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Application of Whale Optimisation Algorithm in Injection Moulding Process

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ABSTRACT

In injection moulding process, shrinkage and warpage is two of the imperfection that has been pay attention for. Defected products are not only affect its visual, but might disrupt its functionality. Hence, a combination of good combination of parameter setting over optimisation is compulsory to minimize them. Whale Optimisation Algorithm (WOA) is a latest algorithm with a high potential for solving optimization issue. In this study, WOA is proposed to estimate optimal parameters in injection moulding process. It was proven that WOA has greatly outperformed the result of simulation for all injection moulding responses, Shrinkage in x direction (Sx), Shrinkage in y direction (Sy) and warpage (W) by 23.0589%, 20.7530% and 94.5545% respectively.

Key words : Whale Optimisation Algorithm, Shrinkage, Warpage, Optimisation, Injection Molding Process

1. INTRODUCTION

Injection moulding process is a technique for mass production of plastic parts. It is widely used due to its flexibility and low processing cost [1]. However lighter and thinner design can easily cause defect to the product due to the unbalance pressure distribution [2]. Shrinkage and warpage are some of the most common defect occur in injection molding process [3]. Production of the moulded parts with unevenness of shrinkage in any segment of parts possibly will result the warpage defect. Warpage values can be determined by the shrinkage unevenness level and part stiffness [4].Defect on the product may affect its functionality and appearance.

Optimisation of the processing parameter is a convenient technique to reduce and prevent defect on the moulded products. Traditionally, production engineer used trial-and- error method in order to find the optimum parameters values [5], [6]. Since the production engineer require at least 10 years' experience to be acknowledge as an expert, the number of expert versus demand of industry does not synchronize [7], [8]. Since only one test can be done at once, it makes the setting process become complex and difficult .Due to the high production cost and longtime consumption, this technique are no longer relevant [9], [10]. Since there is no guideline for fractional design in Design of Experiments (DOE), a method with experimental strategy named Taguchi method was invented in late 40s. This method using modified and organized procedure of DOE [11], [12]. Parameter optimization using Taguchi has been widely applied in injection moulding process [13]–[17]. Unfortunately, this technique made it impossible for continuous process parameter since it based on literature which can be seen as unreliable and not effective. Response Surface Methodology (RSM) then developed which provide flexibility in dealing with low-dimensional problems. This technique involve less task in comparison with another conventional technique. However, the RSM analysis result may affected by the reliance and interaction among responses [18]. Therefore, some of the previous studies integrate RSM with another technique such as machine learning algorithm for better accuracy in highly nonlinear responses [19], [20].

The machine learning algorithm is recognized for its proficiency on features visualization and modification of a cluster of parameter. It also can well customize a huge number of parameters that can ensure a proper working system [21]. Chen and Kurniawan [10] applied Taguchi, Genetic Algorithm (GA), Back-Propagation Neural Network (BPNN) and Particle Swarm Optimisation-Genetic Algorithm (PSO-GA) hybrid for multi-objective optimization [22]. Experimental validation demonstrates that the proposed two-stage optimisation method's perfomance provide higher stability for warpage and shrinkage reduction. Meanwhile, Najihah et al. [23] integrate mathematical algorithm from RSM using GA and the shrinkage value was found to be decrease. Hazwan et al. [24] applied RSM and Glowworm Swarm Optimization (GSO) to find optimal parameter and found that warpage value decrease by 39.1%. Due to the effectiveness of the machine learning algorithm in optimization of process parameter, researchers has various options and techniques to be apply for defect reduction. Meanwhile, the evolution of optimization algorithm keep growing by years [25]. In 2016, Whale Optimization Algorithm (WOA) was developed. This algorithm was stimulated by nature manners of humpback whale when they are hunting [26]. The fact that WOA improve the candidate solution in each step make it different with other algorithm. WOA which has never applied in injection moulding process might has potential to produce a great optimization.

In this paper, the objective of this paper is to find the optimal parameter in order to enhance shrinkage and warpage value in injection moulding. RSM and WOA utilised to find optimal parameter and a front panel housing with shrinkage and warpage issues selected as the case study [27]. The result then will be analyze and compare.

2. RESEARCH METHOD

The methodology of this study can be divided into two phases which are simulation and Design of Experiment (DOE) and WOA optimisation. Autodesk Moldflow Insight (AMI) 2012 software was used to perform simulation. Then the parameter and its range were obtained from simulation result and assessment on the past researchers. Using Design Expert 7 software, the DOE was conducted and list of experiment created from the input variable and output response. WOA codes are applied using MATLAB.

2.1 Simulation and Design of Experiment

The first phase of the study begins with the part design of a specimen that is going to be used as a case study. To makes the study fit current trend of product design in market, front panel housing (Figure 1.) [28] with curvature shape was. Acrylonitrile Butadiene Styrene (ABS) material was selected due its wide application in plastic products. Shrinkage value in both x and y axis will be measure as shown in Figure 2.

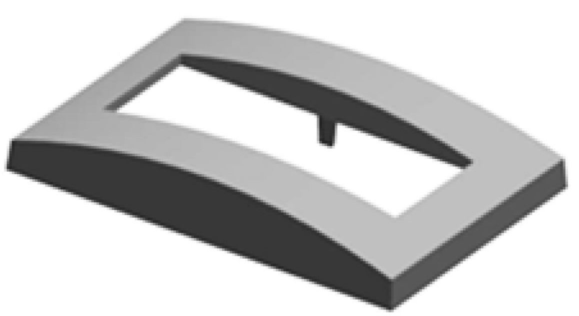

Figure 1: Design of Front panel housing

Figure 3 shows the simulation process flow. Firstly, the designed part and gating system were imported into AMI 2012 software. The straight cooling circuit was chosen for core and cavity insert. Four analysis were conducted to obtain necessary parameter range that influence shrinkage and warpage the most (Moulding Window, Fill, Fill+Pack and Cool Finite Element Method (FEM)). The DOE was conducted via Design Expert 7 software with RSM method. DEO was defined through rotatable central composite design (CCD), where the variable parameter chosen are cooling time, mould temperature, packing pressure and melt temperature. To analyse the results from the simulation, Analysis of Variance (ANOVA) is a platform used for making sure the function mathematical models are valid. Residual plots and normal probability were referred to make sure each response model are relevant. The predicted model of each response also produce here.

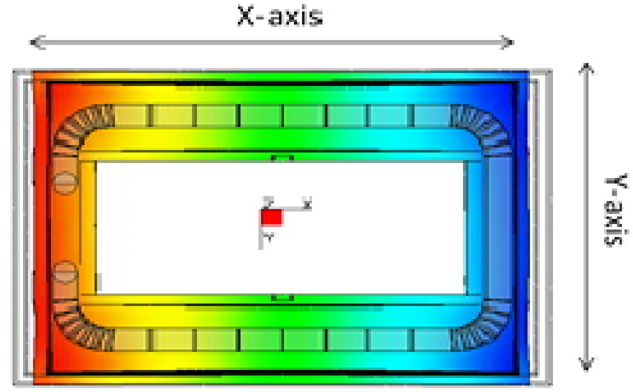

Figure 2: x and y axis measurement of Front Panel Housing

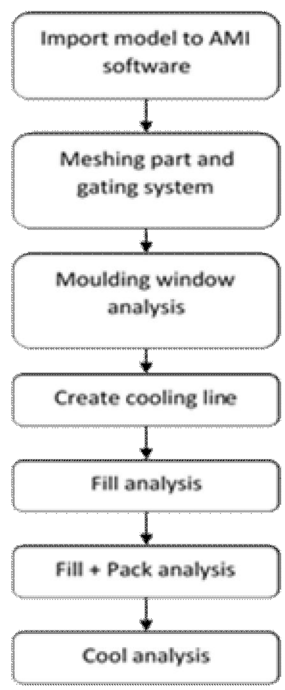

Figure 3: Simulation Process

2.2 Whale Optimization Algorithm (WOA)

Together with the mathematical model obtained from RSM, WOA were applied to look for the best parameter set. The WOA start by declaration of population size (n), parameter (a), coefficient vector A and C also the maximum number of iteration (Max). Then the mathematical model for each responds which act as objective function along with the lower and upper boundary for each parameter were set up.

The searching method of WOA basically by shrinking encircling or via spiral course (Figure 4). Mathematically, this searching behavior modeled as two phase:

2.2.1 Encircling prey

The models for searching prey are:

$$D=|C \cdot X_{rand}-X| \quad (1)$$

$$X\,(t+1) = X_{rand}-A \cdot D \quad (2)$$

Where *A* and *C* are coefficient vector where simplify from equation (3) and (4) where *'a'* decrease linearly from 2 to 0 range meanwhile *'r'* is the random number between 1 to 0.

$$A=2 \cdot a \cdot r-a \quad (3)$$

$$C=2 \cdot r \quad (4)$$

However, if the value of $A<1$, equation (5) and (6) are used.

$$D=|C \cdot X^*(t)-X(t)| \quad (5)$$
$$X\,(t+1) = X^*(t)-A \cdot D \quad (6)$$

t is the present iteration, *X* is the point vector and *X** represent current best point.

2.2.2 Update Spiral Position

Equation (7) represent position update where *'p'* is a random number from 1 to 0, *'b'* is a representative for spiral shape constant and *'l'* value is between -1 to 1.

$$x(t+1)=\begin{cases} X^*(t)- A \cdot D & \text{If } p<0.5 \\ D \cdot e^{bl} \cdot cos(2\mu l)+X^*(t) & \text{If } p\geqslant 0.5 \end{cases} \quad (7)$$

This study had utilized 30 population size and 500 maximum iteration according to the previous work by Mirjalili et al. [23]. Since the responses cannot be in negative value, each fitness were set to be absolute. The lower and upper boundary for respective parameter shown in Table 1.

Table 1: Parameter Range

Parameter	Lower Boundary	Upper Boundary
Melt Temperature (°C)	220	270
Mould Temperature (°C)	40	90
Packing Pressure (Mpa)	35	63
Cooling Time (s)	12	31

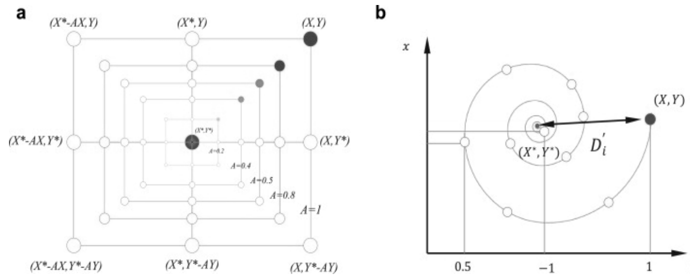

Figure 4: WOA Search Method : (a) shrinking encircling method and (b) spiral updating

3. RESULTS AND DISCUSSION

From the ANOVA analysis, the result shows that all the values of "Prob > F" less than 0.0500 indicates that the models are significant. The final equation in term of coded factor (A-mould temperature, B-melt temperature, C-packing pressure, D-cooling time) from each response (x direction shrinkage (*Sx*), y direction shrinkage (*Sy*) and warpage (*W*)) presented in Table 2.

From the simulation, the recommended value for each parameter obtained which are Mould Temperature (65.0°C), Packing Pressure (49.9MPa), Melt Temperature (245.0°C) and Cooling Time (13.4s). Therefore the response values are 0.613660% for Sx, 0.725233% for Sy and 0.020239mm for W.

For the optimization of Sx by WOA, the best value obtain is 0.472157% where the suggested parameters are 269.9479°C (Melt Temperature), 40°C (Mould Temperature), 31s (Cooling Time) and 63MPa (Packing Pressure). Figure 5 shows that the optimal value gain after the 4th iteration.

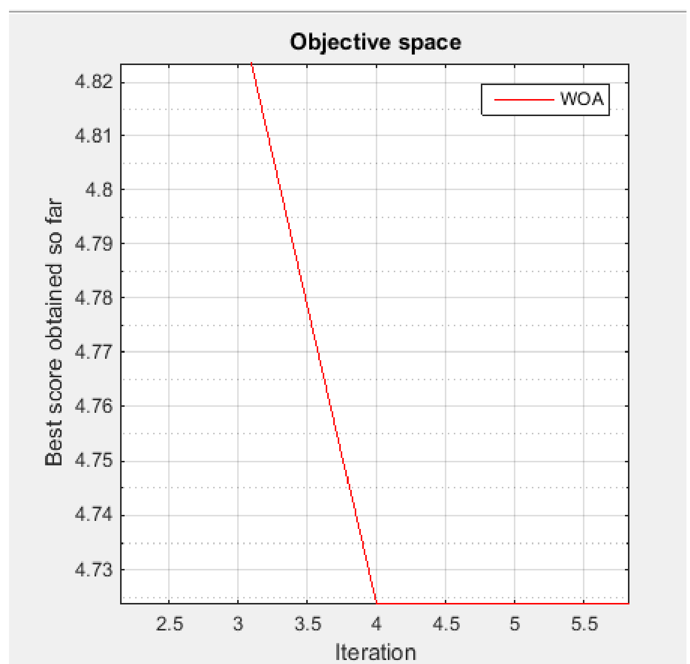

Figure 5: Best Score vs Iteration for Sx Response

On behalf of the optimization of *Sy*, the best value obtain is 0.472157% where the suggested parameters are 239.2901°C (Melt Temperature), 40°C (Mould Temperature), 31s (Cooling Time) and 63MPa (Packing Pressure). Figure 6 shows that the optimal value gain after the 3rd iteration.

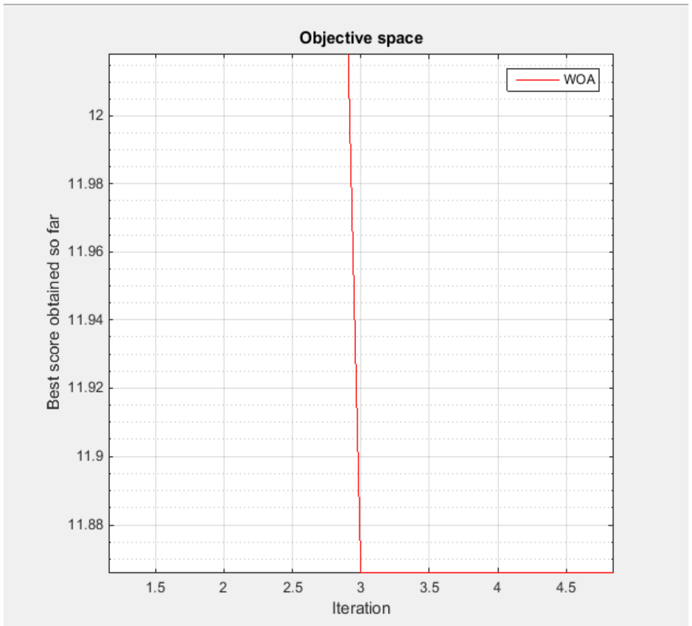

Figure 6: Best Score vs Iteration for *Sy* Response

The best value obtain for *W* is 0.001156mm where the suggested parameters are 226.2852°C (Melt Temperature), 85.68013°C (Mould Temperature), 31s (Cooling Time) and 63MPa (Packing Pressure). Figure 6 shows that the optimal value gain after the 3rd iteration.

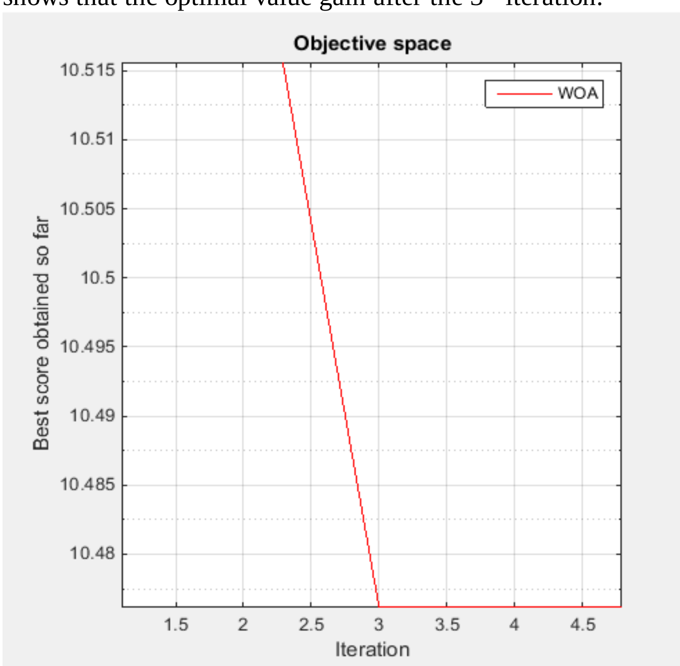

Figure 7: Best Score vs Iteration for *Sy* Response

4. CONCLUSION

Based on Table 3, it can be seen that the application of WOA does gives enhancement on injection moulding process of shrinkage and warpage through parameter optimization. The algorithm also proven to work fast since the optimal value obtained in early iteration. Meanwhile, the recommended parameters are varies depends on the responses.

Table 3: Simulation versus WOA Result

Technique	Response		
	Sx (%)	***Sy (%)***	***W (mm)***
Simulation	0.61366	0.7252	0.0202
WOA	0.47215	0.5747	0.0011
% improve	23.0589	20.7530	94.5545

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