Optimization of Plastic Injection Moulding Process Using Data Mining: A Case Study

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ABSTRACT

Plastic injection moulding (PIM) process is used for converting plastics from its raw material into a kind of a semi-finish or finish product. PIM is a complex process due to the non-linear behaviour of controllable parameters available in producing high quality product. PIM usually used in a mass production line to support high demand and wide range of products, from as simple as electronic devices to as complicated as aerospace devices. Therefore, it is very important to control products from defects and to gain knowledge about parameters, which will influence to the whole PIM process. For this purpose, this paper presents an optimization of PIM process parameters in a fishing reel production via Data Mining methods. Our previous research done to optimize the parameters using Design of Experiments (DOE) methods proves that the PIM process can be optimized by running 16 experiments by two levels of fractional factorial design. In this paper, Data Mining will be utilized to provide optimal parameters of the PIM machine with desired accuracy. First, the important PIM machine parameter data in fishing reel production were collected. Then, the collected data are analysed using the REPTree Decision Tree method for classification. It is found that, this approach brings out the important decision of PIM machine parameters that are useful in obtaining the desired output results. The results from Data Mining method not only provides the same results as statistical method, but also introduces more efficient quality improvement activities with minimal cost and time consumption.

1. INTRODUCTION

Plastic injection moulding (PIM) is a process that transforms molten plastic materials into a form of products that match the design of the mould cavity. PIM is a very important process in a manufacturing technology, which able to produce products for a mass production in a shorter lead time and efficient cost. Nevertheless, nowadays PIM technology is applied to produce sophisticated products that can be used for most applications in the area of aviation and aerospace. Even though, PIM technology has over one hundred forty years of history, currently still present a lot of researches that aims to continuously improve the PIM process. Towards producing a product efficiently, the product should be avoided from defects that will lead to profit loss. Generally, PIM is a complex but highly efficient manufacturing process, which able to produce products with tight tolerances and complex shape design. In that sense, quality control activities are vital to PIM process.

Several researches concerning quality improvement regarding PIM process have been done. L. W. Seow and Y. C. Lam [2] studied cavity balancing that able to eliminate the product surface defects such as weld-lines and air-traps, that might occur due to unbalanced of injection flow. X. Lu and L. S. Khim [3] investigated the significant PIM parameters that would result to the high quality of optical lens. The authors applied statistical approached by using factorial analysis, by taking into considerations of injection speed, holding pressure and mould temperature. The authors found that, the most significant parameters that affect the most the quality of the optical lens is the mould temperature. M. Kurt et al. [4] studied the effects of cavity pressure and mould temperature onto the quality of the final products. The authors discover that, cavity pressure and mould temperature are the most significant factors that affect the shrinkage of the product.

Even though, the above mentioned research able to solve the quality issues of the certain products, by controlling the most significant parameters that will affect the product. However, the methods they applied are lengthy and required much of the machine operation time. For example, conventionally, trials run have to be

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conducted in order to collect data from the PIM processes which lead to the non-productive machining time and inefficient cost. Such process like the statistical factorial method, which set of rules, must be followed in order to investigate the significant parameters. Thus, in this research, instead of conducting trials run for optimize the PIM process parameters, the authors will apply data mining methods which, algorithm will be produced based on the data gathered from the running machine of the PIM process. In this sense, PIM process does not have to stop their routine job schedule for optimization activities. Optimization activities will be much simpler, and increase the repeatability of data collecting. Thus, in this research sets of trained data that used to optimize the PIM process of a plastic fishing reel product will be used for data mining technique. In addition, this research supplies the comparison of the optimized results from both optimization approaches.

2. Plastic Injection Moulding Process

In PIM process, products or moulded parts are produced in discontinuously cycles. The basic sequence of one cycle is shown in Figure 1. The typical PIM process consists of a three phase process consists of injection (filling), holding pressure and plastication (packing), and ejection (cooling) phases. First, the resin or raw material for injection moulding, is usually in pellet form, is fed into the plasticating unit where it will be melted. The plasticating unit consists of a single-screw extruder in which the screw plasticates the pellets to form a melt that is transported forward by the rotation. During this process, the injection nozzle is still closed and the melt is pushed to the front of the screw. As a result, the back pressure will occur which the screw is pushed to the right against the resistance of the barrel. Then, the melt will fill up the mould cavity with certain filling pressure (packing pressure) and required time. Finally, the melt is cooling down and the moulded part will be ejected by sets of ejector pin. The moulded part may free to fall into a collection box or onto a transfer conveyor, or may be removed by an automatic robot.

In this research, fishing reel support arm component as shown in Figure 2 will be used for the optimization activity. This product was selected due to the design that will introduce defects such as the product will tend to twist right after the ejection phase, and the product also suffers from other quality defects such as sink mark and shrinkage.

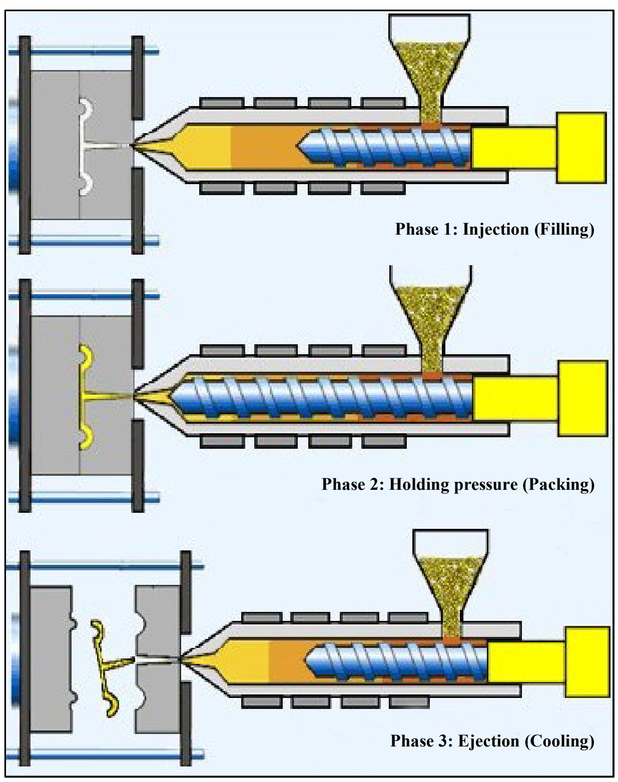
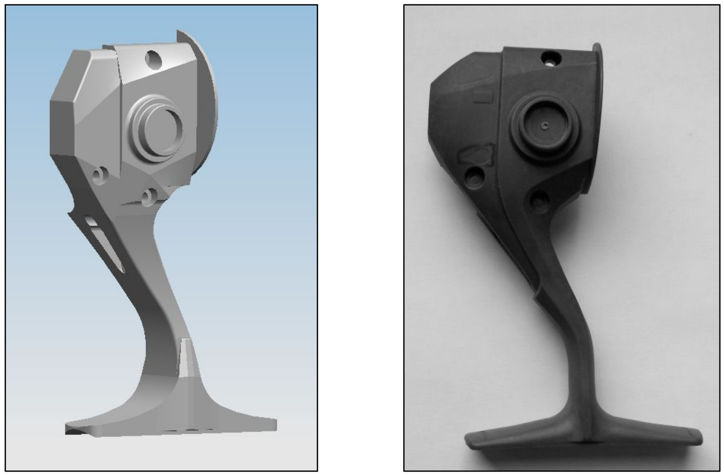


Figure 1. The injection moulding cycle. [1].



a) CAD design b) Real product

Figure 2. Fishing reel support arm used for the optimization activity.

3. EXPERIMENTAL DETAILS

Polyamide-nylon plastic resin is used as the raw material for the fishing reel support arm (refer Figure 2). Previous experiments were planned using a fractional factorial design based on DOE $(2^6)^{1/4}$. All of the parameters were maintained at two levels as such; injection pressure (IP) at 80 and 100 Mpa; melt temperature (MT_A) at 280 and 310 °C; mould temperature (MT_B) at 80 and 100 °C; cooling time (CT) at 25 and 30 seconds; mould runner diameter (RD) at 6 and 7 mm and mould gate size (GS) at 2 and 2.5 mm. For the optimization, 16 experiments were conducted, on the basis of randomly selected input parameters. The results of the experiments as given in Table 1 are based on DOE method. As shown in Table 1, the quality characteristics, which are the responses of these experiments, the filling pressure (packing pressure), filling – temperature distribution profile (bulk temperature), filling time, warpage—sink mark index, and warpage—volumetric shrinkage.

Table 1. Training data: filling pressure, bulk temperature, filling time, sink mark index and shrinkage according to DOE method.

N no.	IP	MT_A	MT_B	CT	RD	GS	Filling Pressure (Mpa)	Bulk Temp. (°C)	Filling time (sec)	Sink Mark Index (%)	Shrinkage (%)
1	80	280	80	25	6	2	80.02	214.22	1.446	0.6377	6.102
2	80	280	100	25	7	2.5	76.16	189.9	1.446	0.7662	8.011
3	80	310	80	30	7	2	71.95	238.35	1.085	1.314	7.115
4	100	280	80	30	7	2.5	78.21	209.46	1.329	0.8485	6.464
5	80	310	80	25	7	2.5	68.38	234.79	1.085	1.286	7.117
6	100	310	100	30	7	2.5	67.79	218.2	1.084	1.245	6.719
7	100	310	80	30	6	2	75.71	241.04	1.066	1.173	6.989
8	100	310	80	25	6	2.5	71.50	237.1	1.066	1.127	7.005
9	80	310	100	25	6	2	74.71	222.20	1.064	1.151	6.561
10	100	280	100	30	6	2	83.36	196.4	1.420	0.7218	5.941
11	80	310	100	30	6	2.5	70.81	220.4	1.064	1.124	6.594
12	100	280	80	25	7	2	81.88	211.28	1.327	0.8453	6.440
13	80	280	80	30	6	2.5	80.03	211.91	1.304	0.7705	6.451
14	100	310	100	25	7	2	70.80	219.4	1.082	1.271	6.675
15	100	280	100	25	6	2.5	79.29	192.3	1.421	0.7028	7.353
16	80	280	100	30	7	2	79.70	193.6	1.446	0.7802	6.048

A machine learning technique known as a top-down induction decision tree will be used to analyse the data gathered from the previous experiments. The advantages of decision trees over other machine learning technique such as neural networks (NN) and inductive logic programming (ILP) are decision trees are simple to understand and easy to interpret, it works perfectly with little data preparations and it can be validated using statistical tests. Thus, in this research, a decision tree and a set of rules can be derived that will show clearly the relationship between the various input parameters such as injection pressure, melt temperature, mould temperature, cooling time, runner diameter and gate size, and the output parameters namely filling pressure, bulk temperature, filling time, sink mark index and shrinkage.

4. Data Mining Process

In recent years data mining has become a very popular technique for extracting information from the database in different areas due to its flexibility of working on any kind of databases and also due to the surprising results [5]. The goals of data mining are to construct data mining models (e.g., a decision tree classifier, regression model, and segmentation) from their databases, to use these models for a variety of predictive and analytic tasks, and to share these models with other applications [6].

In this research, data mining process will require the following four sub-tasks:

1. *Pre-processing data*. It consists of data collecting activities and cleaning the data from noise, incomplete and inconsistent.
2. *Patterns search*. Data mining algorithm based on the decision tree method is used to analyse the data patterns.
3. *Analysis*. The output of the decision trees is investigated and verify either statistically or theoretically
4. *Interpret findings*. The findings are interpreted for further actions and improvement activities.

First, data preparations are the most important activities because the data will be used as an input of a data mining algorithm. The data must be reformulated so that it can be handled by the algorithm. The data in Table 1 has to be classified as follows:

(a) The following six parameters are selected as the attributes [A1, A2, …., A6]:
  1. IP: injection pressure (Mpa),
  2. MT_A: melt temperature (°C),
  3. MT_B: mould temperature (°C),
  4. CT: cooling time (sec),
  5. RD: runner diameter (mm),
  6. GS: gate size (mm).

(b) The outputs of the PIM process are filling pressure, bulk temperature, filling time, sink mark index and shrinkage. All the outputs will be treated separately. The effect of the input parameters on filling pressure will be analysed and the activity repeated for the other outputs. In this study, two output classes, i.e. *Class '1'* and *Class '2'* as have been taken. *Class '1'* is depend on the output is below the splitting value, and *Class '2'* vice versa. Table 2 shows the splitting value, which will be used as a split point of a decision tree, and it is chosen based on the mean value of the outputs in the training set.

Table 2. The output classes depend on the mean value of the outputs in the training set.

Output Criteria	**Mean Value (Splitting point)**	***Class 1***	***Class 2***
Filling Pressure (Mpa)	75.64	Lower than 75.64	Higher than 75.64
Bulk Temperature (°C)	215.66	Smaller than 215.66	Larger than 215.66
Filling Time (Sec)	1.23	Less than 1.23	Longer than 1.23
Warpage – sink mark index	0.99	Smaller than 0.99	Larger than 0.99
Warpage – shrinkage volumetric index	6.72	Smaller than 6.72	Larger than 6.72

In this study, REPTree decision tree algorithm will be applied. REPTree stands for Reduced Error Pruning Tree [7], its build a decision tree using information gain/variance reduction and prunes it using reduced-error pruning (using a separate pruning-set of pruning). REPTree method is optimized for speed, so that it only sorts values for numeric attributes. In additions, REPTree also deals with missing values by splitting instances into pieces. REPTree algorithm lets user to set the minimum number of instances per leaf, maximum tree depth (which is useful when boosting trees), minimum proportion of training set variance for a split (numeric classes only), and number of folds for pruning [8].

REPTree uses information gain as its attribute selection measure. First, the attribute with the highest information gain is chosen as the splitting attribute for node *N*. Node *N* represents the tuples of partition *D* (data partition). The expected information needed to classify a tuple in *D* is given by:

$$Info\ (D) = -\sum_{i=1}^{m} p_i log_2(p_i) \qquad (1)$$

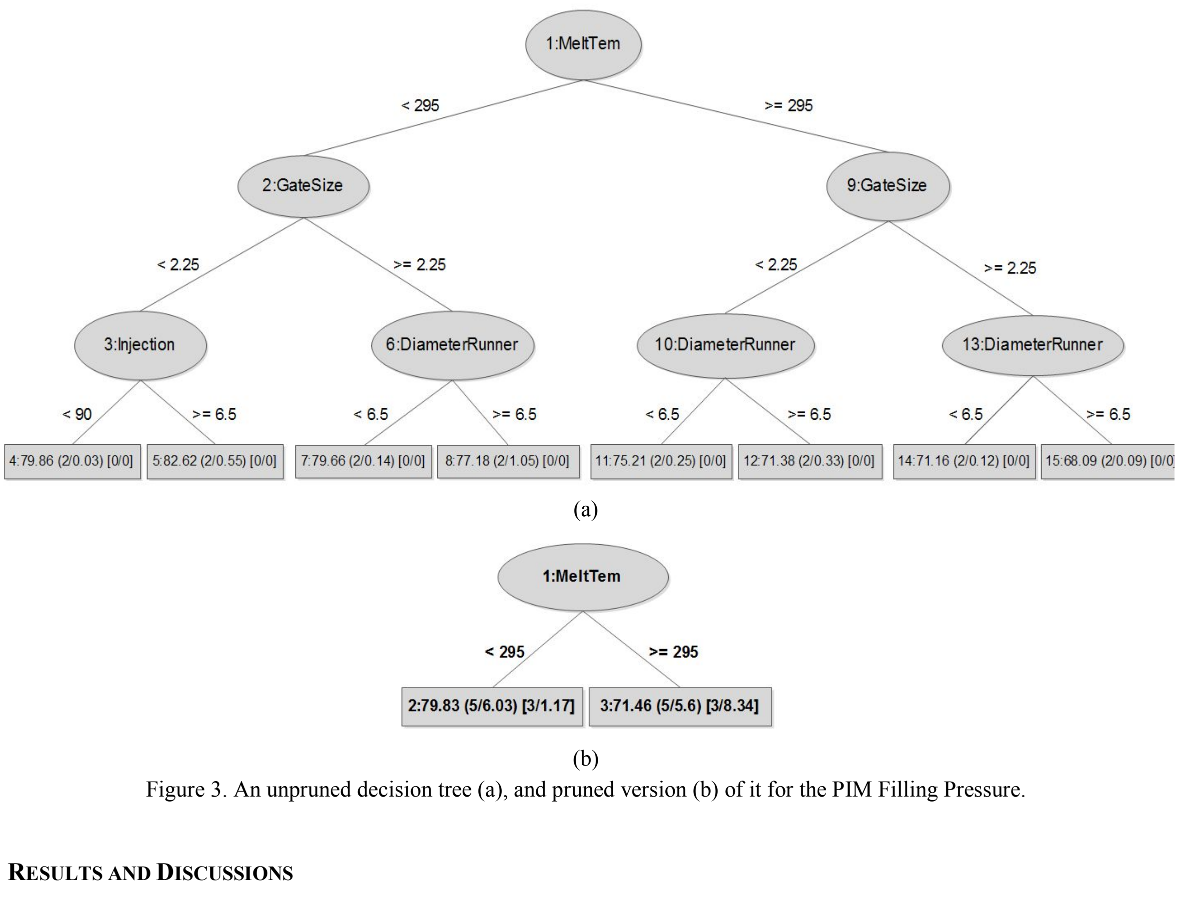
From the equation (1), *Info(D)* is also known as entropy of *D,* and p_i is the nonzero probability that an arbitrary tuple in *D* belongs to class C_i and estimated by $|C_{i,D}|/|D|$. As the result, tuples in *D* were partitioned on some attribute *A* having *v* distinct values, $\{a_1, a_2, \ldots a_v\}$, as observed from the training data. Next, after *D* is partitioned, the expected information required to classify a tuple from *D* based on the partitioning by *A*, $Info_A(D)$ need to be measured.

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j) \qquad (2)$$

where the term $\frac{|D_j|}{|D|}$ acts as the weight of the *j*th partition. The smaller the expected information required, the better partitioning were created to produce an exact classification of the tuples. Then, the information gain for attribute *A* needs to be calculated. The attribute *A* with highest information gain, *Gain(A)*, is chosen as the splitting attribute at node *N*.

$$Gain(A) = Info(D) - Info_A(D) \qquad (3)$$

Finally, the built REPTree decision trees need to be pruned. Tree pruning approach is to remove branches that reflect from anomalies in the training data due to noise or outliers. As an example, an unpruned tree and a pruned version of it are shown in Figure 3.



(b)

Figure 3. An unpruned decision tree (a), and pruned version (b) of it for the PIM Filling Pressure.

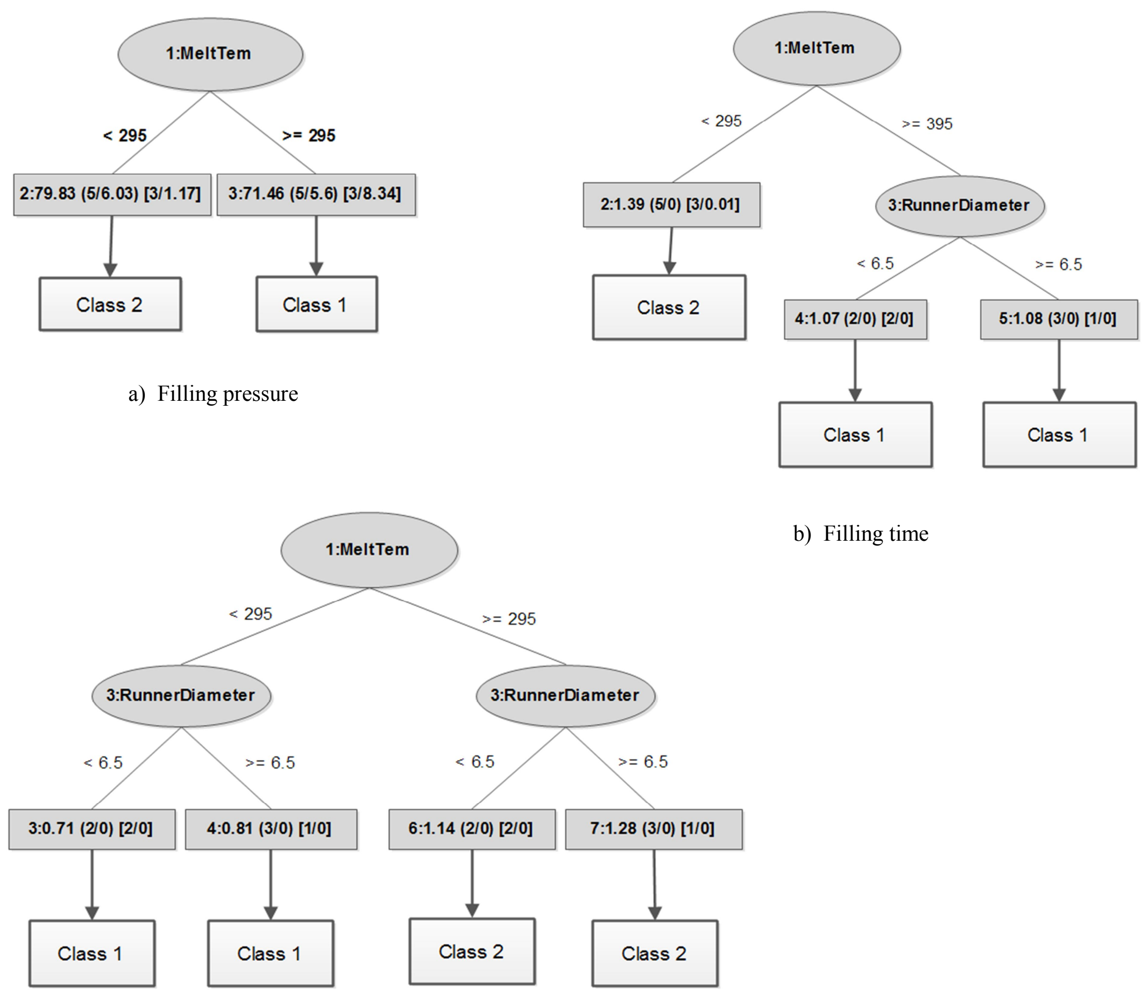
5. Results and Discussions

As a result, Figure 4a shows the graphical representation of the decision tree. Class 1 refers to filling pressure less than 75.64 Mpa and Class 2 refers to filling pressure greater than 75.64 Mpa, where 75.64 is the mean of the filling pressure on the training data set. From the decision tree it is seen that the MT_A is the most important parameter influencing filling pressure.

The output of the program for filling time is given in Figure 4b, representing the decision tree graphically. Class 1 refers to filling time less than 1.23 seconds and Class 2 refer to filling time greater than 1.23 seconds, where 1.23 is the mean of the filling time values in the training set. From the tree it is seen that MT_A and RD are important parameters influencing filling time.

The output of the program for sink mark index is given in Figure 4c, representing the decision tree graphically. Class 1 refers to sink mark index less than 0.99 percent and Class 2 refer to filling time greater than 0.99 percent, where 0.99 is the mean of the sink mark index values in the training set. From the tree it is seen that MT_A and RD are important parameters influencing sink mark index.

As results for bulk temperature and shrinkage, REPTree algorithm found that all parameters are not significant thus, does not influence both outputs in this experiment. Since, induction decision trees allow being validated using statistical tests. The results obtained from the decision trees will be verified by applying the analysis of variance (ANOVA).



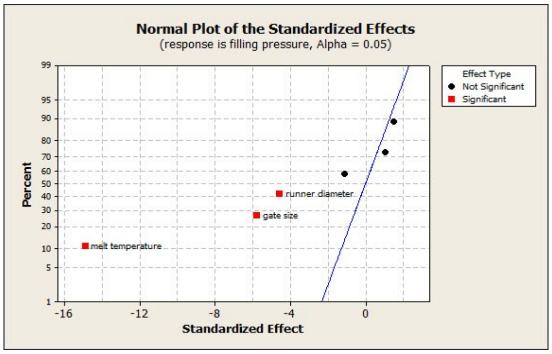
a) Filling pressure

b) Filling time

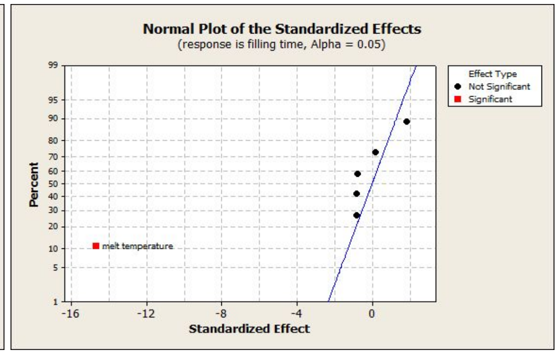
c) Warpage - sink mark index

Figure 4. Graphical representation of tree for: a) Filling pressure, b) Filling time, c) Warpage- sink mark index.

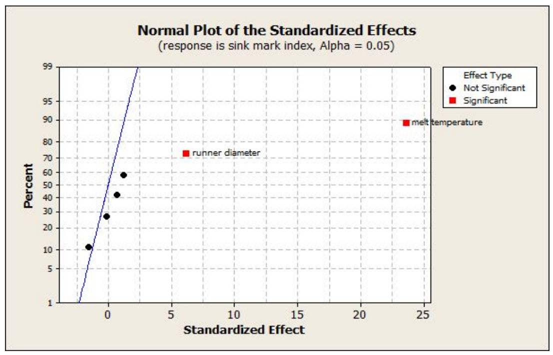
Verification results from ANOVA shows the same significant parameters, as given by the REPTree decision tree method. Figure 5a, 5b and 5c shows the normal plot diagrams of the significant parameters that affect the PIM process of the fishing reel support arm. Table 3 summarize all the significant parameters for the PIM process of the fishing reel support arm according to the graphical representation from Figure 4.



a) Filling pressure



b) Filling time



c) Warpage - sink mark index

Figure 5. Normal plot for: a) Filling pressure, b) Filling time, c) Warpage - sink mark index.

Table 3. Summary of all the significant parameters for the PIM process.

Responses	Conditions	Significant parameters	Optimal settings	Estimated output
Filling pressure	Smaller the better	Melt temperature	Equal or higher than 295 °C	71.46 Mpa
Filling time	Smaller the better	Melt temperature	Equal or higher than 295 °C	1.07 seconds
		Runner diameter	Less than 6.5 diameter	
Warpage - sink mark index	Smaller the better	Melt temperature	Less than 295 °C	0.71
		Runner diameter	Less than 6.5 diameter	

From the results, first, melt temperature is the most significant factor that affects the filling pressure. Filling pressure happens in packing stage, (second stage, refer Figure 1). In this stage, filling pressure is used to fill up the remaining volume of the cavity, so that shrinkage can be avoided [4, 9]. Figure 4a shows, lower melt temperature will result to higher filling pressure and vice versa. Lower melt temperature will keep the melt viscosity high and high pressure is needed to flow the melt to fill the cavity. M. Kurt et al. [4] also found that the melt temperature is the most influence factor that will affect the quality of the final products. The authors as well reported that the effect of filling pressure on mould temperature is less than melt temperature.

Second, parameters that influence filling time are the melt temperature and runner diameter. Filling time is the time taken to fill the cavity volume in the packing stage. Figure 4b shows, to achieve a smaller amount of filling time, high melt temperature and big runner diameter are required. In this sense, the melt can flow easily and filling time is reduced. But then, if the melt temperature is too high, the viscosity of the melt is higher too.

This will result to increase the cooling time and allowing shrinkage to occur. Hence, selecting the suitable melt temperature and runner diameter is important in order to achieve better product quality.

Finally, parameters that influence warpage are the melt temperature and runner diameter. Warpage results from differential shrinkage in the material of the moulded part that caused by internal residual stresses. Warpage can cause the moulded part to warp or twist. Figure 4c shows, in order to reduce warpage, both melt temperature and runner diameter should be smaller. Theoretically, if both melt temperature and runner diameter are set to a smaller amount, the packing time will increase. These happen because, at low melt temperature and small runner diameter, the melt resistance in filling up the cavity volume will be higher, thus the packing time will increase. From other research, X. P. Dang [10] also discover that, warpage can be reduced when the packing time is increased.

6. Conclusions

This study introduces a novel approach to find optimal parameter settings for plastic injection moulding process. An efficient optimization methodology using REPTree algorithm is introduced for optimizing the machine parameter settings for fishing reel support arm product. The algorithm highlights that, the most significant factors for producing the high quality fishing reel support arm are the melt temperature and runner diameter. For verification, the results from REPTree algorithm were compared statistically by applying ANOVA technique. From the verification, both methods were revealed the same results. Thus, the REPTree algorithm approach is very useful and able to highlight the important factors that will affect the plastic injection moulding process. The output from this approach can be used as an input for other optimization model for further optimisation activities (i.e. factorial design for testing more than one factor at a time). In that sense, the optimization activities will be more efficient, which by only consider the significant factors into account. In this manner, the degree of freedom in making errors of wrong judgement can be reduced. Finally, proposed approach also can be applied to other optimization activities of manufacturing processes, which able to reduce production lead time and increased the repeatability for quality control activities.

Acknowledgements

NS and JB: This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2010-0025650).

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