reddy, M.C.S. (2017). Optimization of process parameters on injection moulding machine with LLDPE reinforced flyash using Taguchi. International Journal of Advanced Engineering Research and Science, 5, 164-171. https://dx.doi.org/10.22161/ijaers/nctet.2017.me.2.

Taguchi, G., Chowdhury, S. & Wu, Y. (2004). Taguchi’s Quality Engineering Handbook, John Wiley & Sons.

Wang, Z.H., Wen, F.C., Li, Y.T. et al. (2023). A novel sensing feature extraction based on mould temperature and melt pressure for plastic injection moulding quality assessment. IEEE Sensors Journal, 23, 7, 7451-9.

Wang, B.W., Nian, S.C. & Huang, M.S. (2022). Strategies for adjusting process parameters in CAE simulation to meet real injection molding condition of screw positions and cavity pressure curves. The International of Advanced Manufacturing Technology, 122 (3-4), 1339-51.

Wen-Chin, C., Manh-Hung, N., & Pei-Hao, T. (2018). An Intelligent Manufacturing System for Injection Moulding. Proceedings of Engineering and Technology Innovation, 8(2), 09 – 14

Wuest, T., Christopher, I. & Klaus-Dieter, T. (2014). An approach to monitoring quality in manufacturing using supervised machine learning on product state data. Journal of Intelligent Manufacturing, 25 (5): 1167–80. doi:10.1007/s10845- 013-0761-y.

Xu, Y., Xie, P., Fu, N. et al. (2022). Self-optimization of the V/P switchover and packing pressure for online viscosity compensation during injection molding. Polymer Engineering & Science, 62(4), 1114-23.