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Optimizing Plastic Extrusion Process via Grey Wolf Optimizer Algorithm and Regression Analysis

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One of the most widely used methods in the production of plastic products is the extrusion process. There are many factors that affect the product quality throughout the extrusion process. Examining the effects of these factors and determining the optimum process parameters which will provide the desired product characteristics; is important for reducing costs and increasing competitiveness. This study is performed in a manufacturer that produces plastic cups. The aim is to optimize extrusion process parameters of this company in order to achieve 1.15 mm thickness at the produced plastic sheets. For this reason, in order to be able to model the problem as an optimization problem through regression modelling, the thicknesses of the sheet generated with different process parameters were observed during the production processes. Then, considering the desired 1.15 mm sheet thickness, the established model is optimized by running the grey wolf optimizer (GWO) algorithm through the model.

Keywords: Artificial intelligence, Nature inspired algorithms, Optimization, Plastic cub production

Introduction

Plastic extrusion method is a manufacturing method used especially in the production of plastic materials. In this process, in a sleeve coated with a heater, an engine rotates the screw to melt the plastic granules under temperature and pressure. The molten plastic is shaped and cooled along the mould and the production takes place. Many parameters affect product quality during the extrusion process. Optimization of these parameters aims to provide the desired quality and reduce production time, labor and energy costs. The related literature has shown that optimization of extrusion processes for different types of materials are studied by many researchers. Dean & Lightner used statistical methods to optimize the extrusion process. They used statistically designed experiments to optimize the extrusion process parameters to obtain the desired responses such as optical reflected mechanical properties.[1] Zhou & Paik optimized food extrusion process parameters.[2] They used artificial neural networks (ANN) and genetic algorithm (GA) together for this purpose. Optimizing process conditions in food extrusion is extremely difficult due to the involvement of multiple process variables and lack of knowledge about their interactions. A neural network was developed and trained to map highly nonlinear relationship between input variables and process output. A GA based system is then developed to search the best set of parameter values. Engels & Diedel optimized tile extrusion process.[3] In this study, the extrusion process for traditional and technical ceramic applications is considered. The goal was to reduce the deviation of rectangularity of the tiles, by implementing a stable extrusion process based on the developed new material parameters. Chen *et al.* researched the optimized Ti-6Al-4V titanium alloy equal-channel angular extrusion (ECA) method for investigation.[4] The effective stress-strain distribution, the die load at the exit, and the damage factor distribution are investigated under different ECA extrusion conditions. Taguchi method (which is a well-known design of experiment technique) is employed to optimize the extrusion process parameters. Fowler *et al.* studied on the effects of polymer extrusion filter layering configurations using simulation-based optimization.[5] In optimizing the forming parameters of the Twist Extrusion process, Iqbal *et al.* used response surface methodology (RSM) to improve the hardness and tensile strength of the aluminium alloy AA6061T6.[(6)] They considered temperature, forming load, and the number of passes to AA6061T6 alloy subjected by twist extrusion process to extreme plastic

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deformation. Responses namely tensile strength and hardness increased considerably. The die concept was optimized by Tomassini to create a thermoplastic profile of rigid polyvinylchloride (PVC).[7] Due to its inherent weakness (since it degrades at 140°C) and via extrusion tests, this material is hard to process. They used computational fluid dynamics (CFD) simulations of ANSYS software for die design. Extrusion was performed using the parameters of the process: flow rate (screw speed) and material temperature. The results were compared by considering the geometry and the final dimensions of the profile, the mass flow, the pressure and the temperature of the head were equally satisfactory with those obtained by the simulation. Al-Refaie & Musallam studied to improve the efficiency of the polyethylene extrusion process.[8] They used goal programing method for this purpose. Output cycle time, roll weight, distance between emitters, and thickness, are tried to be optimized.

Literature review indicates that artificial intelligence (artificial neural networks etc.), operations research (goal programing etc.), computer simulations (fluid dynamics etc.), design of experiment techniques (RSM, Taguchi, factorial design) and statistical methods are previously used for optimization of extrusion process. Different optimization techniques have been developed in this field. This study was carried out at a manufacturer that meets the plastic cups requirement of the food sector. The aim of the study is to find the mathematical relationship between the thickness of the produced sheet and the extrusion process parameters process by determining regression equation and to find out the optimum factor levels of process parameters in order to obtain the target sheet thickness. The factors are determined as: roller rotation speed, extrusion speed, pump speed, pressure, and withdrawal speed of the moulded product. The effect of this parameter combination on the sheet thickness produced by the extrusion process is not previously investigated. The purpose of this paper was to solve the related problem by using the ‘grey wolf optimizer (GWO) algorithm’ (which is a nature-inspired artificial intelligence technique). The GWO algorithm is a modern metaheuristic algorithm. It simulates the hunting behavior of the wolves, is a modern and efficient approach for solving optimization problems and engineering design problems.[9–11] The classical approaches are also useful however the motivation for this study is to show the readers the GWO algorithm — which has just recently started to be used in real industry problems — in the plastic extrusion process. In summary, this study has got novelty in the field of extrusion process parameter optimization in terms of used parameter combination and optimization technique.

Materials and Methods

The Discussed Plastic Extrusion Process

Extrusion process is widely used in the production of plastic products. In extrusion process, the plastic granules are melted under temperature and pressure. The molten plastic is shaped and cooled along the mould and the production takes place. In this study plastic sheet production line that is produced by Suzhou New Co. (model year: 2014) with 400 kg/h capacity is used for the experiments. In the extrusion process discussed in this study, after the raw material is melted, it is turned into a sheet under a certain pressure. In this process; ZN55 slider, homopolymer, calcite, burr, paint, antistatic, copolymer are mixed in previously determined ratios to prepare the raw material. In this study, the content of the raw material is fixed to determine the effects of the other process parameters clearly. In this study, in order to provide the thickness of the sheet coming out from the extrusion process to be at the desired thickness of 1.15 mm; the optimum values of the (i) roller rotation speed, (ii) extrusion speed, (iii) pump speed, (iv) pressure, and (v) withdrawal speed of the moulded product are investigated. These process parameters can be set by the operator.

Roller rotation speed is one of the important parameters to achieve the desired material thickness. In extrusion process, plastic material is forced to spread over a wide surface, forced through a thin channel. The melt passing through this thin channel is conveyed to the cylinder group, which consists of cylinders acting as plastic moulds. The material is compressed between the rollers to thin its thickness. By circulating water inside these cylinders for cooling, the plastic material is cooled while at the same time gradually thinning. In this phase the roller rotation speed has effect to obtain the desired thickness. In order to understand the effects of extrusion speed (in other words: extrusion rate) and pump speed on the process, it is first necessary to examine the state of the molten plastic in the flow position. During the extrusion process, when the melt starts to touch the surface of the mould, which is colder than itself, a crust is formed, consisting of layers that are partially frozen or freezing in the areas in contact with the surface. This shell is formed on both mould sheet surfaces because the mould sheet engraving surface temperatures have a lower temperature than the melt temperature. As the molten plastic continues to flow at the set extrusion speed, the crust that begins to form begins to thicken and harden. Sufficient extrusion speed is required for the movement of the molten plastic before this hardening and thickening shell stops the extrusion flow. As the extrusion speed increases (the ratio of flow length to wall thickness), the injection speed should increase. The increase in cooling rate in thin-walled parts has revealed the need to increase the extrusion speed. Under normal conditions, the firm's expectation is that the products are of high quality and the production amount of the product per unit time is maximum. However, breakage may occur in the material at high speeds. Increasing the amount of product coming out of the mould more than necessary will force the plastic material at the exit of the mould. At the same time, deformations may occur in the product as the raw material from the mould cannot be cooled and vacuumed sufficiently. To prevent this, if the line speed is reduced, this will decrease the production amount per unit time and thus the efficiency. In addition, the extrusion speed highly affects the rotating speed of the rollers (cylinders), the pump speed and pressure. When the line speed is too high, too many melts come in, and in this case the quality of the material deteriorates. When the line speed is too low, the melt does not come completely.

Pressure is the other important parameter of the extrusion unit. The pressure causes the extrusion screw to act like a piston, and sends the molten plastic waiting in front of the screw into the mould. This pressure affects both the speed of the screw and the process of filling the mould very closely. The function of the extrusion pressure is to fill the mould by sending molten material as quickly as possible into the mould. For this reason, the extrusion pressure is chosen at the highest possible value. An important consequence of the high pressure value selected is that it allows low operating temperatures to be selected. Thus, the cycle time is shortened by making significant savings in the part cooling times. The important point here is to determine the extrusion pressure size and the time to be applied very well. Because the pressure values selected higher and lower than necessary will have negative effects on both the part and the machine and the mould.

'Withdrawal speed of the moulded product' refers to the speed that ensures that the plastic sheet coming out of the rollers remains taut during winding.

Regression Modelling

This section is about the modelling of the relation between the factors and the response of plastic extrusion process by means of regression modelling. This mathematical model then will be optimized using GWO algorithm in next section. Mathematically modelling the relations between the factors (input variables) and the response (output variable) by regression is one of the widely used statistical methods. The experimental results obtained from the extrusion line are used in this study to model the mathematical relationship between the factors (roller rotation speed, extrusion speed, pump speed, pressure, and withdrawal speed of the moulded product) and the response (plastic sheet thickness). The model for 2nd order polynomial regression that is used for modelling the relationship between the thickness of the plastic sheet and the factors is demonstrated in Eq. (1). This model will be used by GWO algorithm for optimization in next section.

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

where u is the observation number, Y_u is the response (plastic sheet thickness), X_{iu} are coded values of the i^{th} factor; β_0, β_i, β_{ii} and β_{ij} are the coefficients for the linear, quadratic and interaction terms of the mathematical model; and e_u is the residual.[12,13] The matrix notation of the model is:

$$Y = \beta X + \varepsilon \quad \dots (2)$$

Y and X represents the output and the input matrices respectively. ε is the matrix which is composed of the residual terms. Β matrix is composed of regression coefficients and calculated by Eq. (3).[(12,13)]

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

After the mathematical model is determined, then in order to determine whether the used factors in the model are sufficient or not, coefficient of determination (R^2) is calculated. The calculation of R^2 is expressed by Eq. (4):

$$R^2 = \frac{\beta^T X^T Y - n\overline{Y}^2}{Y^T Y - n\overline{Y}^2} \quad \dots (4)$$

If the factors are sufficient (R^2 is closer to 1) then the model's significance is determined by hypothesis tests. ANOVA (Analysis of Variance) is a commonly used method for this type of hypothesis test. There are two types of hypothesis: H0 and H1; where H0 is called as null hypothesis while the H1 is called as alternative hypothesis. In this test; mean square treatments (MS Treatments) is compared with the mean square error (MSE). If H0 is true, this means the factors has no effect on the response. To determine the significance of H0, the ratio F_0 (which is calculated by Eq. (5)) is compared with the critical F value (that is obtained from the 'F Statistical Table' for (v1: $m-1$) and (v2: $n-m$) degrees of freedom values (m: number of β terms; n: number of experimental runs, v1 and v2 are the F-Table parameters).[13]

$$F_0 = \frac{SS_{\text{Treatments}}/(m-1)}{SS_{\text{Error}}/(n-m)} = \frac{MS_{\text{Treatments}}(MS_{Tr})}{MS_{\text{Error}}(MSE)} = \frac{\left(\beta^T X^T Y - n\overline{Y}^2\right)/(m-1)}{(Y^T Y - \beta^T X^T Y)/(n-m)} \quad \ldots (5)$$

If $F_0 < F_{\alpha,m-1,n-m}$ (where α is the significance level) then H0 is accepted and the model isn't significant. If $F_0 > F_{\alpha,m-1,N-m}$ this means H1 is accepted and the model is significant.[13]

Grey Wolf Optimizer (GWO) Algorithm

Several nature inspired meta-heuristic algorithms have been widely used for engineering optimization problems. Artificial bee colony, particle swarm, genetic algorithm, ant colony etc. are the popular optimization algorithms those are widely used in the last decades.Another new metaheuristic that is also inspired from nature has been proposed named as Grey Wolf Optimizer (GWO) algorithm by Mirjalili *et al.* (2014).[9] GWO has been implemented to several optimization problems successfully by simulating the hunting behaviors and the social hierarchy of the grey wolves in the nature.[9–11,14] GWO is used to evaluate the optimum values of process parameters if the regression model calculated in the previous section is significant. In the nature, in a wolf pack there are four types of grey wolves and they are arranged in hierarchical order such as alpha (α), beta (β), omega (ω), and delta (δ). The main operation of the GWO algorithm is to update the current positions of the wolves α, β and δ.[9] It is called Delta (δ) if a wolf is not an alpha, beta, or omega. Delta wolves have to submit to alphas and betas, but they dominate the omega. The fittest solution was considered to be the alpha (alpha) in order to mathematically model the social hierarchy of wolves when developing the GWO algorithm. Also the second and third best solutions are named beta (β) and delta (δ), respectively. Finally, omega (ω) is believed to be the rest of the candidate solutions.[9,14] In addition, the behaviour of the wolves such as (i) encircling prey, (ii) hunting, (iii) attacking prey (exploitation), and searching for prey (exploration) are implemented by the following steps:

Step 1:

The first step of hunting is encircling phase. Grey wolves encircle prey during the hunt and this is modelled by the Eqs (6) and (7) below:[9]

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

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

where, $\overrightarrow{X_P}$ and $\vec{X}$ are the position vector of the prey and the grey wolf, respectively; t is the current iteration number. $\vec{A}$ and $\vec{C}$ are coefficient vectors:

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \quad \ldots (8)$$

$$\vec{C} = 2\overrightarrow{r_2} \quad \ldots (9)$$

Over the course of iterations components of $\vec{a}$ are linearly decreased from 2 to 0. Also r_1 and r_2 are random vectors in [0, 1].

Step 2:

In the GWO algorithm optimization phase is named as the hunting. It is guided by α, β, and δ. The ω wolves follow these three wolves. The alpha (best candidate solution), beta, and delta are believed to have better knowledge of the possible prey position. In order to oblige other search agents (including omegas) to update their positions according to the location of the best search agent, the first three best solutions obtained to date should therefore be saved. To provide this, the Eqs (10) – (12) are proposed:[9]

$$\overrightarrow{D_\propto} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|, \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \quad \ldots (10)$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\left(\overrightarrow{D_\alpha}\right), \quad \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\left(\overrightarrow{D_\beta}\right), \quad \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\left(\overrightarrow{D_\delta}\right) \quad \ldots (11)$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \quad \ldots (12)$$

Step 3:

In the third step of the algorithm, the grey wolves finish the hunt by attacking the prey. In the algorithm, the value of $\vec{a}$ is decreased to model the behaviour of approaching to the prey. The fluctuation range of $\vec{A}$ is decreased by $\vec{a}$. A random value from the interval

[−a, a] is the fluctuation range. Over the course of iterations; $\vec{a}$ is decreased from 2 to 0. The wolves attack to the prey when the random values of $\vec{A}$ are in the range of [−1, 1].[(9)] Besides these three key stages, the grey wolves also scan with the guidance of the alpha, beta and delta positions. These wolves diverge from each other in pursuit of prey and converge to strike prey. $\vec{A}$ is utilized with random values greater than 1 or less than −1 to oblige the search agent to diverge from the prey. By this way, exploration is emphasized and GWO can search globally. To favor exploration and avoid from local optimum; GWO uses a component $\vec{C}$. This component contains random values between 0 and 2 and by this way it provides random weights. This assists the GWO algorithm to avoid local optima.[9,14] For more comprehensive information on the algorithm, readers may be invited to see Mirjalili *et al.*[9]

Results and Discussion

This study aims to ensure that the thickness of the plastic sheet coming out of the extruder used in the production of plastic containers is 1.15 mm. For this purpose the factors – those have effect on the thickness of the plastic sheet are determined and listed in Table 1.

Table 1 — Factors list

Parameter	Unit	Code
Roller Rotation Speed	rpm/min	X_1
Extrusion Speed	rpm/min	X_2
Pump Speed	rpm/min	X_3
Pressure	bar	X_4
Withdrawal Speed of the Moulded Product	rpm/min	X_5

The observed responses are given in Table 2. In this table due to commercial confidentiality, the factor levels are given by their coded values between [−1, 1] where −1 is the minimum observed value for the factor level and +1 is the maximum observed factor level for the factor. To optimize it by using GWO, using a regression model generated with coded values between [−1, 1] is recommended.[9–11] In the first stage; regression model is determined. Then the GWO is run through this model to evaluate the optimum factor levels for this regression model. The models have been derived from a small number of runs observed from the extrusion line. Statistical analyses have been used for calculating the regression coefficients, R^2 and ANOVA. Then GWO to calculate the optimum factor levels those provide 1.15 mm plastic sheet thickness. GWO is coded in MATLAB (R2016a).

Regression model for the coded factor units (which is calculated by using Eqs (1) – (3)) is given as Eq. (13). According to the preliminary modelling work the R^2 is calculated as 41.29% for linear model, 55.87% for the model that have linear + squares terms, and 81.96% for the model that have linear + interaction terms. Finally the R^2 for the full quadratic model is calculated as 95.09%. So the full-quadratic model seems to be best fits the relation between the factors and the response:

$$Y = 1.24457602836565 + 0.389847779144176X_1 - 0.38781227435604X_2 - 0.0217199331148022X_3 + 0.14004823063716X_4 + 0.105447925474521X_5 + 0.181033246687892X_1^2 + 0.00919533324415009X_2^2 +$$

Table 2 — Observed responses (coded values)

Run	Coded Factor Levels					Response	Run	Coded Factor Levels					Response
	X_1	X_2	X_3	X_4	X_5	Y		X_1	X_2	X_3	X_4	X_5	Y
1	0.2000	−0.3333	0.7635	−1.00	0.2121	1.20	14	0.0000	0.3333	0.7833	1.00	−0.3939	1.17
2	−0.5000	−0.3333	0.7241	−1.00	0.2121	1.19	15	−0.2000	−0.3333	0.5172	1.00	0.2121	1.18
3	0.0000	−0.3333	1.0000	−1.00	0.2121	1.18	16	−0.5000	−0.3333	0.4581	1.00	0.2121	1.18
4	0.0000	−0.3333	0.8424	−1.00	−0.3939	1.20	17	−0.5000	0.5556	0.5567	1.00	0.2121	1.18
5	−0.5000	−0.3333	0.7044	−1.00	−0.0909	1.17	18	0.1000	−0.3333	0.7833	0.00	0.2121	1.19
6	0.0000	−0.3333	1.0000	−1.00	0.2121	1.18	19	−1.0000	−0.3333	0.3103	1.00	−0.6970	1.18
7	0.0000	0.3333	0.5468	1.00	−0.3939	1.17	20	−1.0000	−0.3333	0.3103	1.00	−0.6970	1.18
8	0.0000	0.3333	0.4384	1.00	−0.3939	1.16	21	0.0000	−0.3333	0.5271	1.00	0.2121	1.20
9	−1.0000	1.0000	0.3399	−1.00	−0.0909	1.16	22	0.0000	−0.3333	0.5271	1.00	0.2121	1.19
10	−1.0000	−0.1111	0.3498	1.00	−1.0000	1.22	23	1.0000	−0.3333	0.8719	1.00	1.0000	1.18
11	−1.0000	−0.1111	0.2512	1.00	−1.0000	1.19	24	−1.0000	−0.3333	0.2414	1.00	−0.3939	1.18
12	−0.7000	1.0000	0.2611	1.00	−0.8182	1.18	25	0.9000	−1.0000	0.8621	1.00	0.6970	1.21
13	0.0000	0.3333	−1.0000	1.00	−0.3939	1.16	26	−1.0000	−0.3333	0.3695	1.00	−0.3939	1.20

$$0.00688907296732012X_3^2 - 0.0699536554093207X_4^2 + 0.0554877166763128X_5^2 - 0.187700456907906X_1X_2 - 0.543820857535601X_1X_3 - 0.02353061547933X_1X_4 + 0.00594272818227021X_1X_5 + 0.683431842408077X_2X_3 - 0.0331959267258176X_2X_4 - 0.14249196194778X_2X_5 - 0.277292172213976X_3X_4 - 0.199659965594009X_3X_5 + 0.00159803546548685X_4X_5 \quad \ldots (13)$$

The R^2 is calculated as 95.09% and this value indicates that these five factors have the ability to explain the change at the response. Model's significance is determined by ANOVA. ANOVA results are summarized in Table 3. According to this table, if the $F_0 > F - critical$, H0 is rejected. This implies that the model is significant.

When the ANOVA analysis results were examined, it was concluded that the regression equation was significant at 95% confidence level (which means of significance level (α) = 5% = 0.05). Performance for the fitted model is displayed in Table 4. In this Table, Y_i is the observed value from the extrusion line, $\hat{Y}_i$ is the expected value predicted from the fitted model. PE (prediction error) can be evaluated by Eq. (14). According to the results given in Table 4, the mathematical model for the plastic sheet thickness good fits the observations and the overall PE is less than 0.6%. Then the GWO is used to calculate the optimum factor levels to obtain 1.15 plastic sheet thickness using the regression equation. Fifty search agents are used in GWO. A maximum number of iterations of 20000 have been set.

$$PE_i(\%) = \frac{|Y_i - \hat{Y}_i|}{\hat{Y}_i} \times 100 = \frac{\varepsilon_i}{\hat{Y}_i} \times 100 \quad \ldots (14)$$

Optimization results are presented in Table 5 by coded values between [−1, 1]. When the regression equation is used to predict the response using these factor levels; plastic sheet thickness is predicted as 1.149995 ($\cong 1.15$) which is very close to the target thickness.

The confirmation results are given in Table 6. In this table, mean value for 9 runs ($\overline{Y}_i$) – which is named as 'observed thickness' - is compared with the 'expected thickness' which is predicted by GWO. Observation values in the table are given in millimeters (mm). [R1–R9] represents the confirmation test numbers. Mean value for the

Table 3 — ANOVA results (for the 95% confidence level)

Source of the Variation	Degrees of Freedom (df)	Sum of Squares (SS)	Mean Squares (MS=SS/df)	F_0=MStr/MSE	F-Critical = $F_{0.05,20,5}$	Result
Regression	20	SS_{Tr}= 0.005340	MS_{Tr}= 0.000267	4.837	> 4.56	Model Significant
Residual Error	5	SS_E= 0.000276	MS_E= 0.0000552			

Table 4 — Performance of the regression model

Run (i)	Y_i	$\hat{Y}_i$	$PE_i(\%)$	Run (i)	Y_i	$\hat{Y}_i$	$PE_i(\%)$	Run (i)	Y_i	$\hat{Y}_i$	$PE_i(\%)$
1	1.20	1.2009	0.076	10	1.22	1.2237	0.303	19	1.18	1.1807	0.058
2	1.19	1.1850	0.422	11	1.19	1.1870	0.253	20	1.18	1.1807	0.058
3	1.18	1.1807	0.059	12	1.18	1.1790	0.089	21	1.20	1.1932	0.569
4	1.20	1.1973	0.224	13	1.16	1.1599	0.005	22	1.19	1.1932	0.269
5	1.17	1.1754	0.456	14	1.17	1.1706	0.049	23	1.18	1.1796	0.038
6	1.18	1.1807	0.059	15	1.18	1.1762	0.321	24	1.18	1.1817	0.147
7	1.17	1.1666	0.288	16	1.18	1.1868	0.569	25	1.21	1.2110	0.084
8	1.16	1.1651	0.438	17	1.18	1.1805	0.039	26	1.20	1.1945	0.458
9	1.16	1.1600	0.000	18	1.19	1.1900	0.000	—	—	—	—

Table 5 — Factors list

Parameter	Unit	Abbreviation	Optimum Factor Levels (Coded)
Roller Rotation Speed	rpm/min	X_1	−0.1467
Extrusion Speed	rpm/min	X_2	0.2434
Pump Speed	rpm/min	X_3	0.3952
Pressure	bar	X_4	1.0000
Withdrawal Speed of the Moulded Product	rpm/min	X_5	−0.0248

Table 6 — Confirmations for the optimization results

Confirmation Tests (Observed values for the test runs (R)) (Y_i)									Mean Observed Thickness (a)	Expected Thickness (b)	PE (%) between (a) and (b)	Target (mm)
R1	R2	R3	R4	R5	R6	R7	R8	R9	$\bar{Y} = \sum (Y_i)/9$	GWO $(\hat{Y})$	$PE(\%) = 100 \times \lvert a - b \rvert / b$	
1.16	1.14	1.15	1.15	1.14	1.15	1.15	1.15	1.15	1.148888	1.149995	0.0962 (<1%)	1.15

observed plastic sheet thickness values is calculated as 1.148888 ($\cong 1.15$) for the optimum factor levels.

According to the results of confirmation tests for optimum process parameters – which are calculated by GWO - indicate that the prediction $(\hat{Y})$ is close to the mean observed thickness $(\bar{Y})$ calculated from experimental results (Y_i). The PE is calculated as 0.000962 (0.0962%) which is almost nearly zero. The sheet thickness is obtained as 1.1488 mm which is very close to the target plastic sheet thickness (1.15 mm). Results indicate that the GWO has good prediction performance. The results are also confirmed by using social group optimization (SGO) algorithm which is an effective optimization technique that is recently proposed by Satapathy and Naik.[15] SGO is motivated by the idea of human social activity in order to solve a complex problem. Codding is performed by using MATLAB (R2016a). The SGO $(\hat{Y})$ is calculated as 1.149999. The results of GWO and SGO are very close to the observed value and by this way the results of the GWO are also confirmed.

Conclusions

This study addressed the problem of using GWO to decide the optimum process parameters of a particular plastic extrusion process of a plastic cup manufacturer. The aim was to obtain 1.15 mm plastic sheet thickness for the semi-product produced by the extrusion line. The relation between the plastic sheet thickness and the factors those have effect on the response is modelled by regression equation then GWO is usedfor performing the optimization. GWO has not been previously used for this type of problem and has novelty for this problem. Also, the process parameter combination of this paper is not previously studied. For being able to model the problem some experimental observations are obtained from the plastic extrusion line. GWO algorithm aims to evaluate the optimum factor levels to obtain the target response. Optimum factor levels (for roller rotation speed, extrusion speed, pump speed, pressure, and withdrawal speed of the moulded product) are calculated as −0.1467, 0.2434, 0.3952, 1.000, −0.0248 by coded values respectively (because of the commercial confidentiality the coded values did not transformed to uncoded original values). The results and the efficiency of GWO have been verified by the results of the confirmation tests provided in Table 6. The results show that the GWO algorithm provided good results for the extrusion process problem dealt with.

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