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Optimizing Plastic Injection Process Using Whale Optimization Algorithm in Automotive Lighting Parts Manufacturing

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In this study, using the whale optimization algorithm (WOA), one of the recent optimization algorithms inspired by nature, the plastic injection process parameters of an automotive sub-industry company were tried to be optimized. For this purpose, we tried to provide the maximum weight criterion for the "356 MCA Plastic Housing" (which is an automotive lighting part) produced by plastic injection method. The decrease in the weight of the product indicates that the material injected into the mold is missing and naturally indicates that there will be quality problems. In order to achieve this aim, the best factor levels were tried to be determined for the mold temperature (°C), injection speed (m/s), injection pressure (bar), holding time (s), and injection time (s), which are the controllable parameters of injection process. Factors and factor levels addressed using WOA have not been studied for this type of problem before and this is the novelty aspect of this research. Experiments performed to confirm the findings for optimum process parameters proved that the WOA method can be successfully applied to improve plastic injection process parameters. This study contains information for practicing researchers in terms of showing how the nature-inspired algorithm WOA can be applied in practical field studies.

Keywords: Artificial intelligence, Nature inspired algorithms, Optimization, Regression

Introduction

Today, the production of plastic parts of automotive lighting elements is widely carried out with the help of the plastic injection process. This process is the process of bringing the melted plastic raw material into the desired shape by injecting it into the mold. If the geometry (and therefore the internal volume) is fixed for the special mold prepared for each special plastic part that is intended to be produced, and if the mold can be fully filled with the raw material in theory, then the produced product will also be in the desired geometry. As the product has its ideal geometry, it also has an ideal weight to reach. When the product is in its ideal geometry, then this also means that the product is at the maximum weight it should be. Since the mold for each product is fixed, the maximum weight that the product can reach is actually a fixed value and is equivalent to the ideal weight value of the product. However, due to the values of the process parameters, when the mold cannot be filled completely and properly (in other words, when enough plastic raw materials cannot be injected into the mold), deformity due to the missing amount (therefore low product weight) is observed. It is a big problem to produce accessories and assembly parts produced by plastic injection in the desired geometry and surface quality, and incorrectly determined process parameters can cause a large amount of scrap. Outstanding studies on plastic injection molding (PIM) process optimization in the literature are as follows.

Chen *et al.* presented a study on multi-input single-output PIM process optimization. They used Taguchi, back propagation neural networks (BPNN), analysis of variance (ANOVA), genetic algorithm (GA) and Davidon-Fletcher-Powell (DFP) method. Packing pressure, injection time, injection velocity, and velocity pressure switch position are determined as the process parameters, and the weight of product is measured as the response.[1] Chen *et al.* used Taguchi for optimizing multi-input multi-output (MIMO) plastic injection process.[2] Khan *et al.* (2010) used combined grey relational and principle component analysis (PCA) for process parameters of PIM. While compressive strength, flexural strength, and tensile are measured as the responses; holding pressure, holding time, melt temperature, and injection time are the factors those have affect on these responses.[3] Yin *et al.* predicted the war page at the products produced

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by PIM and performed optimization for the injected plastic parts. BPNN is used for the predictions. They selected the factors namely melt temperature, mold temperature, cooling time, packing time and packing pressure.[4] Xu *et al.* used particle swarm optimization (PSO) algorithm and ANN together (PSONN model) to optimize MIMO-PIM process parameters namely injection pressure, mold temperature, melt temperature, injection time, holding time, holding pressure, cooling time. They measured product weight, flash, and volume shrinkage as the responses.[5]

AlKaabneh *et al.* proposed using combined Taguchi and analytical hierarchical process (AHP) together to optimize PIM. They used the factors namely filling time, mold temperature, melt temperature, flow/pack switch, holding pressure, pressure holding time, coolant inlet temperature.[6] Bhattacharya & Bepari used grey relational analysis for optimizing PIM process parameters.[7] Chen & Kurniawan used GA, Taguchi, BPNN, and hybrid GA-PSO to perform optimization on the PIM process parameters. Injection velocity, packing time, packing pressure, cooling time, and melt temperature are selected as the factors, while length is the response. [8]Santhana kumar & Adalarasan used grey Taguchi based response surface methodology (GT-RSM) for PIM process optimization. They selected injection pressure, packing pressure, melt temperature, and cooling time as the factors those have to be optimized, while mechanical properties of injection moulded polypropylene/E-glass composites are selected as the response.[9] Kuo & Liao studied on dimensional accuracy of Fresnel lens during PIM process. The factors namely melt temperature, packing pressure, mold temperature, and injection speed tried to be optimized using Taguchi.[10] Chen *et al.* used RSM, Taguchi, and hybrid GA-PSO to optimize PIM process. They measured warpage and length as the responses. Injection velocity, packing pressure, melt temperature, cooling time, and packing time are determined as the factors those have to be optimized.[11] Tian *et al.* used Taguchi to optimize the PIM process parameters, such as injection velocity, melt temperature, packing pressure, cooling time, and packing time; while warpage and product length are measured as the responses.[12] Gao *et al.* proposed a new optimization method based on classification model to optimize PIM process parameters namely melt temperature, mold temperature, injection time, injection pressure, packing velocity, screw rotational speed, and cooling time. They aimed to prevent quality defects in products.[13] Feng & Zhou used radial basis functions (RBF) and GA to optimize PIM parameters to provide the desired response values for warpage, shrinkage, and weldline. They determined the factors those have effect on these responses as melt temperature, cooling time, injection time, mold temperature, packing pressure, and packing time.[14] Zakaria *et al.* used WOA to optimize injection moulding process. They used melt temperature, packing pressure, mould temperature, and cooling time as the factors to be optimized. Shrinkage (for x and y directions) and warpage for the case product is measured as the responses.[15] Sreedharan *et al.* used RSM and principle component analysis (PCA) based weighted grey relational analysis (GRA) for optimizing the sequential plastic injection process parameters to obtain desired warpage, weldline, length, and various metal plating thicknesses values.[16] Fen *et al.* (2020) presented a study on PIM process optimization using ANOVA, ANN, Taguchi, and GA. They determine the factors as melt temperature, mold temperature, cooling time, flow rate, and four parameters related to variable pressure profile. Weld line, warpage, and clamp force are measured as the responses.[17] Karaoglan & Baydeniz used Taguchi to find the best factor level combination for mold temperature, holding time, injection speed, injection pressure, and injection time factors of plastic injection process.[18]

In addition to these studies the review presented by Kashyap & Datta on optimization of plastic injection molding process parameter is well summarizes the related studies.[19] Also the review presented by Fei *et al.* on PIM process optimization using Taguchi is a good source to review the used factor combinations for PIM in the literature.[20]

As can be observed from the literature review that, PIM process optimization is studied by many researchers however optimizing PIM process parameters namely mold temperature (°C), injection speed (m/s), injection pressure (bar), holding time (s), and injection time (s) to maximizing the product weight by using WOA is not previously investigated. This is the novelty aspect of this study. The aim is to prevent the manufactured plastic housing parts from quality defects by providing the mold full-filled by the injection machine. The WOA algorithm is a modern metaheuristic algorithm. It simulates the hunting strategies of humpback whales, is a nature-inspired and efficient approach for solving optimization problems and engineering design problems. The classical approaches are also useful however the motivation for this study is to show the readers that how to use the WOA - which has recently started to be used in real industry problems - in the plastic injection process.

Materials and Methods

Regression Modelling

In most applied optimization problems, it is important to find a suitable approximation for the mathematical relation between the measured output variable (response) and the input parameters (factors) those has effect on the variation at the response. Regression modeling is a widely used method to fit the mathematical model to the original observation values collected from the workshop. For this purpose usually first order (to model linear relations) or second order (to model parabolic relations) polynomials are employed. These low-order polynomials are called as regression models. In this paper, the form of the mathematical relation between the factors and the responses are also modeled by using regression modeling. Then whale optimization algorithm (WOA) is used to calculate the optimum factor levels those provide to obtain the desired response values.

Our preliminary trials and the some research results those are presented in the literature proved that the relation between the plastic injection process parameters (mold temperature (°C), injection speed (m/s), injection pressure (bar), holding time (s), and injection time (s)) and the weight of the final product (response) are nonlinear. Also it is well known that in the literature that there are interactions between these factors. Because of these reasons we used second order regression equations with interaction terms in the modelling phase. Eq. (1) represents a general regression model that includes linear terms (X_i), quadratic (second order) terms (X_i^2), and the interaction terms (X_iX_j). The parameters of the model are given under the βvector that is given in Eq. (2). If the βvector is calculated, then this means that the mathematical model is determined:[21,22]

$$Y_u = \beta_0 + \sum_{i=1}^{n} \beta_i X_{iu} + \sum_{i=1}^{n} \beta_{ii} X_{iu}^2 + \sum_{i<j}^{n} \beta_{ij} X_{iu} X_{ju} + e_u \quad \ldots(1)$$

$$\beta^T = [\beta_0, \beta_1, \beta_2, \ldots, \beta_n] \quad \ldots(2)$$

where u represents the observation (run) number, β_0 is the constant term, β_i is the regression model coefficients of the linear terms while β_{ii} and β_{ij} are the regression model coefficients for the quadratic terms and interactions respectively. The β coefficient can be calculated by matrix operations and an example matrix notation is given in Eqs (3) and (4) for a data set composed of N runs and a mathematical model with m=7 regression coefficient. In the example given in Eq. (4) only 2 factors (x_1 and x_2) are used for simplicity:[21,22]

$$\beta = (X^T X)^{-1}(X^T Y) \quad \ldots(3)$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \ldots \\ y_N \end{bmatrix} X = \begin{bmatrix} 1 & x_{11} & x_{21} & x_{11}^2 x_{21}^2 & x_{11}\, x_{21} \\ 1 & x_{12} & x_{22} & x_{12}^2 x_{22}^2 & x_{12}\, x_{22} \\ 1 & x_{13} & x_{23} & x_{13}^2 x_{23}^2 & x_{13}\, x_{23} \\ & & \ldots & & \\ 1 & x_{1N} & x_{2N} & x_{1N}^2 x_{2N}^2 & x_{1N} x_{2N} \end{bmatrix} \quad \ldots(4)$$

Y is a column vector consisting of the observed response values. In this example notation there are N experimental runs. X is the input matrix consisting of the factor levels. The first column of this matrix is composed of 1s. This is a general rule in regression modeling to represent the constant terms. Then in each column the factor values are placed at the order that is mentioned in Eq. (1). In the example given in Eq. (4), it is assumed that there are two factors (X_1 and X_2) and there are nonlinear (second order) relations and interactions between these factors and the response. Coefficients of the regression equation are given in β vector. R^2 (coefficient of determination) is used to understand if the factors in the model is sufficient to explain the changes in response and calculated by Eq. (5).[21,22]

$$R^2 = \frac{\beta^T X^T Y - n\overline{Y}^2}{Y^T Y - n\overline{Y}^2} \quad \ldots(5)$$

R^2 is expected to be closer to 1. In this case, we should understand that there is no need to add additional factors to the model. If the number of factors are sufficient (if R^2 is close to 1), then the significance of the mathematical model given in Eq. (1) have to be tested. This test can be performed by using ANOVA which uses F-test (a widely used statistical hypothesis test). In ANOVA, two hypotheses are tested (H0: model is insignificant and H1: model is significant). H1 hypothesis must be true to continue with the calculated regression models to whale optimization. We can use the p-value method. If the p-value is less than the α (0.05=%5 for this study at 95% confidence level), then this means the model is significant.[21,22] In this study we obtained p-value from the ANOVA analysis report of Minitab statistical analysis program.

Whale Optimization Algorithm (WOA)

Whale optimization algorithm (WOA) is one of the recently invented optimization algorithm that is inspired from the nature and proposed by Mirjalili and Lewis.[23] WOA mimics the hunting strategies of humpback whales and effectively used for tackling optimization problems. WOA is a swarm based meta-heuristic algorithm such as particle swarm optimization (PSO) algorithm, artificial bee colony (ABC) algorithm, ant colony optimization (ACO) algorithm, bat algorithm (BA), grey wolf optimizer (GWO) algorithm, and etc. The main difference between the WOA and the previously presented swarm-based algorithms is its hunting behavior simulation mechanism. WOA uses the simulated hunting behavior with random or the best search agent to chase the prey. Also WOA uses a spiral to simulate bubble-net attacking mechanism of humpback whales. WOA has three operators to simulate the (*i*) encircling prey, (*ii*) bubble-net foraging behavior of humpback whales, and (*iii*) search for prey.[23]

Encircling prey (*i*) is recognition phase of the location of prey (which means determining the optimum factor levels those give the desired response value) and encircling them. Mathematical simulation of this natural behavior (first step of the algorithm) is proposed by Mirjalili and Lewis as given below:[23]

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)\right| \quad \ldots(6)$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \quad \ldots(7)$$

where $\vec{X}$ and t indicates the position vector and the iteration number respectively. X^*indicates the position vector for the best solution (and should be updated as long as there is a better solution). Element-by-element multiplication is represented by '.' and the coefficient vectors are presented by $\vec{A}$ and $\vec{C}$: [23,24]

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad \ldots(8)$$

$$\vec{C} = 2.\vec{r} \quad \ldots(9)$$

Over the course of iterations, $\vec{a}$ is linearly decreased from 2 to 0. $\vec{r}$ is a random vectors between 0 and 1. The fluctuation range of $\vec{A}$ is decreased by $\vec{a}$ in the random range $[-a, a]$.[23,24]

Bubble-net foraging behavior of humpback whales (*ii*) is the second phase of the algorithm. This is the special hunting method of the humpback whales in the nature. Humpback whales prefer to hunt small preys (such as fishes and etc.) close to the surface of the sea. It has been done by creating distinctive bubbles along a circle. Humpback whales dive around the prey and then start creating bubble in a spiral shape around the prey. Then it swims up toward the surface and feeds. This maneuver (which is called as spiral bubble-net feeding) is mathematically model by Eq. (10) given below. In this equation, two approaches namely '(a) shrinking encircling mechanism' and '(b) spiral updating position' are used together. Humpback whales swim around the prey with (a) and (b) simultaneously with the assumption of 50% to choose between either to update the position of whales: [23,24]

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} if p < 0.5 & \text{(a)} \\ \vec{D}'.e^{bl}.cos(2\pi l) + \overrightarrow{X^*}(t) if p \geq 0.5 & \text{(b)} \end{cases} \quad \ldots(10)$$

In this approach, distance ($\vec{D}$) between the (X,Y) (where the whale is located) and (X^*,Y^*) (where the prey is located) is calculated in first. Then a spiral equation is then created between the position whale and prey to mimic the helix-shaped movement of humpback whales. Where $\vec{D}' = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right|$ (distance of the i^{th} whale to the prey – which is the best solution obtained so far). The b is a constant which defines the shape of the logarithmic spiral, l is a random number between -1 and 1.[(23,24)]

Search for prey (*iii*) is the last phase. Humpback whales search randomly according to the position of each other and to simulate this mechanism random values for $\vec{A} > 1$ and $\vec{A} < -1$ are used to force search agent to move far away from a reference whale. The location of a search agent in the exploration phase is changed according to a randomly chosen search agent instead of the best search agent found so far, in comparison to the exploitation phase. Using this method and using $\left|\vec{A} > 1\right|$ together, provides WOA to avoid local optima. By this way WOA can perform a global search. The related mathematical mechanism is given in Eqs (11) and (12): [23,24]

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\right| \quad \ldots(11)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \quad \ldots(12)$$

$\overrightarrow{X_{rand}}$ depicts the random position vector (a random whale) that is chosen from the current population. The detailed information about WOA can be referred from Mirjalili and Lewis.[23]

Results and Discussion

The data used in this study were realized in an automotive supplier industry where automotive lighting and ventilation equipment is produced. For this purpose, the production of "356 MCA Plastic Housing", one of the lighting element components given in Fig. 1, by the plastic injection process has been discussed. In order to prevent quality problems in the product, WOA was used to optimize the process parameters. Product weight is not the only criterion to meet the quality criteria of the product, but it is the most important indicator. Before checking many different quality criteria such as relative surface quality, shrinkage and warpage, one of the most important control points is the maximum product weight. The experimental design study for quality improvement was carried out on the injection machine with HAITIAN-300 TON (mold closing force 3000 kN). The biggest problem with the "356 MCA Plastic Housing" plastic part produced by PIM process is failure to provide the desired quality level and not to assembly to the lighting carrier housing. At the same time, the fact that the nail parts break easily during the assembly of the housing is included in the records as another output for poor quality, although not in all of the products. In principle, if the mold can be completely filled with the raw material, then the produced plastic part will also be in the geometry it desired. This means the weight approaches to its theoretical maximum weight (which is upper weight limited by the geometry of the mold). However, due to the process parameter values, when the mold cannot be completely and properly filled, deformity is observed as a consequence of the missing raw material quantity (therefore low product weight– see Fig. 2).

In this paper, we aim to maximize the response namely the weight (g) of the final product. The factors namely mold temperature (X_1) (°C), injection speed (X_2) (m/s), injection pressure (X_3) (bar), holding time (X_4) (s), and injection time (X_5) (s) are the factors of the mathematical model those having effect on the mentioned response. We will perform the optimization in three steps: *(i)* design an experiment and obtain the experimental results from the experimental set-up (HAITIAN-300 TON), *(ii)* fit the regression models to these experimental results, (*iii*) use the WOA to determine the optimum factor levels those provides the desired response values. To obtain experimental data, Taguchi L27 design is used. The factor levels are given in coded form. First reason is the commercial privacy. The second is that when optimizing with the nature-inspired algorithm WOA, it is more appropriate to use a model built with coded values to avoid local optimum values and to make the model independent of units of factors. The coding is performed by using Eq. (13)

Fig. 1 — "356 MCA Plastic Housing"

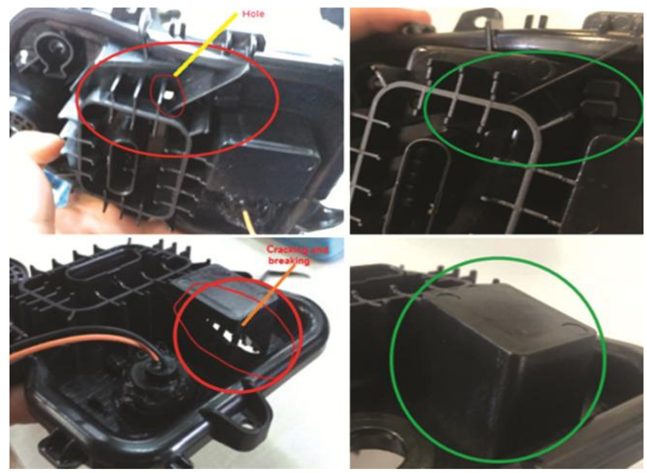

Fig. 2 — Sample defective product images which belong to injection process

$$X_{coded} = \frac{X_{uncoded} - ((X_{max} + X_{min})/2)}{(X_{max} - X_{min})/2} \quad \ldots(13)$$

The designed experiments and the response (weight values in grams) (observed from the HAITIAN-300 plastic injection machine) are given in Table1.

Minitab-16 statistical analysis program has been used for regression modeling and to perform required

Table 1 — Experimental design and observations

Run (i)	Coded Factor Levels					Response	Run (i)	Coded Factor Levels					Response
	X_{i1}	X_{i2}	X_{i3}	X_{i4}	X_{i5}	Y_i		X_{i1}	X_{i2}	X_{i3}	X_{i4}	X_{i5}	Y_i
1	−1	−1	−1	−1	−1	129.48	15	0	0	1	−1	1	132.43
2	−1	−1	−1	−1	0	131.85	16	0	1	−1	0	−1	129.53
3	−1	−1	−1	−1	1	132.63	17	0	1	−1	0	0	131.40
4	−1	0	0	0	−1	129.98	18	0	1	−1	0	1	132.58
5	−1	0	0	0	0	131.45	19	1	−1	1	0	−1	130.28
6	−1	0	0	0	1	132.65	20	1	−1	1	0	0	131.50
7	−1	1	1	1	−1	130.10	21	1	−1	1	0	1	132.93
8	−1	1	1	1	0	131.75	22	1	0	−1	1	−1	130.15
9	−1	1	1	1	1	133.10	23	1	0	−1	1	0	131.15
10	0	−1	0	1	−1	129.73	24	1	0	−1	1	1	132.55
11	0	−1	0	1	0	131.58	25	1	1	0	−1	−1	129.03
12	0	−1	0	1	1	132.48	26	1	1	0	−1	0	130.70
13	0	0	1	−1	−1	129.53	27	1	1	0	−1	1	132.55
14	0	0	1	−1	0	131.20	–	–	–	–	–	–	–

analysis (R^2 and ANOVA). Eq. (14) shows the calculated regression model (which is calculated by using Eqs (1–3)).

$$Weight(Y) = 131.2066667 - 0.119444444X_1 - 0.095555556X_2 + 0.083333333X_3 + 0.177222222X_4 + 1.449444444X_5 + 0.161666667X_1^2 + 0.056666667X_2^2 + 0.213333333X_3^2 - 0.145X_4^2 - 0.191666667X_5^2 - 0.020833333X_1X_5 + 0.085X_2X_5 - 0.004166667X_3X_5 - 0.118333333X_4X_5 \quad \ldots(14)$$

The R^2 is calculated as 98.27% using Minitab. This result indicates that these five factors are sufficient to model the change in weight. In statistical analysis 95% and 99% confidence levels are the most widely used levels. So we performed ANOVA under 95% confidence level (Type-I error (α) =5% =0.05). The p-value=0.000 (for the regression model) obtained from Minitab is compared with α=0.05 and because of being p-value < α then this means the model is significant. The prediction performance (PE) of the mathematical model calculated using Eq. (15) is presented in Table 2. We used Minitab for the predicting the expected weight ($\hat{Y}_i$) values.

$$PE_i(\%) = \frac{|Y_i - \hat{Y}_i}{\hat{Y}_i} 100 \quad \ldots(15)$$

when the performance results are examined, it is clearly observed that the overall prediction error (PE) is less than 0.2%. When the results of R^2, ANOVA, and PE are evaluated together, it is clearly indicated

Table 2 — Performance results for the mathematical model

Run (i)	Y_i	$\hat{Y}_i$	PE_i (%)	Run (i)	Y_i	$\hat{Y}_i$	PE_i (%)
1	129.48	129.75	0.21	15	132.43	132.55	0.09
2	131.85	131.45	0.31	16	129.53	129.57	0.03
3	132.63	132.76	0.10	17	131.40	131.30	0.08
4	129.98	129.83	0.12	18	132.58	132.64	0.05
5	131.45	131.49	0.03	19	130.28	130.17	0.09
6	132.65	132.77	0.09	20	131.50	131.70	0.15
7	130.10	130.15	0.04	21	132.93	132.85	0.06
8	131.75	131.78	0.02	22	130.15	129.91	0.19
9	133.10	133.02	0.06	23	131.15	131.41	0.20
10	129.73	129.95	0.17	24	132.55	132.53	0.01
11	131.58	131.39	0.14	25	129.03	129.06	0.03
12	132.48	132.45	0.03	26	130.70	130.89	0.14
13	129.53	129.43	0.08	27	132.55	132.33	0.17
14	131.20	131.18	0.01	–	–	–	–

that these models can be effectively used for optimization. For the optimization, the WOA is used.[23,24] The algorithm is coded in MATLAB (R2016a), and run on a PC having Intel Core i5 −2.4 GHz processor and 4 GB RAM. We determined WOA parameters after some preliminary trials. The parameters of WOA are set to 40 search agents and maximum 500 iterations. The problem is formulized as a multi-objective continuous optimization problem with the given constraints in Eq. (16). In this optimization problem, the WOA is used as the search algorithm on the response surface of the regression equation.

Min Y s.t. $X_1 \in[-1,1]$; $X_2 \in[-1,1]$; $X_3 \in[-1,1]$; $X_4 \in[-1,1]$; $X_5 \in[-1,1]$ …(16)

WOA is calculated the optimized coded factor levels as mold temperature (X_1) (°C)= −1, injection speed (X_2) (m/s) = −1, injection pressure (X_3) (bar) = +1, holding time (X_4) (s) = +0.2, and injection time (X_5) (s) = +1. For this optimized coded factor level combination; the weight is predicted as 133.24 gr by using Eq. 14. For these optimum factor levels 5 replications are performed at HAITIAN-300 plastic injection machine to confirm the mathematically calculated weight value. Mean of 5 replications are calculated as 133.27gr. The PE is calculated as 0.02% which is very close to zero. Considering the mold volume, the maximum theoretical weight that can be obtained for "356 MCA Plastic Housing" is expected to be 133.5 gr according to analytical calculations. This result shows that the optimization result is very close to the theoretical weight. According to these results, it can be concluded that with combining regression modelling and the WOA an effective optimization of the plastic injection process parameters to obtain maximum weight can be performed.

The results are also confirmed by using GA and social group optimization (SGO) algorithm. GA is the well-known and widely used nature-inspired algorithm and is a good reference to compare.[25] Also the SGO is the recently presented effective optimization technique.[26] The goal is to confirm whether the WOA result is a global optimum or a local optimum. Codding is also performed by using MATLAB (R2016a) and these two algorithms are run through the regression model given in Eq. (14). For the parameter tuning of WOA and GA, we used the results of some preliminary runs. With no additional tuning parameters besides the maximum number of iterations and population size, WOA is easier to implement. Tuning GA parameters is the more difficult when it is compared with WOA and SGO. Because there are four main critical parameters those have to be tuned (population size, crossover rate, mutation rate, maximum number of iterations). As with WOA, the parameters of SGO are also easy to set. Population size is determined as 10 for both SGO and GA. To determine SGO parameters we referred Satapathy & Naik[26] and set to self-introspection factor (c) = 0.2, number of fitness function evaluations (FEs) = 3000. We determined GA parameters after some preliminary trials. The mutation rate (mr) and crossover rate (cr) are selected as 0.4 and 0.5, respectively. The maximum number of iterations is set to 10000. SGO and GA computed the same factor levels as WOA and estimated the weight value at 133.24 gr. The exploration capabilities of WOA, SGO, and GA are nearly same for the problem handled in this study. The CPU time for WOA and SGO are very close to each other, and a bit better than GA. The CPU time of WOA, SGO, and GA are calculated as 3, 2, and 9 seconds, respectively. When the performance of WOA and SGO compared with performance of GA; WOA and SGO has lower dependency on the initial solutions obtained and continue to explore around the best solutions. They have good balance between exploration and exploitation. The purpose of benchmarking here is to show the readers whether the WOA solution is stuck to the local optimum without us realizing it. So both GA and SGO are also predicted the same factor levels with WOA which proves the optimized weight value of WOA is not local optimum, it is global. The rate of growth of time taken with respect to input is defined as the time complexity and since the same regression equation (and same constraints for the factors) is used as input; there is no significant difference between these three methods in terms of time complexity for the problem presented in this study.

Conclusions

This study addressed the problem of using WOA to decide the optimum PIM process parameters of a lighting part namely "356 MCA Plastic Housing". The goal is to maximize the product weight. The mathematical relation between the weight and the factors those have effect on the response (namely mold temperature (°C), injection speed (m/s), injection pressure (bar), holding time (s), and injection time (s)), is modelled by regression modelling. ANOVA is used to test the model significance and then WOA is used for performing the optimization. WOA has not been used for this factor combination and it is the novelty aspect of this research. Optimum factor levels for mold temperature, injection speed, injection pressure, holding time, and injection time are calculated as −1, −1, +1, +0.2, and +1 by coded values respectively. Because of the commercial confidentiality the coded values did not transformed to uncoded original values, however it is clearly observed that the weight is maximized. The results and the efficiency of WOA have been verified by the results of the confirmation tests. To confirm the WOA prediction for the weight, 5 replications are performed. The prediction error between the observed and the predicted weight is calculated as 0.02% which is very close to zero. The benchmark of WOA results with GA and SGO are also proved that this result is the global optimum. The overall results of this study indicate that WOA can be easily and effectively used for real industrial problems by combining regression modelling. Reproducing the code is relatively simpler in SGO when it is compared with WOA and GA. SGO adopts the greedy selection strategy and this strategy avoids getting stuck at the local optimum. However the tuning the parameters of WOA is more simple. It uses a spiral equation to mimic the hunting behavior of humpback whales. Number of whales is the only critical parameter that needs to be set. GA is relatively most complex one according to the reproducing the code and tuning the algorithm parameters when it is compared with WOA and SGO. In this study we used WOA (without hybridization) and we used SGO and GA to confirm the results of WOA. SGO and GA are also useful for this problem, however the motivation for this study is to show the readers that how to use the WOA in the plastic injection process. In the future research, this study can be extended by using additional algorithms those are presented in the literature.

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