Multi Response Optimisation of Injection Moulding Process Parameter Using Taguchi and Desirability Function

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Abstract. In this study, the optimum injection molding process parameter of warehouse plastic pallets is identified. Compressive strength and part weight are the selected quality characteristic. Barrel temperature, injection speed and holding pressure are the selected process parameter. Taguchi optimization method and desirability function is used to identify the most effective process parameter on the compressive strength and part weight. Based on the conducted experiment, 241 °C of barrel temperature, 72 mm/s of injection speed and 11 MPa of holding pressure, optimise the compressive strength to 5242 kg and part weight to 11.6 kg. The optimised process parameters are studied with an actual experiment and the percentage error of optimised process parameter are identified which is 4.6% for compressive strength and 0.2% for part weight. Moreover, a quantitative relationship between the process parameter and the selected quality response is established using regression analysis. The percentage error of the prediction model for compressive strength is 10% and for part weight is 0.3%. Thus, the prediction model used in this study is effective and practical. This research is beneficial for all the plastic moulding industry which produce plastic pallets. The results can save cost on material consumption and also ensure high product quality.

Keywords: Injection moulding · Optimisation · Taguchi · Desirability function · Regression analysis

1 Introduction

Warehousing is an important part of any manufacturing industry as it is a link between producers and consumers. Plastic pallet is used by the manufacturing industry to keep its products in the warehouse for easy forklift handling. In the disposable of the warehouse, the use of plastic pallets material has grown rapidly for several years due to its performance, durability, and quality compared to wooden pallets. These plastic pallets are produced by a manufacturing company using injection moulding machines. Injection molding is known as an effective process for the mass production of plastic parts with complicated forms.

Determining optimal process parameter settings critically influences productivity, quality, and cost of production in the plastic injection molding (PIM) industry. Previously, production engineers used either trial-and-error method or Taguchi's

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parameter design method to determine optimal process parameter settings for PIM. However, these methods are unsuitable in present PIM because of the increasing complexity of product design and the requirement of multi-response quality characteristics. Stability control of production is an important aspect of injection molding. However, challenges continue to exist with respect to improving product quality stability to achieve a faster forming speed and higher automation for injection molding because the injection process is usually disturbed by several inevitable variations. The difficulty in overcoming the fore-mentioned inevitable disturbances and achieving dynamic control of product quality is related to establishing a quantitative relationship between product quality and process variables.

In this research, the multi-response optimisation problem of injection molding of plastic pallets is studied systematically to produce a high-quality part with lower cost. Changes in processing conditions can lead to improvements or degradation of accuracy, shape, surface finish, and fracture resistance and many other part properties and characteristics. The primary use of process models is to predict these effects. So, a quality prediction model based on the process parameter is established to monitor product weight variation online.

2 Literature Review

First of all, most researchers did not conduct any confirmation test on the optimised process parameter. A confirmation test is to identify the gap between the optimised parameter and the actual experimental results. This is to confirm whether the optimisation method that has been used in any research is valid or not. Sajjan et al., Harshal et al., Osarenmwinda et al., Sreedharan et al., Gurjeet, Pradhan et al., Rish et al. and Rathi [1–8], their optimised process parameters are not tested in the real experiment to validify their conducted studies. The gap or error between optimised parameter and the actual parameter is not studied in some of the previous researches. So, there is no evidence on the accuracy of the optimisation.

Furthermore, the research conducted by Altan [4] need a lot of computational work and it may cause an industry higher cost to own software like Matlab, Autocad and so on. Matlab was used to write a backpropagation type of algorithm which is used to train the prediction neural network. Other than that, 500,000 cycles need to be done in order to build this prediction neural network. This may cause severe cost on production, productivity and also higher leap time for the testing. Another study by Huizhuo et al. [9], used Mouldflow analysis to identify the influential process parameter before the experiment. The software is also used to analyse the quality index of the injection moulded parts. The Mouldflow Insight software (MPI) is very expensive and not a cost-effective method to optimise the process parameter for injection mouldings. Then, Researcher like Yizong et al. [10] used CADMOLD to do melt simulation for his studies. It is used to simulate the PS melt flow inside the mould cavity by lines propagate through the 3D model indicating the flow path of the PS melt. However, this method is quite costly and need to invest in the software to do such analysis. A small medium enterprise is not capable to buy or invest on the CADMOULD to conduct such studies and it is practically hard for the injection moulding industry to optimise the process parameter.

Finally, researchers also ignored the productivity of the injection moulding process in order to optimise the process parameter for better quality. Faruk et al. [11] studies involve time variable like cooling time and from the optimisation, it is identified that cooling time of the 40 s give the minimum flow shrinkage for the product. The optimal cooling time for minimum shrinkage is slightly higher which is the 40 s. This can directly influence the product cycle time and can lead to less production output. The study by Anand and Kumar [12] obtain optimal tensile strength with a process parameter of 220 °C for processing temperature, 130 Mpa for injection pressure, 20 s for the cooling time and 70 mm/sec of injection speed. Although the cooling time of 20 s can give higher tensile strength for PP material, it also can increase the cycle time of the whole process whereas can affect productivity. Rathi [8] believed that higher part weight is the better quality. Although it is technically correct, this will increase the cost due to the higher CPVC material consumption by the injection moulding machine in order to prevent shorts-shorts. Furthermore, this assumption of weight corresponds to short shorts possibilities cannot be applied for bigger products like a car bumper, containers or plastic pallets. Even a small tiny hole in the product cannot be seen in the part weight differences and this will lead to a wrong analysis on the short-shorts possibilities.

3 Methodology

Figure 1 below shows the research flowchart for the process parameter optimisation. This research consists of three main stages of process parameter optimisation. The stages are Phase 1: selecting key variable and quality response, Phase 2: optimising process parameter, and Phase 3: establishing a quantitative relationship. Before optimising the process parameter, the variables that need to be considered must be known

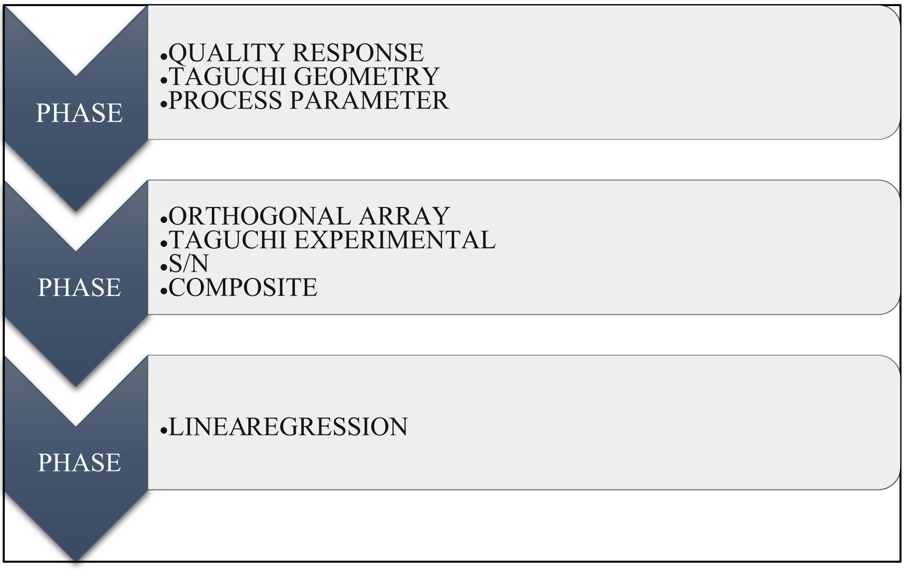

Fig. 1. Flow chart of optimisation

in order to have a successful parameter optimisation. The first phase is about determining all the component values required in design regarding the first objectives. The 2nd phase is to optimise the identified parameters and the 3rd is to establish a quantitative relationship between the process and quality.

3.1 Phase 1: Selecting Key Variable and Quality Response

The first phase is about selecting a suitable process parameter which can directly influence the selected products quality. So, the first step in phase 1 is to select the quality of the product which we want to study and optimise. The quality of a product can be categorized into three properties: (a) dimensional properties (for e.g., weight, length, and thickness), (b) surface properties represented by the appearance of surface defects (for e.g., sink marks and jetting), and (c) mechanical or optical properties (for e.g., tensile and impact strength). Proper studies on previous researches have been done before selecting the important quality characteristics. Based on the studies conducted by Yang and Gao [13], the performance of a manufacturing process and its quality control are monitored through product weight because the quality is inversely proportional to variability and this is reflected in the product weight variation while product weight is closely related to other quality properties. Zhou et al. [14] also supported and considered part weight as an important quality characteristic in their studies. Optimisation of the weight of the plastic pallets is usually done by the operators in the plastic injection molding industry for material savings. Even though they can reduce the part weight as low as possible satisfying dimensional properties and surface properties but still they failed to satisfy the mechanical properties. This is due to the correlation between the part weight and the part compressive strength. A very low part weight can result in a low compressive strength which causes the plastic pallets to only cater a small amount of weight. Therefore, the compressive strength of the plastic pallets is also considered in this study for the part weight optimization. Once the quality characteristics are selected, their corresponding process parameters are found thru several previous research works. A brief explanation is given in Sect. 4, Subsect. 4.1 for the selected process parameters. After the parameter is selected, the preliminary test had to be done to identify the maximum, minimum and average value of the parameter to construct the Taguchi experiment table.

3.2 Phase 2: Optimising Process Parameter

In this phase, the design of the experiment is selected based on the orthogonal array table and the selected Taguchi design is used to run the experiment. After the experiment, each product weight is measured and tested for compression strength. Later, this data is used to perform S/N analysis for parameter optimisation. Finally, the composite desirability function is integrated with the Taguchi method for multi-response process parameter optimisation.

3.3 Phase 3: Establishing a Quantitative Relationship

In this phase, regression analysis is used to establish a quantitate relationship between the process parameter and the selected quality characteristics. Regression analysis mathematically describes the relationship between a set of independent variables and a dependent variable. There are numerous types of regression models that can be used. This choice often depends on the kind of data that we have for the dependent variable and the type of model that provides the best fit.

4 Results and Discussions

4.1 Selected Key Process Parameter

The initial melt temperature is affected by barrel heating and shear heat due to screw rotation. Barrel temperature is one of the frequently adjusted parameters in the plastic industry in order to get better quality results. Since this process parameter has a direct influence on the product quality, it has been selected for this research study. Adjustments in the melt specific volume can be achieved through the holding stage in which the main function involves compensating for the instability of the melt properties Zhou et al. [13]. Despite changes in the melt specific volume during the injection stage, it is still possible to control the holding stage to compensate for the melt specific volume. So, the holding pressure has been selected as another process parameter to study its influence on the compressive strength. Latest studies on compressive strength conducted by Ginghtong et al. [14], they have selected three parameters like melt temperature, injection speed and holding pressure. Their studies show that the contribution of the injection speed to the quality characteristic is the highest compared to the other selected parameter. So, the injection speed has been selected in this study to be optimise for better quality output. Table 1 below shows the selected process parameter for this study.

Table 1. Selected process parameter

Process parameter	Reason	Source
Barrel temperature	Influence on melt specific volume	Zhou, Zhang, Mao, and Huamin [13]
Holding pressure	Influence on melt specific volume	Zhou, Zhang, Mao, and Huamin [13]
Injection speed	Higher significance effects on compressive strength	Ginghtong, Nakpathomkun, and Pechyen [14]

4.2 Process Parameter Optimisation

A consistent experimental operation was applied to ensure similar conditions for the production of each test series. Prior to re-commencing production, a waiting time of 15 min was required to allow the barrel temperature to reach the setting number and become homogenous. Furthermore, a condition of thermodynamic equilibrium was indispensable for the reproducibility of the experiments. Thus, a total of 10 products were produced for each barrel temperature, and only the last 3 products were used for the measurement. Table 2 below shows the result of product weight and compressive strength after the testing.

Table 2. Experiment result

Test	Barrel temperature (°C)	Injection speed (mm/s)	Holding pressure (MPa)	Compressive strength (kg)	Part weight (kg)
1	240	72	11	5160.2	11.78
2	240	80	22	6376.7	11.78
3	240	88	33	6091.1	11.78
4	250	72	11	4407.8	11.70
5	250	80	22	4900	11.72
6	250	88	33	4454.9	11.62
7	260	72	11	5626.7	11.62
8	260	80	22	4716.1	11.63
9	260	88	33	4810.4	11.65

The test results were evaluated in terms of signal/noise (S/N) ratio. The S/N was calculated by larger is better for compressive strength and smaller is better for part weight. This is to determine the effect of injection parameters on selected quality characteristics. The calculated signal to noise ratio for both quality responses is listed as in Table 3 below.

From the signal to noise analysis the most significant parameter that affects the compressive strength and part weight is identified. It can be seen from Figs. 2 and 3 that the most important parameter for maximum compressive strength and minimum part weight is Barrel temperature followed by holding pressure. Injection speeds show the least effects on both selected quality characteristics. The figures also show that the most suitable value of each process parameter. The optimal injection moulding conditions for the maximum compressive strength were 260 °C barrel temperature, 11 MPa holding pressure, and 80 mm/s injection pressure. The optimal injection moulding conditions for the minimum part weight were 260 °C barrel temperature, 22 MPa holding pressure, and 80 mm/s injection pressure. However, Taguchi and signal to noise ratio alone cannot optimise multi responses. It has to be integrated with desirability functions in order to optimise both compressive and part weight quality.

The calculated signal to noise ratio of both compressive strength and part weight is converted into the dimensionless function using the desirability method. This is to

Table 3. S/N ratio for both responses

Test	Barrel temperature (°C)	Charging speed (mm/s)	Holding pressure (MPa)	Compressive strength (kg)	S/N ratio	Part weight (kg)	S/N ratio
1	240	72	11	5160.2	77.7169	11.78	−21.33
2	240	80	22	6376.7	76.0919	11.78	−21.36
3	240	88	33	6091.1	75.9343	11.78	−21.44
4	250	72	11	4407.8	75.793	11.70	−21.36
5	250	80	22	4900	75.9176	11.72	−21.39
6	250	88	33	4454.9	72.9768	11.62	−21.38
7	260	72	11	5626.7	75.0051	11.62	−21.39
8	260	80	22	4716.1	73.4728	11.63	−21.39
9	260	88	33	4810.4	73.6438	11.65	−21.36

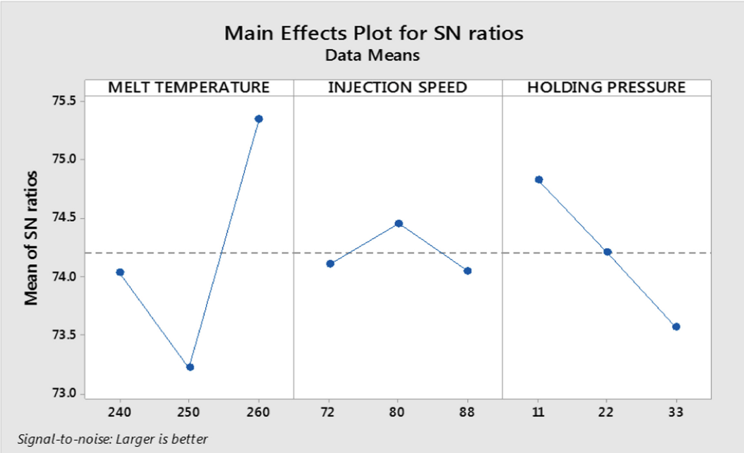

Fig. 2. Signal to noise ratio plot for compression strength

integrate both responses into a dimensionless function called composite desirability. From this composite desirability, the most desirable value is considered as the optimal value. Table 4 below shows the individual desirability for each response and also the composite desirability.

The optimal values of the parameters are determined to maximise overall desirability (D), by applying a reduced gradient algorithm with multiple starting points. Figures 4 and 5 below shows the optimal parameter setting for individual responses. After investigating each response variable as an objective function individually, all response variables are optimised using the desirability function approach, while two response variables are considered as objective functions simultaneously.

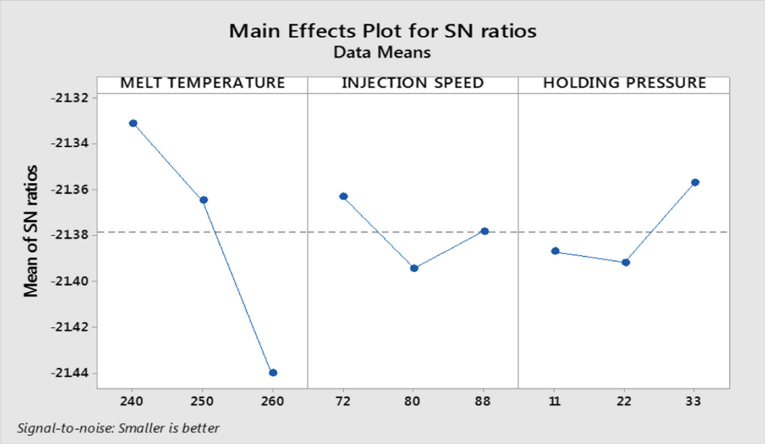

Fig. 3. Signal to noise ratio plot for part weight

Table 4. Desirability of both responses.

Compressive strength (kg)	Part weight (kg)	Compression individual desirability	Part weight individual desirability	Composite desirability
5160.2	11.79	0.190058	0.390147	0.272306
6376.7	11.82	0.137427	0.597395	0.286528
6091.1	11.8	0.084795	0.804643	0.261209
4407.8	11.725	0.47076	0.374216	0.419722
4900	11.75	0.418129	0.581464	0.493079
4454.9	11.63	0.681287	0.208032	0.37647
5626.7	11.645	0.751462	0.358285	0.518881
4716.1	11.655	1	0	0
4810.4	11.67	0.961988	0.192101	0.429883

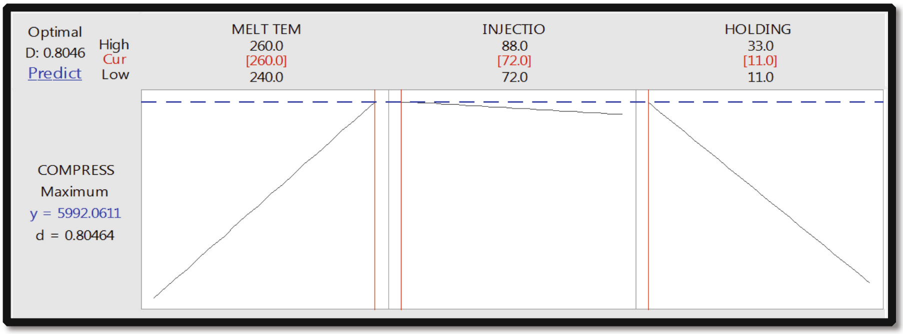

Fig. 4. Compressive strength as the response for individual optimization

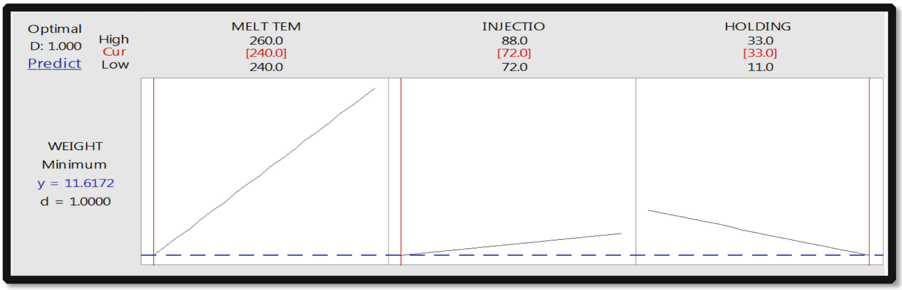

Fig. 5. Part weight as the response for individual optimisation

In Fig. 6, all the response variables are optimised simultaneously. Comparing the results obtained from the Taguchi design of experiment, the individual desirability function approach, and the composite desirability function approach, it can be seen that although optimising each response variable individually will provide a better result for each response variable but still the optimal parameter values will be different when each response variable is optimised individually. For example, considering the compressive strength variable as a response, the optimal values of factors barrel temperature, injection speed, and Holding pressure are obtained as 260, 72 and 11 respectively. However, when part weight is considered as a response variable, the optimal values are different. Considering the entire response variable as objective functions simultaneously in the composite desirability function method generates one general value for all the parameters of the algorithms, which leads to an optimal value of all the response variables. The summary of the results obtained from the composite desirability function approach is presented in Table 5.

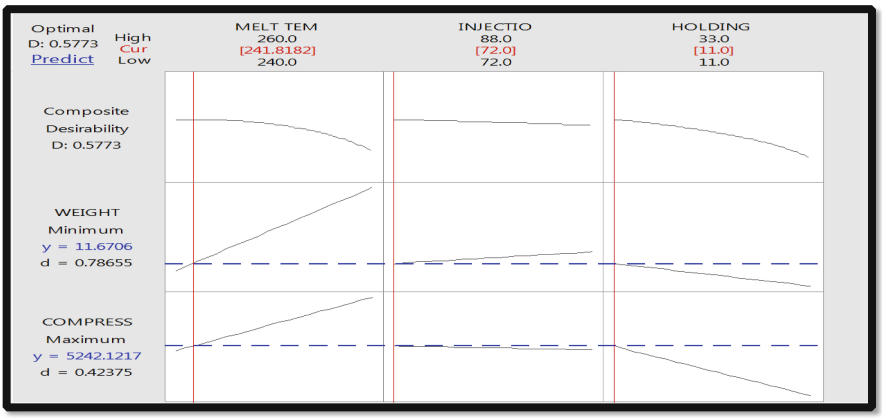

Fig. 6. Composite desirability function approach (multi responses optimisation)

Table 5. Results of multi-response optimisation

Responses	Factors			Predicted responses	Desirability value
	Barrel temperature	Injection speed	Holding pressure		
Compressive strength	241 °C	72 mm/s	11 MPa	5242 kg	0.57773
Part weight				11.67 kg	

The best set of process parameter is 241 °C of barrel temperature 72 mm/s injection speed and 11 MPa of holding pressure. This parameter will optimise the part quality to 5242 kg of compressive strength and can result in the part weight of 11.6 kg. Once the optimal combination of process parameters and their level was obtained, the final step is to verify the estimated result. A confirmation test is performed to validate the results of Taguchi optimisation and provide evidence that interaction effects between factors are low. In practice, it is very hard to state with confidence how close the experiment number must come to the predicted values for the agreement to be considered good. Hence, it can only be applied to the present set of parameters. The confirmation injection test was set up with the optimal combination using the same material and injection machine. A plastic pallet was moulded and compressive strength test is performed. The average compressive strength and part weight were calculated. The value of average compressive strength and part weight obtained from the confirmation experiment was then compared with the estimated value as shown in Table 6.

Table 6. Confirmation test of optimised parameter

Responses	Optimisation prediction	Actual result	Error
Compressive strength	5242 kg	5500 kg	4.6%
Part weight	11.67 kg	11.7 kg	0.2%

All experimental values are within a 20% difference from predicted results. As error values must be smaller than 20% for reliable statistical analyses, error values below 20% were accepted in the literature Kuram et al. [15]. The predicted results had very close values with the experimental results, thus the optimisation approach used in this study is effective and practical.

4.3 Quantitative Relationship Between Process Parameter and Quality

Regression analysis was a statistical tool for the investigation of relationships between variables. R-Square is correlation coefficient and should be between 0.8 and 1 in multiple linear regression analyses, Ozcelik [15]. The purpose of R-Square value is the prediction of future outcomes on the basis of other related data. It provides a measure of how well results are appropriate to be predicted by the model. A linear model between injection moulding parameters and quality characteristics were created. The model is shown in Eqs. 1 and 2.

$$\begin{aligned} \textit{Compressive strength} = & -23028 + 86.2\,\textit{Barrel temperature} + 123.6\,\textit{injection speed} \\ & - 42.6\,\textit{holding pressure} \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Weight} = & 9.827 + 0.00733\,\textit{Barrel temperature} + 0.00125\,\textit{injection speed} \\ & - 0.00182\,\textit{holding pressure} \end{aligned} \tag{2}$$

The relationship between process parameters and the ensuing product quality is expressed in a mathematical equation using regression equation with an R(square) of 84% for compressive strength and R(square) of 82% for part weight. This means that, all the factors of the process explain 84% of the differences in the compressive strength and explain 82% of the differences on the part weight. The model result was best explained by values of the regression coefficient, R-square, close to 1.

5 Conclusion and Future Works

In this study, the optimal injection moulding process parameter of warehouse plastic pallets are identified. Compressive strength and part weight are selected as quality characteristics. Barrel temperature, injection speed, and holding pressure is selected as the process parameter based on previous researches. After that, the value of each process parameter is determined by running pre-testing. The selected process parameters are used to conduct an experiment based on Taguchi experimental design. The compressive strength and part weight for each experiment were identified. Those results are used to optimise the process parameter using Taguchi and desirability functions.

For Taguchi optimisation, S/N ratio is calculated for both responses and the optimal process parameter are identified. The optimal injection moulding conditions for the maximum compressive strength were 260 °C barrel temperature, 11 MPa holding pressure, and 80 mm/s injection pressure. The optimal injection moulding conditions for the minimum part weight were 260 °C barrel temperature, 22 MPa holding pressure, and 80 mm/s injection pressure. The calculated signal to noise ratio of both compressive strength and part weight is converted into the dimensionless function using the desirability method. The best set of process parameter that is optimised using desirability functions is 241 °C of barrel temperature 72 mm/s injection speed and 11 MPa of holding pressure which optimise the part quality to 5242 kg of compressive strength and 11.6 kg of part weight. The percentage error of optimised process parameter for compressive strength is 4.6% and for part weight is 0.2%. The response variable of the optimised process parameter had very close values with the experimental results, thus the optimisation approach used in this study is effective and practical.

Moreover, a quantitative relationship between the process parameter and the selected quality response is established using regression analysis. The constructed regression model can be validated using the R-square. The relationship between process parameters and the ensuing product quality is expressed in a mathematical equation using regression equation with an R-square of 84% for compressive strength and R-square of 82% for part weight. This means that all the factors of process explain 84% of the differences in the compressive strength and explain 82% of the differences on the part weight. The percentage error of the prediction model for compressive strength is 10% and for part weight is 0.3%. For reliable statistical analyses, error values must be smaller than 20%. Since comparisons were done according to average experimental values and the errors are within the acceptable range. Thus, the prediction model used in this study is effective and practical.

By optimisation, the product weight is reduced about 0.2 kg with optimum compressive strength. The pallet production for 1 day is about 1200 pieces, with 0.2 kg of material saving for each pallet, we can save around 240 kg of polypropylene per day and 7200 kg of material per month. The price range of 1 kg of recycled polypropylene in Malaysia is around Rm 2.70–Rm 2.90. Taking the minimum price, we can save around Rm 20,880 per month and RM 250,560 annually, ensuring better product quality.

Future developments of this work may be the extension of the DoE plan to other uninvestigated parameters, like packing time or injection pressure, and the mechanical characterization of the polymer through Charpy and Hopkinson bar tests. Moreover, in-cavity sensors information or barrel heater can be investigated. The relationship between the melt properties inside the barrel before the injection and the product quality can be studied. An online process parameter monitoring and adjustment can be achieved using the quantitative relationship between the Melt flow in the barrel and the product quality.

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