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Optimizing injection molding parameters to minimize and prediction potential for flashing defects

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Abstract

The injection molding process is a manufacturing process that can produce products in a short time in large quantities, in the injection molding process the factor of setting process parameters plays a significant role in product quality, so it requires special treatment. The purpose of this study is to find the optimal parameters in the injection molding process of yogurt container lid with polypropylene material, so that the process can reduce the incidence of flashing defects that result in the emergence of initial waste in the industrial environment. The method used in this research was to create a Response Surface Methodology Box-Behnken Design (RSM-BBD) optimization model and an Artificial Neural Network (ANN) model approach in analyzing optimal parameters and predicting the appearance of flashing defects in a designed cycle. The results obtained from this research were the optimal parameters from the RSM and ANN model recommendations, namely the clamping force setting of 70 tons, holding time 0.1 seconds, and holding pressure. The ANN model provided the highest level of prediction accuracy with an R^2 value of 100% and a prediction error rate of 7.9689E-09. In comparison, the RSM model obtained a prediction accuracy level with an R^2 of 71% with an error rate of 0.24315.

Keywords:
Injection molding, RSM, ANN, optimization, model.

1 Introduction

The growth of the global plastics industry has increased significantly, the phenomenon can be seen in 2019 has touched USD 72.28 billion and is predicted to continue to grow [1]. The development of products made from plastic materials encourages economic improvement in the plastic industry sector; the injection plastic molding process, which is part of the industrial sector, also helps develop products or equipment needed by the community, such as machine components, electronic devices, food packaging, and even household appliances[2][3][4][5][6]. Injection plastic molding is one of the manufacturing processes that produce products with a high level of precision and can produce large quantities of products, and this is because the injection molding process applies high requirements followed by strict tolerances in the production process[7][8]. In the injection molding process, the main factor that affects product quality is parameter settings such as injection temperature, injection pressure, holding time, and several other parameters. The influence of parameter settings on the injection molding process is 60%-70%. Therefore, process parameters require special attention to produce quality products without defects [9]. Improper process parameters can cause several defects in injection molding products, such as short shots, flashing, bubbles, shrinkage, warpage, and burning[10]. These defective products can potentially create plastic waste, so action is needed to overcome this problem.

One way to prevent the emergence of a product failure or defective product from the injection molding process is by quality design. Quality design development started from the design of experiments, Taguchi Method, and Response Surface Methodology (RSM) [9][11][12][13]. Designing a quality product using RSM method has advantages in determining the significance of interactions, the number of squares of parameters, visualising 3D response surfaces, and of course optimising parameters. In particular, RSM-Box-Behnken is a popular method in the research industry in modelling a prediction and optimising parameters to meet the intended response variable[14]. Some studies use RSM as an optimization step to produce quality products, Ali [15] conducted research using the RSM method obtained optimal parameters at mold temperature 60°C, injection time 4 s, and the number of gates 2. From the optimization results, RSM can provide predictions of direct experiments by 85%. Not only that, a study from Miza optimization using RSM reduced the warpage value by 26% compared to the recommendation from the injection molding simulation software [16]. Along with the development of the manufacturing process, the injection molding process requires more accurate quality prediction. Artificial Neural Network (ANN) is a method part of Artificial Intelligence (AI) that has currently shown practical performance in the identification of a variable relationship containing complex nonlinearities. In addition, ANN can find a hidden pattern in data, so that to give consideration of the response variables such as the effects of injection temperature, injection speed, injection pressure, and cooling time. Therefore, it allows ANN to be able to provide predictions of whether a product is defective or not [17][18]. The ANN method applied to the injection molding process could provide optimal parameter recommendations and reduce product weight by 0.14% [19]. Also, the ANN method could give predictions close to the results. In solving the shrinkage problem, the ANN model can accurately predict 98.34% and suggest the optimal parameters of the injection molding process [20].

The urgency of the research is to overcome errors in setting process parameters, resulting in product defects that have the potential to pollute the manufacturer's environment. This research carries the novelty of carrying out a continuous optimization using the RSM method and continued with ANN optimization, that to be able to provide optimal parameter results and accurate predictions. Product quality can be maintained and simultaneously and can reduce the number of product defect events. Through the promotion of industry awareness in the early production waste follow-up process, this optimization development also realizes the implementation of the Minister of Environment and Forestry Regulation No.75 of 2019 which was passed in 2019 [21].

2 Research Methods/Materials and Methods

2.1 Optimization Model

After the initial phase of determining which variables would be controlled and which would be independent, the procedure of injection plastic molding carried out.

In order to create a flashing defect prediction model, the model that was developed through the optimization of the Response Surface Methodology (RSM) and the Artificial Neural Network (ANN) approach was implemented. After that, the model is examined for its responsiveness to actual and test data, as well as for the determination of the most appropriate parameter suggestions, as illustrated in Fig. 1.

2.2 Material

The plastic material used in this study was polypropylene material produced by Yungsox 1450D Taiwan, as shown in Fig. 2. The polypropylene material had specifications of melt index: 45g/10min, mold shrinkage: 1.3-1.7%, and melting point: 170°C.

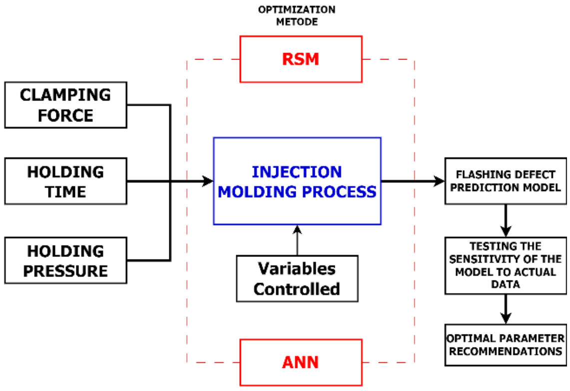

Fig. 1. Model optimization.

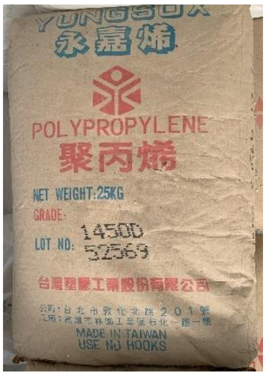

Fig. 2. Polypropylene material.

2.3 Injection Molding Machine

The experimental process used a Victor Taichung injection molding machine (Vs-250 EES) shown in Fig. 3. The machine has the specifications of clamping force: 250 tons, screw diameter: 55 mm, injection rate: 260 cm^2/sec, screw speed: 203 rpm, and hydraulic system pressure: 170 Psi.In addition, in this experiment, the mold used is a multi-cavity type which will produce 2 products in each cycle.

Fig. 3. Plastic injection molding machine Victor Taichung (Vs-250 EES).

The product that was produced because of this experiment is a Lid Yogurt Container, as shown in Fig. 4.

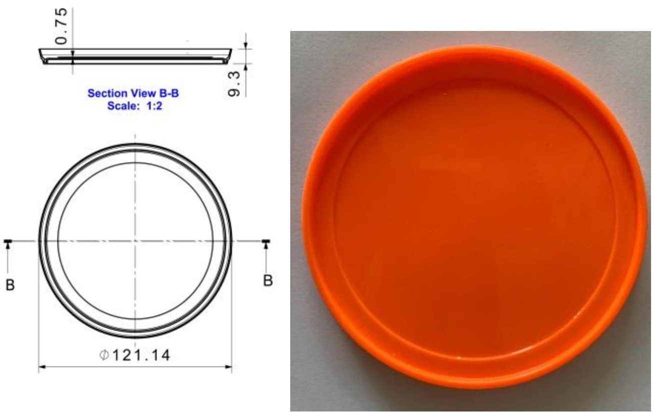

Fig. 4. Design and product of Yogurt Container Lid.

2.4 Injection Molding Process

Fig. 5 shows the injection molding procedure that was used for this research. The first phase of the process is known as the plasticization phase, and it begins with the heating of the plastic material in the heating barrel. The material will advance with the press of the screw, which will, over the course of time, result in the plastic substance becoming melted. The clamping phase is the second step, and during this phase, an oil pressure system is used to operate the clamping mechanism.

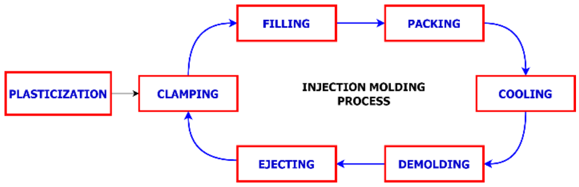

Fig. 5. Injection molding process.

This system regulates how optimal the clamping is to prevent the plastic melt from overflowing. The third stage of production is known as the filling phase, and it is during this stage that the molten plastic is forced out of the nozzle and into the cavity. In the fourth phase, known as packing, the pressure inside the cavity is kept constant to compensate for the volume reduction. The molten plastic that is contained within the cavity will be forced to gradually become more solid by the cooling channel as part of the fifth stage, which is the cooling phase. The sixth step is called demolding, and it refers to the process that occurs when the mold is opened and the product is joined to the cavity. The final phase is called "ejecting", and during this step, the product is expelled from the cavity via the ejection mechanism.

2.5 Process Parameters

During the course of the trials, the process parameters presented in Table 1 were subjected to a range of different adjustments.

Table 1. Independent variable

Parameters	Level		
Clamping force (ton)	30	50	70
Holding time (second)	0.1	0.5	0.9
Holding pressure (bar)	30	60	90

Table 1 shows the selection of process parameters and their levels, based on the PP material data sheet, machine conditions, and previous studies. The experiments presented show differences from Lee J research[22]where the author focused on identifying the melting temperature, injection speed, cooling time, mold temperature, packing time, and packing pressure to predict the diameter of a product. This study emphasised a more industrial approach by adjusting clamping force, holding time, and holding pressure to minimise the occurrence of flashing defects. In addition, there were specific parameter settings for the control variables, which included an injection speed of 45%, an injection pressure of 45 bar, an injection temperature of 210°C, an injection time of 0.5 seconds, and a cooling time of 1 second.

2.6 Evaluation of Successful and Defect Flashing Products

In this study, the product defect that were discovered were flashing problems. Flashing is the condition of excessive plastic material due to process parameter conditions that passes through the edge of the cavity, resulting in products that do not match the design[23]. Fig. 6 is an example of a product with a flashing defect.

The identification of flashing defect in products YogurtLid Containers is carried out directly in Table 2, where products that are found to have flashing defects are assigned the code 1, while products that are found to be free of such defects or products success are assigned the code 0.

Fig. 6. Flashing defect products[23].

Table 2. Product defect identification

Product	Quality	
	Flashing	Success
		0
	1	

2.7 Response Surface Methodology Design

For the purpose of this investigation, Response Surface Methodology (also known as RSM) was developed in order to optimize the process parameters. The Box-Behnken RSM optimization was utilized in this investigation. A total of 15 base runs were conducted as part of this study, and each run was replicated ten times. The configuration of the analyzed parameters is presented in Table 3.

Table 3. RSM Box-Behnken parameter design

Level	Clamping force (ton)	Holding time (s)	Holding pressure (bar)
-1	30	50	70
0	0.1	0.5	0.9
+1	30	60	90

The mathematical model of product quality prediction formed from RSM is generally as shown in Eq. 1.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_k x_k + e \tag{1}$$

The estimation of the product quality is identified by the variable "y," while the factors that have an impact on "y" are indicated by the set of parameters represented by "x" in Eq. 1[24].

2.8 Artificial Neural Network Design

Abbreviation ANN stands for artificial neural network and refers to a modeling tool known as an artificial neural network. This modeling tool depends on iteration or learning methods by modifying the model concept to match human brain networks. In Fig 7, this investigation made use of three different types of inputs: clamping force, holding time, and holding pressure. Input layers, hidden layers, and output layers make up the framework of the ANN model's structure. Elements that are typically referred to as nodes or neurons can be found in each layer. Additionally, each node has a weight, which is used to assess how strongly the nodes are connected to one another.In this model, learning is applied 1000 times.

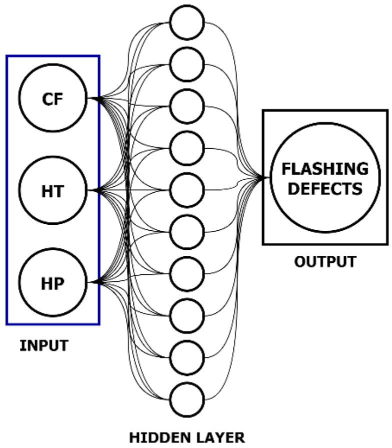

Fig. 7. ANN model.

2.9 Test Data/Verification

The prediction results from RSM and ANN will be tested with the designed experimental results as shown in Table 4.

Table 4. Test data

Parameter			Probability of defect
CF (ton)	HT (s)	HP (bar)	
30	0.1	30	0
30	0.1	60	0
30	0.1	90	0
30	0.5	30	0
30	0.5	60	1
30	0.5	90	1
30	0.9	30	0
30	0.9	60	1
30	0.9	90	1
50	0.1	30	0
50	0.1	60	0
50	0.1	90	0
50	0.5	30	0
50	0.5	60	1
50	0.5	90	1
50	0.9	30	0
50	0.9	60	1
50	0.9	90	1
70	0.1	30	0
70	0.1	60	0
70	0.1	90	0
70	0.5	30	0
70	0.5	60	0
70	0.5	90	0
70	0.9	30	0
70	0.9	60	0
70	0.9	90	0

The results of the tests and verifications performed on the designed product are presented in Table 4, which may be found here. The data from each cycle is used to make a comparison of the number of flashing defects with the number of replications for each manufacturing cycle 10 times. Meanwhile, Fig. 8 depicts the RSM and ANN prediction result testing scheme.

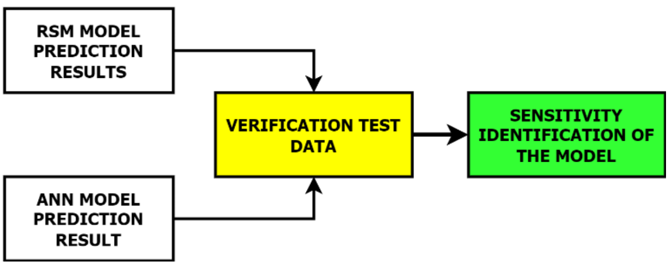

Fig. 8. Data testing scheme.

The Root Mean Squared Error (RMSE) and the coefficient of determination (R^2) are used in the process of testing models. These metrics demonstrate how sensitive the RSM and ANN models are to the test/verification data contained in Eq. 2 and Eq. 3 [25].

$$RMSE = \sqrt{\sum \frac{(y_{pred}-y_{ref})^2}{N}} \tag{2}$$

$$R^2 = 1 - \frac{\sum(y_{ref}-y_{pred})^2}{\sum(y_{ref}-\overline{y_{ref}})^2} \tag{3}$$

In the equation sequentially y_{pred}, y_{ref}, $\overline{y_{ref}}$, and N represents the model prediction results, verification/test data results, average verification data results, and number of cycles, respectively.

3 Results and Discussion

3.1 RSM Optimizations

Table 5 shows the several elements that can increase or decrease the likelihood of flashing errors occurring. It has been determined that the parameters of clamping force, holding time, and holding pressure have a significant influence on the faults of flashing products (p-value less than 0.05).

Table 5. Anova

Source	DF	P-Value
Clamping force	1	0.000
Holding time	1	0.000
Holding press	1	0.000

Using a quadratic graph, Fig. 9 presents the findings that resulted from determining the effect that clamping force parameters have on the possibility of flashing errors. The clamping force position at 50 tons has the highest defect probability, with a flashing defect probability of 0.95.

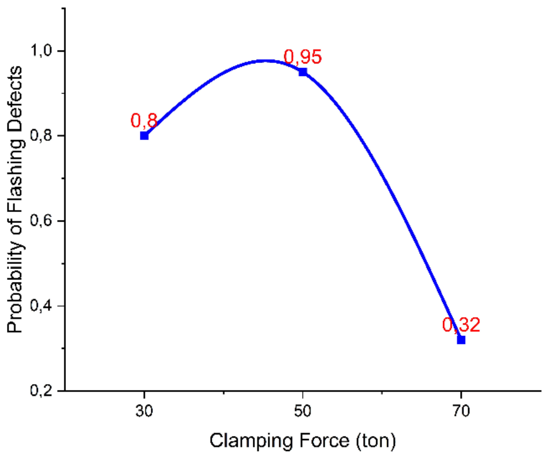

Fig. 9. Graph of the effect of clamping force on flashing defects.

The clamping force position at 70 tons has the lowest defect probability, with a flashing defect probability of 0.32. This condition is supported by research from Huan [26] which explained that setting the clamping force low causes the appearance of flasing defects and an increase in the weight of the product, therefore when the clamping force is low it is not able to withstand the overflow of material entering the cavity, resulting in the overflow of material resulting in flashing defects. Therefore, the phenomenon of flasing defects occurs when the clamping force setting is 30 and 50 tons.

Fig. 10 shows the impact that adjusting the holding duration has on the number of flashing flaws. When the holding time position is set to 0.1 second, the value 0.31 indicates the flashing defect probability is at its lowest possible level. When the holding time parameter is set to 0.5 seconds, the flashing defect probability is displayed to be at its highest possible level of 0.92. The effect of increasing the holding time at 0.5 and 0.9 seconds will cause an increase in flashing defects, this condition is due to the increase in holding time duration which provides additional time for the material to push into the cavity so that if there is a gap in the mold, flashing defects will appear[11][2].

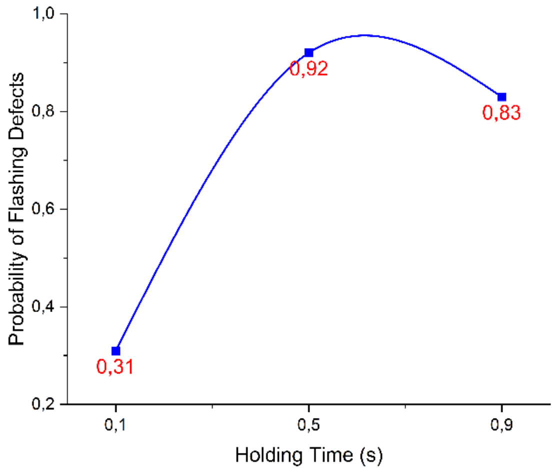

Fig. 10. Graph of the effect of holding time on flashing defects.

In Fig. 11, the holding pressure setting also influences likelihood of flashing errors occurring. When the holding pressure is set to 30 bar, the probability of flashing defects is at its lowest, with a value of 0.34. On the other hand, the probability of flashing defects is at its highest, with a value of 0.91, when the holding pressure is set to 60 bar. According to the results of research by Trotta et al [27] The cause of the increase in the chance of flashing defects at 60 and 90 bar holding time settings is inseparable from the viscosity of polypropylene material, in this study the 210°C temperature setting has indicated that the viscosity of polypropylene is low so that it will facilitate the flow of material filling the cavity[28]. Therefore, when choosing the holding pressure parameter, it provides an opportunity for the molten polypropylene material to slightly push and fill the empty gaps of the cavity and its surroundings, therefore the interaction of the process parameters used in this study is interrelated and related to produce a product without defects.

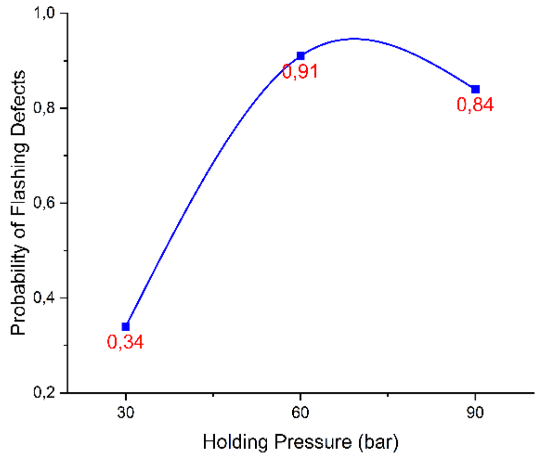

Fig. 11. Graph of the effect of holding pressure on flashing defects.

The answer to the problem of flashing defects can be shown in Fig. 12. The interaction settings of clamping force 70 tons, holding time 0.10 seconds, and holding pressure 90 bar show the minimal chance effect with a value of -0.5875. This value indicates that there is less of a chance for the flashing defects to occur.

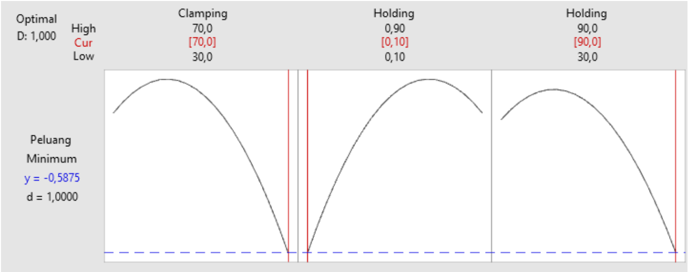

Fig. 12. Optimal parameters of flashing defect minimization.

The mathematical model to predict the chance of flashing defects resulting from RSM-Box Behnken optimization is shown in Eq. 4.

$$\begin{aligned}\text{Flashing Defect Probability} = {} & -4.5180 + 0.111562\ \text{Clamping Force} \\ & + 2.8594\ \text{Holding Time} \\ & + 0.060417\ \text{Holding Press} - \\ & 0.000844\ \text{Clamping Force*Clamping Force} \\ & - 2.1094\ \text{Holding Time*Holding Time} \\ & - 0.000347\ \text{Holding Press*Holding Press} \\ & - 0.028125\ \text{Clamping Force*Holding Time} \\ & - 0.000417\ \text{Clamping Force*Holding Press} \\ & + 0.020833\ \text{Holding Time*Holding Press}\end{aligned} \tag{4}$$

3.2 Results of Artificial Neural Network Model

In this investigation, an ANN model was developed to predict the outcomes of injection molding using a set of parameters that were previously calculated, as shown in Table 1. With the goal of the model being able to prediction with the same level of accuracy as earlier studies, the number of iterations or learning utilized was set at 10,000 times[20]. The prediction results of ANN on the probability of flashing defects are shown in Fig. 13.

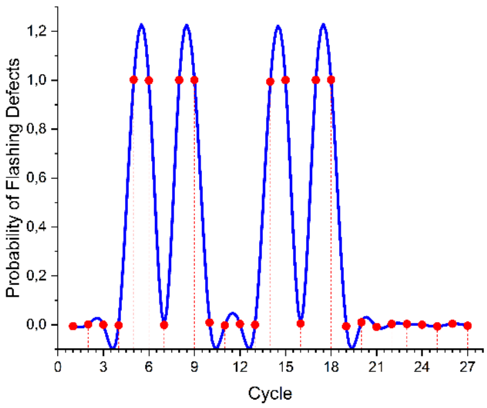

Fig. 13. ANN prediction results for flashing defects.

The findings of the ANN model's predictions indicate that cycles 19–27 with a parameter setting of 70 tons and the interaction of various degrees of holding duration and holding pressure resulted in the lowest flashing defect prediction with a defect risk of 0. Within cycles 1 through 9, the ANN model predictions that there is a one in one risk of a flashing defect occurring in cycles 5, 6, 8, and 9. This is due to the fact that the potential for flashing flaws is increased when a clamping force of 30 tons is used in conjunction with the interaction of holding duration (0.5 and 0.9 seconds) and holding pressure (60 and 90 bar). This is supported by Fig. 10 and 11, which show that the possibility for flashing errors increases in proportion to the degree to which the parameter values for holding time and holding pressure are increased. Therefore, fixing the clamping force at the level of 30 tons does not always reduce the risk of flashing defects to an acceptable level. The trend observed when setting the clamping force level to 30 tons is also observed when setting the clamping force level to 60 tons in cycles 10–18.

3.3 Sensitivity Test of RSM and ANN Models

The comparison of the results of the RSM prediction with the test data is shown in Fig. 14. Based on the graph, it appears that the predictions using RSM have a tendency to miss the test data for several flashing fault predictions.

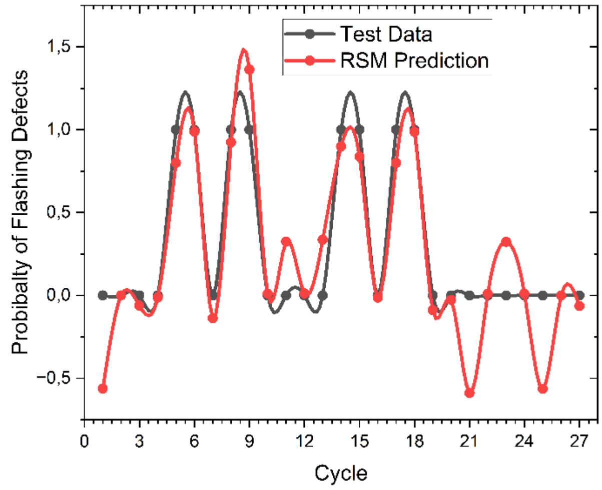

Fig. 14. Prediction of RSM model and test data on flashing defect probability.

It can be observed from Fig. 15 that ANN predictions correspond with the test data, which enables the ANN model to accurately prediction the likelihood of flashing defects. The substantial results that were shown by the ANN model's prediction when it was used in conjunction with the test data shown in Fig. 15.

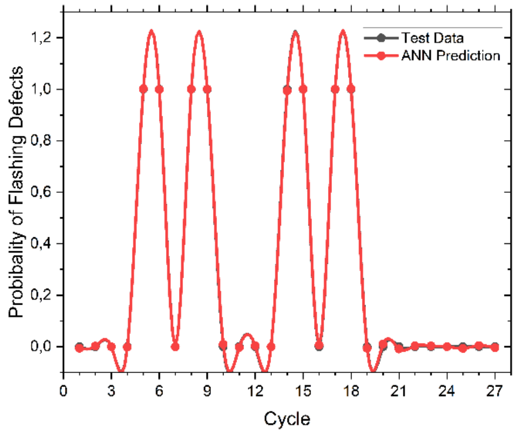

Fig. 15. ANN prediction vs test data against flashing chance defect.

The results of the testing of the models are provided in Table 6, where it shown that the ANN model has the greatest R^2 value with 100%. A high coefficient of determination indicates that the effect that the ANN model has displayed in estimating the possibility of flashing flaws is quite important. The RMSE value of the model is 7.9689E-09, which indicates that the accuracy of the ANN model is high. The model's error rate in estimation the likelihood of flashing defects is minimal, which suggests that the model is relatively accurate. The RSM model has a value of R^2 that is 71.64% and an RMSE value that is equal to 0.24315. The reason for this is because the test graph that is displayed in Fig. 15, which demonstrates multiple errors in prediction the likelihood of product defects.

Table 6. Model sensitivity test

Prediction model	RMSE	R^2
RSM	0.24315	0.7164413
ANN	7.9689E-09	1

Since the model only examines 15 cycles out of a total of 27, it is impossible for RSM not to make a mistake in its prediction. These findings are consistent with the findings of Lee's research [17] when it comes to prediction, ANN models perform significantly better than regression and polynomial models. This is because of the data learning process that the ANN model uses. In addition, research conducted by Jeon[25]demonstrates that the data learning process on intricate and varied ANN models will train the model to make decisions. The results obtained from the use of ideal parameters determined from Response Surface Methodology (RSM) and Artificial Neural Network (ANN) predictions remain consistent when utilizing a clamping force of 70 tons, a holding period of 0.10 seconds, and a holding pressure of 90 bar. The relationship between these characteristics and the quantity of initial production waste is illustrated in Fig. 16, which indicates that the lowest levels of initial production waste from defective goods occur during cycles 19-27. This conclusion was derived from the establishment of these factors. Based on the results of this investigation, the manipulation of parameters has been observed to have a mitigating impact on the generation of plastic waste at its initial point of production. The assertion made in this statement is supported by the research conducted by Tranter [29], who found that the implementation of optimization measures plays a crucial role in maintaining the quality of products. This is done to minimize the probability of potential process failures and energy wastage.

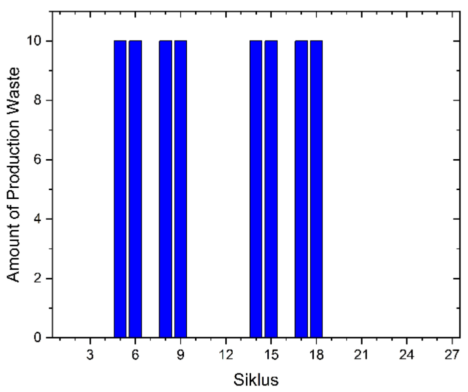

Fig. 16. Total production waste from each cycle.

4 Conclusion

Based on the results obtained from RSM and ANN optimisation modelling in predicting flashing defects and providing optimal parameter recommendations, it was concluded that the optimal parameters were by setting the clamping force at 70 tones, holding period at 0.1 seconds, and holding pressure at 90 bar. In addition, the use of ideal and optimal parameters has the potential to reduce the formation of waste around plastic mold manufacturers, this was evident when cycles 21-27 produced products without defects and minimal product waste. From this study, the ANN model showed superior prediction accuracy, achieving an R^2 value of 99% and a prediction error rate of 0.00445. In contrast, the Response Surface Methodology (RSM) model showed a lower accuracy of 71% and a prediction error rate of 0.24315. This shows that the ANN model will help the prediction results of the RSM model, so that in making a prediction it will be more accurate by combining the two models simultaneously/continuous optimisation such as the RSM and ANN methods.

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