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Experimental Investigation of Mechanical Properties for Injection Molded PA66+PA6I/6T Composite Using RSM and Grey Wolf Optimization

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Abstract: In this study, a multi-objective optimization method was used to improve the mechanical properties and manufacturing conditions of reinforced polyamide 66+PA6I/6T polymer based on injection molding process parameters. For that purpose, the combined approach of response surface methodology (RSM) and Grey Wolf Optimization (GWO) was proposed to minimize and model the quality parameters such as warpage, volumetric shrinkage, and cycle time of the polymer. In the study, Moldflow Insight software was used to simulate and obtain the numerical objective results based on design parameters including fiber ratio, mold temperature, melt temperature, injection pressure, and injection time. Based on optimized design parameters, a test specimen was produced in an injection molding machine to obtain and compare the tensile test results. The Box-Behnken method was applied for the experimental design of the numerical analysis, and the analysis of variance (ANOVA) method was used to investigate the effect of design parameters on the objective parameters in molding. According to the numerical results, it was found that both RSM and GWO methods gave better results than the quality results obtained by the recommended process parameter results as well as these results were consistent with the ANOVA results. It was determined that the RSM was more effective than the GWO method for this experimental design. Also, it was concluded that according to the experimental tensile test results, the best tensile test result was obtained by 60% fiber reinforcement, and the tensile module value increased by 39,4% for this addition ratio based on the optimized process parameters.

Keywords: Grey wolf optimization; Injection molding; RSM; tensile strength

RSM ve Grey Wolf Optimizasyonu Kullanılarak Enjeksiyon Kalıplanmış PA66+PA6I/6T Kompozitinin Mekanik Özelliklerinin Deneysel Olarak İncelenmesi

Öz: Bu çalışmada, takviyeli poliamid 66+PA6I/6T polimerinin enjeksiyon kalıpçılık proses parametreleri temel alınarak, mekanik özellik ve üretim koşullarının iyileştirilmesi için multi-objective optimizasyon metodu kullanılmıştır. Bu amaçla, polimerin kalite parametreleri olan çarpılma, hacimsel büzülme ve çevrim süresini minimize edip modellemek için bütünleşik RSM ve GWO optimizasyon yaklaşımı önerilmiştir. Çalışmada, tasarım parametreleri olan lif oranı, kalıp sıcaklığı, eriyik sıcaklığı, enjeksiyon basıncı ve enjeksiyon süreci gözönüne alınarak nümerik çıktı sonuçlarının elde edilmesi ve simülasyon işleminde Moldflow Insight yazılımı kullanılmıştır. Optimizasyonu yapılmış tasarım parametreleri gözönüne alınarak çekme test sonuçlarının elde edilmesi ve karşılaştırılması için plastik enjeksiyon makinesinde bir test numunesi hazırlanmıştır. Sayısal analiz için Box-Behnken deneysel tasarım metodu ve kalıplama işlemindeki

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Bu makaleye atıf yapmak için
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tasarım parametrelerinin kaliteye olan etkilerini incelemek için ANOVA metodu uygulanmıştır. Elde edilen sayısal sonuçlara göre RSM ve GWO yöntemlerinin her ikisinin de, tavsiye edilen proses değerleriyle elde edilmiş kalite sonuçlarına göre daha iyi sonuçları verdikleri görülmüştür, aynı zamanda bu sonuçlar ANOVA sonuçlarıyla da uyumludur. Yürütülen bu deneysel tasarım için RSM' nin GWO metodundan daha etkili olduğu gözlenmiştir. Ayrıca yürütülen deneysel çekme test sonuçlarına göre, % 60 lif takviyesinin en iyi çekme test sonuçları verdiğini ve optimizasyonu yapılmış olan bu proses parametreleri ile % 60'lık bu lif katkı oranı için elastik modül değerinde % 39,4 lük bir artış olduğu gözlenmiştir.

Anahtar Kelimeler: Grey wolf optimizasyonu; Enjeksiyon kalıpçılık; RSM; çekme mukavemeti

1. Introduction

There are limited studies on reinforced polyamide 66+PA6I/6T composite that has been increasingly used in recent years in the fields of application such as metal replacement, electronic and defense industry due to its superior properties such as good mechanical properties, thermal performance, and resistance to chemicals. It is especially important to minimize warpage, shrinkage, and residual stress which reduces the performance of the final product after the addition of fiber to this polymer in the plastic injection production method. Because, the addition of fiber directly affects the polymer's properties and injection molding parameters as well as the strength, quality, and manufacturing cost of product [1,2,3]. On the other hand, since the plastic injection molding is a nonlinear phenomenon, it is difficult to determine the optimum process parameters. Thus, FEA software is used to predetermine and simulate polymer defects such as warpage, volumetric shrinkage, and unfilled mold as a result of non-uniform heat transfer [4,5]. Possible product defects and mechanical properties and cycle time of product are mostly affected by heat transfer [6]. Thus, simulation coupled with new optimization techniques has been increasingly used to determine the optimum process parameters [7]. RSM and GWO methods are also used for this purpose. The RSM is a mathematical and statistical-based technique used for modeling and optimization purposes. Using this method, the output responses are drawn as surfaces and it is possible to express these surfaces in terms of input design variables. These surfaces can be also used in optimization tasks intended for obtaining optimum designs [8,9]. The GWO method is a new meta-heuristic global optimization technique based on the behavior of grey wolves in nature [10]. The reported literature on polymer composites has mainly focused on the elucidation of the relationship between optimum processing conditions and mechanical properties [11,12].

In a study carried out by Imihezri et al. [13], Autodesk Moldflow® software was used to analyze the design of automotive clutch pedals composites using 30% glass-fiber-reinforced polyamide 6,6. Two types of ribs were compared to determine the one with a lower weight, mold manufacturing cost, and injection pressure. In another study carried out by Kurtaran and Erzurumlu [14] the warpage optimization was studied using finite element (FE) analysis, response surface methodology (RSM), and genetic algorithm (GA). By using RSM, a predictive model was created for warpage. To determine the optimum process parameter values, RSM was combined with a GA method. A response surface model of process parameters in plastic injection molding was presented in a study performed by Chen et al. [15]. According to the results, the proposed model can provide improved stability in the injection molding process. A hybrid optimization method was presented by Yin et al. [16] for the optimization of the injection molding process parameters. A multi-objective optimization model was developed based on orthogonal test design, neural network, and GA.

In a study conducted by Sadabadi and Ghasemi, the impacts of injection molding process parameters such as packing pressure, injection flow rate, and mold wall temperature were investigated using short fiber reinforced polystyrene composites which likely affect fiber orientation and tensile modulus of injection molded parts [17]. In other studies on conventional polymers and fiber-reinforced composites, the relationship between injection molding processing parameters and the shrinkage and warpage defects was evaluated [18,19]. Likewise, shrinkage and warpage defects were significantly affected by hold pressure, injection pressure, and cooling time [20]. In a study on glass fiber reinforced plastic composites, it was shown that when hold time is decreased, the warpage increases by 30%, while the warpage reduces by 60% when the mold temperature is decreased [21].

In this paper, the multi-objective optimization problem of injection molding of the fiber-reinforced composite was studied systematically. For this purpose, the combination approach of response surface methodology (RSM) and Grey Wolf (GW) optimization technique was proposed to minimize and model the quality parameters such as volumetric shrinkage and cycle time of the polyamide 66+PA6I/6T composite through FEA. Based on the optimized design parameters, a polymer test specimen was produced and tested experimentally for its tensile properties.

2. Material and Methods

This study presents a multi-objective optimization method. With the RSM and GWO methods preferred for this purpose, it was aimed to minimize warpage and volumetric shrinkage values between which there is a direct interaction as well as cycle time that is a decisive factor for product cost/efficiency. The addition of fiber to the polymer in question also makes the product's quality and mechanical behavior more complicated. Therefore, it is important to provide the optimum injection molding conditions reliably and efficiently. In the study, after the optimum process conditions were provided, a test specimen was produced and then the stress-strain curves were systematically studied and interpreted.

2.1 Experimental Design

The test material in the study is Polyamide 66+PA6I/6T (EMS Grovery Ltd, trade name: Grivory GV-2H-4H-6H). Where, 2H - 4H, and 6H designations represent the glass-fibre reinforcement by 20%, 40% and 60%, respectively. The properties of this polymer are given below (Table 1). The mold material is Tool steel P-20. The applied standard for tensile testing geometry is ISO 572-2. The geometry and the meshed simulation model of the polymer are shown in Figure 1. In the mesh generation, Dual Domain mesh type with the global edge length on the surface of 3.07 mm; 1830 triangle elements and average aspect ratio of 1.61 was used. The test specimens were produced in Arburg 320 K injection molding machine with technical data shown in Table 2.

Firstly, 5 design parameters (fiber ratio, mold temperature, melt temperature, injection pressure, injection time) were determined. In the study, the Moldflow Plastic Insight software (MPI) program was used for the finite element analysis. By taking into consideration the recommended values in the database of this program, the value ranges for these parameters were created. Accordingly, fiber ratio ranged from 20% to 60%, mold temperature ranged from 80°C to 120°C, melt temperature ranged from 275°C to 295°C, injection pressure ranged from 80 MPa to

120 MPa and injection time ranged from 0.5 s to 1.5 s. The factors and levels of the design parameters are shown in Table 3.

After the parameter value ranges were determined, the RSM Box-Behnken method was applied to save time and reduce the number of experiments. Using this method, the design of 5 factors, each with 3 levels, was made and 46 trials were conducted. Using this method the relationship between input and output variables was expressed as a quadratic mathematical equation. A variance analysis was carried out using the ANOVA method thus the effect of input parameters on the output as well as the reliability of the model were tested. In light of the mathematical equation obtained, the parameter optimization process was made using the GWO method. Further, in the light of optimal design parameter combinations obtained, test specimens were produced in the plastic injection machine and the experimental stress-strain graphs were created in the tensile tester to make necessary comparations and interpretations.

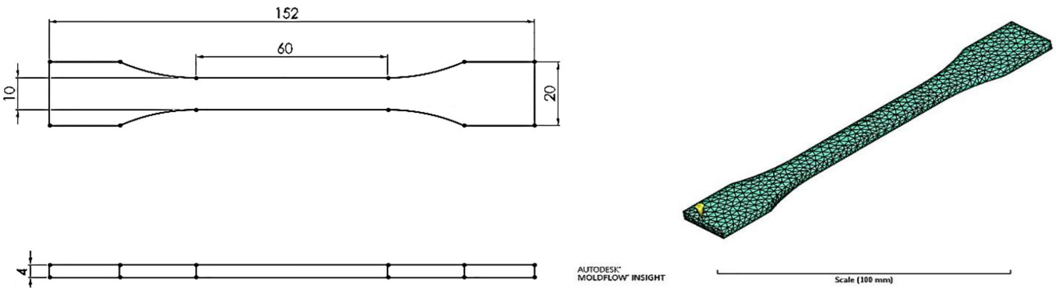

Figure 1. Geometric model and mesh model of the plastic part.

Table 1. Material Properties used in the study

	Poliamid 66+PA6I/6T
Trade name	Grivory GV-2H
Solid density (g/m^3)	1,2865
Melt density (g/m3)	1,0683
Maximum shear rate (s^{-1})	60000
Maximum shear stress (MPa)	0,5
Elastic modulus (MPa)	7302
Poisson ratio	0,387

Table 2. Injection molding machine properties

	Arburg Allrounder 320K
Maximum clamp force (tonne)	70
Screw diameter (mm)	40
Maximum injection rate (cm^3/s)	200
Maximum hydraulic pressure (MPa)	13.9
Maximum injection stroke (mm)	235

Table 3. Factors and levels of Box-Behnken design of experiment (BB-DOE)

Factors	Levels		
	L1 (-1)	L2 (0)	L3 (+1)
Fiber ratio ; %	20	40	60
Mold temperature (T); °C	80	100	120
Melt temperature (T); °C	275	285	295
Injection pressure (P); MPa	80	100	120
İnjection time (t); s	0,5	1	1,5

3. Results and discussion

3.1 Response Surface Method

Response surface methodology is a set of statistical and applied mathematical techniques used for establishing empirical models between quality (objective) characteristics and independent variables (design variables). Using the RSM helps to reduce the cost of expensive analytical methods (e.g. finite element method) and their associated numerical noise. The correlation of the model used in the RSM is a complete second-order correlation model. The second-order model is expressed as Equation (1):

$$Y = \beta_o + \sum_{i=1}^{4}\beta_i\ x_i + \sum_{i=1}^{4}\beta_{ii}\ x_{ii}^2 + \sum_{i<j=1}^{4}\beta_{ij}\ x_i\, x_j \qquad (1)$$

Where β_{o}, β_{i}, β_{ii} and βij are constant value, linear effect, second effect and reciprocal effects of the regression coefficient, respectively. x_i and x_j are independent coded variables. The matrix form of Equation (1) can be expressed in the form of Equation (2):

$$y = X\beta + \varepsilon \qquad (2)$$

Equation (2) can be solved using the least square method to obtain correlation coefficients.

3.2 Analysis of variance

The ANOVA was used to determine the statistically significant parameters affecting the quality characteristics in the designed experimental study. Using the ANOVA method, the effects of fiber ratio, mold temperature, melt temperature, injection pressure, and injection time on warpage, volumetric shrinkage, and cycle time were analyzed based on the orthogonal experimental results (Table 4). The warpage, volumetric shrinkage and cycle time results obtained by the ANOVA method are shown in Table 5 and Table 6, respectively. Accordingly, the main factors having a significant effect on these three quality characteristics were identified. Based on the P-value results, the output parameters were prioritized as follows:

For Warpage: A > AB > A^2 > B, for Shrinkage; A > A^2 > E > E^2 > C and for Cycle time; A > B > C > AB

As shown in Table 5, it can be concluded that the most important parameters are A and B for warpage; A, E, and C for shrinkage and A, B and C for cycle time according to their P-values of less than 0.05. Furthermore, as can be shown in Table 6, the R^2 values for them were 99.96%, 99.13%, and 97.44% respectively, and the reliability of the prediction model can be further tested by the R^2 method. The adjusted R-squared values of three response surface models were found to be 99.92%, 98.43%, and 95.40%, respectively. Hence, the three prediction models for W, V, and C can be used to describe the corresponding design variables and three objectives with good precision.

Table 4. Experimental results for quality characteristics

	A	B	C	D	E	Warpage (mm)	Shrinkage (%)	Cycle time (s)
	20	80	285	100	1	0,7469	16,59	19,7748
2	60	80	285	100	1	0,2212	11,48	17,2681
3	20	120	285	100	1	0,8408	16,61	26,7714
4	60	120	285	100	1	0,2212	11,48	17,2681
5	40	100	275	80	1	0,4288	12,13	17,2718
6	40	100	295	80	1	0,4321	12,79	20,7690
7	40	100	275	120	1	0,4288	12,13	17,2718
8	40	100	295	120	1	0,4321	12,79	20,7690
9	40	80	285	100	0,5	0,4018	10,98	16,6358
10	40	120	285	100	0,5	0,4707	10,78	22,6349
11	40	80	285	100	1,5	0,3991	12,43	16,4116
12	40	120	285	100	1,5	0,4456	12,45	22,4049
13	20	100	275	100	1	0,7803	16,18	20,7750
14	60	100	275	100	1	0,2082	11,19	12,7738
15	20	100	295	100	1	0,7974	17,00	24,7720
16	60	100	295	100	1	0,2082	11,77	16,2681
17	40	100	285	80	0,5	0,4267	10,71	19,1353
18	40	100	285	120	0,5	0,4271	10,89	19,1353
19	40	100	285	80	1,5	0,4271	12,44	18,9078
20	40	100	285	120	1,5	0,4271	12,44	18,9078
21	40	80	275	100	1	0,4011	12,12	14,7735
22	40	120	275	100	1	0,4517	12,14	20,2697
23	40	80	295	100	1	0,4004	12,79	18,2687
24	40	120	295	100	1	0,4717	12,80	24,7650
25	20	100	285	80	1	0,7823	16,60	22,7730
26	60	100	285	80	1	0,2080	11,48	14,7691
27	20	100	285	120	1	0,7823	16,60	22,7730
28	60	100	285	120	1	0,2080	11,48	14,7691
29	40	100	275	100	0,5	0,4255	10,56	17,1370
30	40	100	295	100	0,5	0,4485	11,19	20,6335
31	40	100	275	100	1,5	0,4242	12,10	16,9111
32	40	100	295	100	1,5	0,4293	12,77	20,9040
33	20	100	285	100	0,5	0,8048	14,90	22,6365
34	60	100	285	100	0,5	0,2107	11,47	14,6349
35	20	100	285	100	1,5	0,7758	16,57	22,9119
36	60	100	285	100	1,5	0,2067	11,47	14,7097
37	40	80	285	80	1	0,4023	12,46	16,2724
38	40	120	285	80	1	0,4533	12,47	22,7675
39	40	80	285	120	1	0,4023	12,46	16,2724
40	40	120	285	120	1	0,4533	12,47	22,7675
41	40	100	285	100	1	0,4269	12,46	19,2694
42	40	100	285	100	1	0,4269	12,46	19,2694
43	40	100	285	100	1	0,4269	12,46	19,2694
44	40	100	285	100	1	0,4269	12,46	19,2694
45	40	100	285	100	1	0,4269	12,46	19,2694
46	40	100	285	100	1	0,4269	12,46	19,2694

Fiber ratio **B-** Mold temperature **C-** Melt temperature **D-** Injection pressure **E-** Injection time

Table 5. ANOVA results for warpage (**1**), volume shrinkage (**2**), cycle time

	Sum of Squares			**df**			**F-values**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Model	1,4	145,22	427,33	20	20	20	2783,66	141,66	47,65
A	1,33	96,19	230,48	1	1	1	52964,56	1876,65	514,05
B	0,0117	0,0008	120,84	1	1	1	465,99	0,0148	269,52
C	0,0003	1,79	56,12	1	1	1	12,55	34,9	125,17
D	1,00E-08	0,002	0	1	1	1	0,0004	0,0395	0
E	0,0004	7,83	0,0165	1	1	1	16,25	152,69	0,0369
AB	0,0022	0,0001	12,24	1	1	1	87,58	0,002	27,29
AC	0,0001	0,0144	0,0632	1	1	1	2,9	0,281	0,1409
AD	0	0	0	1	1	1	0	0	0
AE	0,0002	0,6972	0,0101	1	1	1	6,21	13,6	0,0224
BC	0,0001	0	0,2501	1	1	1	4,26	0,0005	0,5577
BD	0	0	0	1	1	1	0	0	0
BE	0,0001	0,0121	8,41E-06	1	1	1	4,98	0,2361	0
CD	0	0	0	1	1	1	0	0	0
CE	0,0001	0,0004	0,0616	1	1	1	3,18	0,0078	0,1374
DE	4,00E-08	0,0081	0	1	1	1	0,0016	0,158	0
A^2	0,0451	24,41	0,2141	1	1	1	1793,54	476,3	0,4774
B^2	0,0001	0,0051	3,69	1	1	1	4,59	0,0994	8,22
C^2	0	0,0074	0,6186	1	1	1	1,96	0,1449	1,38
D^2	0	0,0128	0,2923	1	1	1	0,7932	0,2502	0,6519
E^2	7,27E-06	4,53	0,5012	1	1	1	0,2887	88,47	1,12
Residual	0,0006	1,28	11,21	25	25	25			
Lack of Fit	0,0006	1,28	11,21	20	20	20			
Error	0	0	0	5	5	5			
Cor. Total	1,4	146,5	438,54	45	45	45			

Table 6. R^2 results for warpage, volume shrinkage and cycle time

Source	**Std. Dev.**	**R^2**	**Adjusted R^2**	**Predicted R^2**	**PRESS**
Warpage	0,0050	0,9996	0,9992	0,9982	0,0025
Shrinkage	0,2264	0,9913	0,9843	0,9650	5,13
Cycle time	0,6696	0,9744	0,9540	0,8978	44,84

3.3 Establishment of the Response Surface Model

The final equation for warpage, shrinkage, and cycle time in terms of coded factors obtained from the regression of values are as follows :

$$W = 0{,}4269 - 0{,}28865\,A + 0{,}027075\,B + 0{,}00444375\,C - 0{,}00505625\,E - 0{,}023475\,AB + 0{,}00625\,AE + 0{,}005175\,BC - 0{,}0056\,BE + 0{,}0719208\,AA + 0{,}0036375\,BB$$

$$S = 12{,}46 - 2{,}45187\,A + 0{,}334375\,C + 0{,}699375\,E - 0{,}4175\,AE + 1{,}6725\,AA$$

$$C = 19{,}2694 - 3{,}79542\,A + 2{,}74823\,B + 1{,}87285\,C - 1{,}74915\,AB + 0{,}649871$$

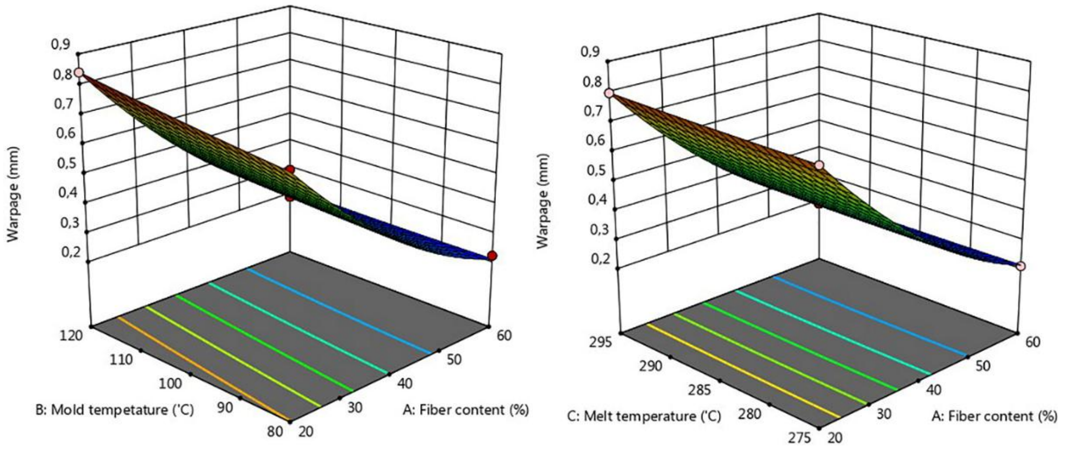

Figure 2. The plot of predicted warpage as a function of **(a)** mold temperature and fiber ratio **(b)** melt temperature and fiber ratio

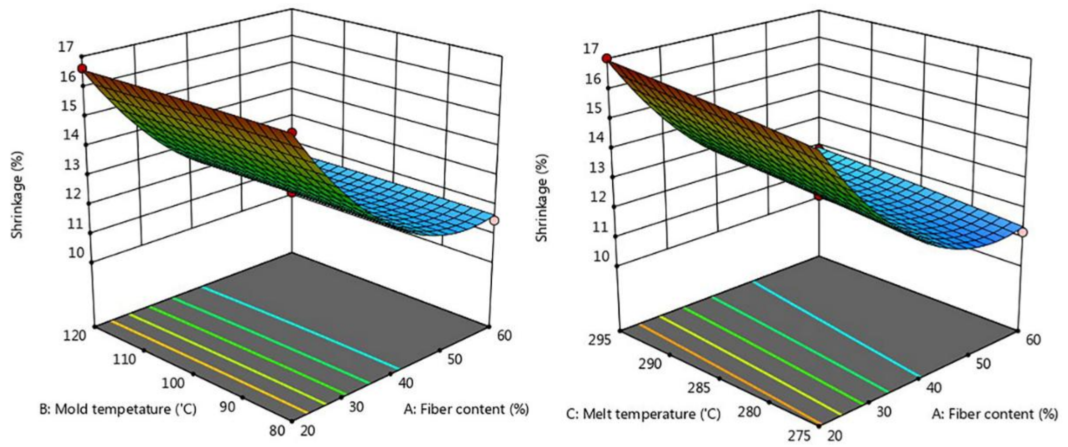

Figure 3. The plot of predicted shrinkage as a function of **(a)** mold temperature and fiber ratio **(b)** melt temperature and fiber ratio

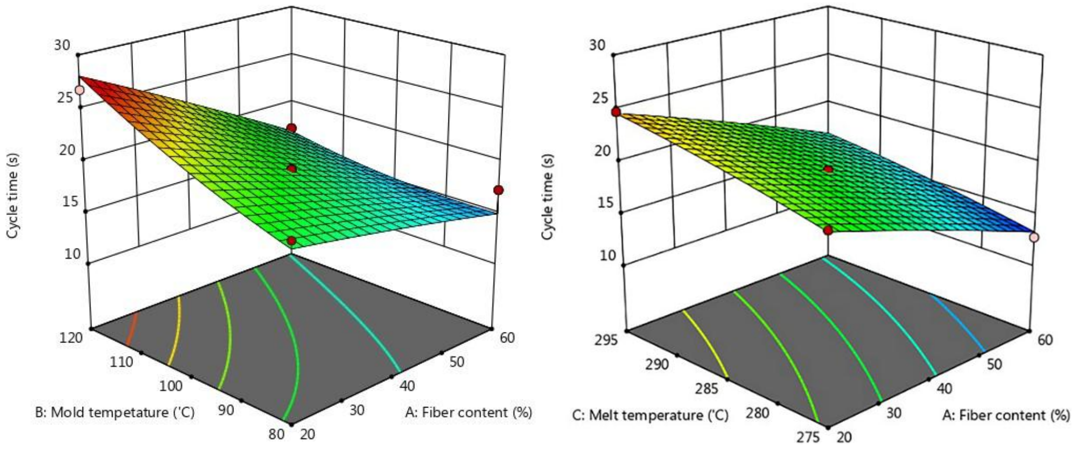

Figure 4. The plot of predicted cycle time as a function of **(a)** mold temperature and fiber ratio **(b)** melt temperature and fiber ratio

According to the mathematical equation and interaction graphics obtained by using the RSM as shown in Figure 2, 3 and 4, it can be concluded that the minimum warpage, shrinkage, and cycle time values can be obtained for minimum melt temperature, injection pressure and injection time (for experimental design value ranges in Table 3) and the best result is obtained by a fiber ratio of 60%.

3.4 Grey Wolf Optimization (GWO)

The GWO algorithm developed by Mirjalili et al [10]. simulates the hunting strategy and leadership hierarchy of grey wolves in the wild. Grey wolves at the top of the food chain usually live in a pack. To simulate the leadership hierarchy, four types of grey wolves namely alpha (α), beta (β), delta (δ), and omega (ω) are included. The fittest solution is considered as the alpha (α) to mathematically model the social hierarchy of wolves in GWO. Therefore, the second-best solution is defined as beta (β), and the third-best solution is defined as delta (δ). And the remaining possible solutions are assumed to be omega (ω). Hunting, chasing, and tracking for prey, encircling prey, and attacking prey which constitutes three main steps of GWO algorithm are employed while designing GWO. The encircling behavior seen in grey wolves while hunting can be modeled by the following equations:

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{3}$$

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t) \right| \tag{4}$$

where t is the current iteration, D, A, and C are coefficient vectors, X_p and X are the position vector of prey and grey wolf, respectively. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{5}$$

$$\vec{C} = 2.\vec{r_2} \tag{6}$$

where components of a linearly reduce from 2 to 0 in the course of iterations and r_1, r_2 are random vectors in [0, 1]. The hunting is usually carried out under the leadership of alpha wolves but sometimes beta and delta wolves may also participate in hunting. Delta and omega wolves are responsible for taking care of wounded wolves in the herd. Thus, because alpha wolves have better knowledge about the possible location of prey, we select them as the candidate solution. The grey wolves attack the prey until it stops moving and then finish the hunt.

In this study, the GWO was used in optimization of the design parameters based on the relationship models established using the response surface method. Three optimization objectives included warpage, volumetric shrinkage and cycle time. The selected design parameters were fiber ratio (A), molding temperature (B), melting temperature (C), injection pressure (D) and injection time (E). The multi-objective optimization model can be defined as follows:

Find A, B, C, D and E

Min$f(x)$ = (warpage, volumetric shrinkage and cycle time)

Subjected constraints : warpage < 0.25 mm
shrinkage < 12 %
cycle time < 25 s

$20\% < C_f < 60\%$
$80\ °C < T_{mo} < 120\ °C$
$275\ °C < T_{me} < 295\ °C$
$80\ MPa < P_{inj} < 120\ MPa$
$0.5\ s < t_{inj} < 1.5\ s$

For the GWO method, number of variables (dim) = 4, maximum number of generations (Maximum iterations) = 100, number of search agents = 20, the lower bound of variables l_b=[−1,−1,−1,−1,-1], the upper bound of variables u_b=[1,1,1,1,1]. Matlab software was used to obtain convergence curves in the optimization process.

Table 7. Pseudocode of the grey wolf optimizer.

```
Initialize the grey wolf population Xi (i = 1, 2, . . . , n)
Initialize a, A, and C
Calculate the fitness of each search agent
Xα = the best search agent
Xβ = the second-best search agent
Xδ = the third-best search agent
        while (t < Max number of iterations)
                for each search agent
                        Update the position of the current search agent by the above equations
                end for
                Update a, A, and C
                Calculate the fitness of all search agents
                Update Xα, Xβ, and Xδ
                t=t+1
        end while
return Xα
```

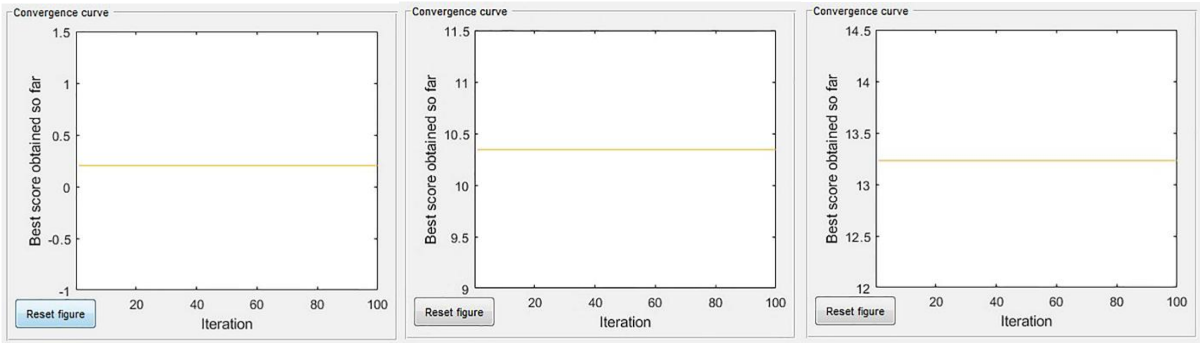

Figure 5. Grey wolf optimization results for **a)** warpage **b)** shrinkage **c)** cycle time

Table 8. Optimized condition obtained by applying the desirability function approach.

Method	Fiber ratio (%)	Mold temperature (°C)	Melt temperature (°C)	Injection pressure (MPa)	Injection time (s)	Warpage (mm)	Shrinkage (%)	Cycle time (s)
RSM	60	88	275	80	0,5	0,205	10,321	12,873
GWO	60	92	275	80	0,5	0,20634	10,3435	13,2306
Recommended	60	100	290	120	1	0,209	11,62	15,269

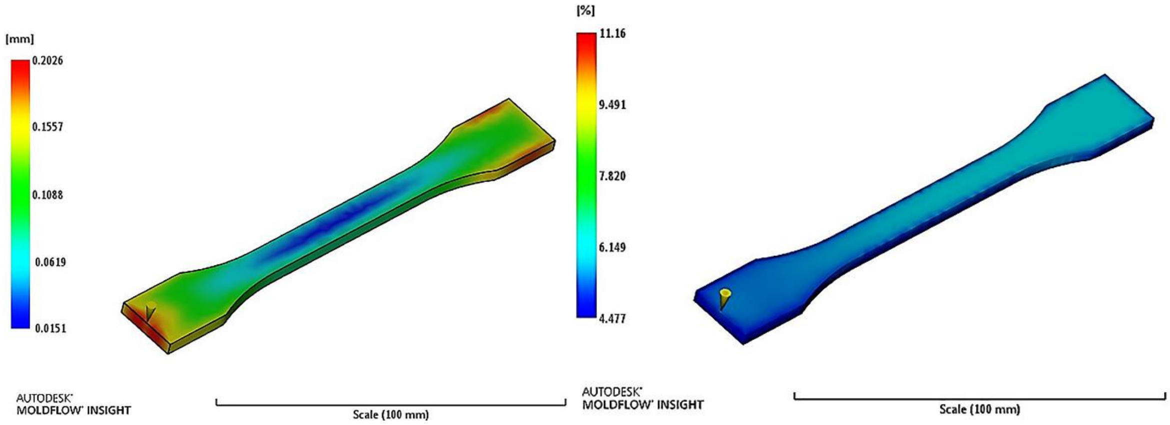

Figure 6. Moldflow simulation of predicted values **(a)** warpage **(b)** volumetric shrinkage

3.5 Tensile Test Results

The tensile test was carried out in INSTRON 4411 tensile tester. The tensile tests were performed in a climate-controlled environment where the ambient temperature was kept at 20 +/- 3 °C. The test specimens were held for at least two days before the tensile testing. Five test samples were used in each testing set.

As can be seen in Figure 7, the addition of fiber to the polymer caused a significant increase in tensile module value. This increased rate is higher in the strain range of 0% and 0.5% and it was also observed that for each fiber ratio, the tensile modulus values obtained by optimization show better performance compared to the values obtained by the recommended design parameters.

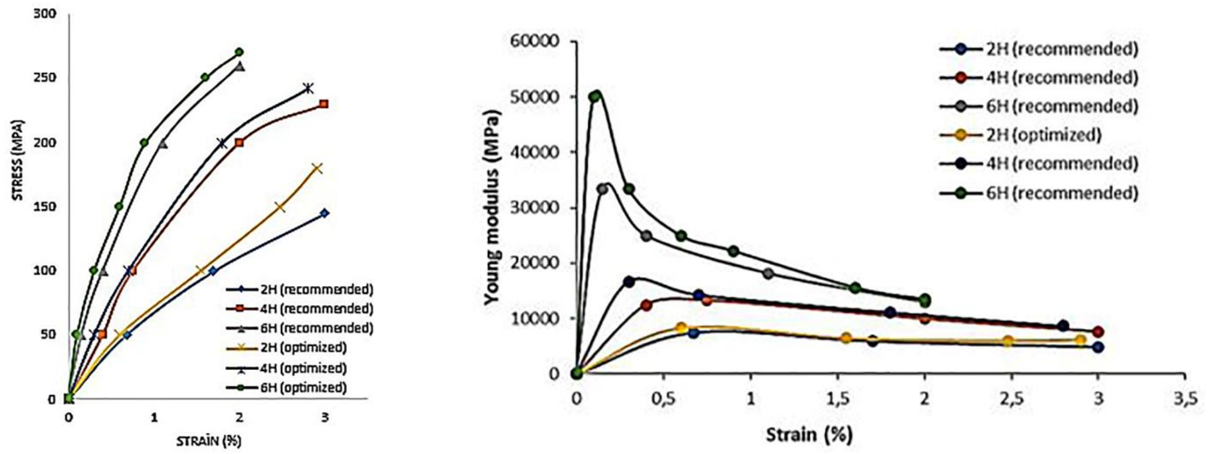

Figure 7. Tensile test results

4. Conclusion

In this study, the effect of five parameters on warpage, volumetric shrinkage, and cycle time of polyamide 66+PA6I/6T injection molded part was determined using the RSM and GWO methods. After the design variables were optimized, the interaction between these optimized design variables was investigated based on the objective values and tensile modulus of the polymer composite. A plastic test specimen was tested based on the design parameters. The selected design parameters included fiber ratio, melt temperature, mold temperature, injection pressure, and injection time. It was observed that the stress-strain curves obtained by the analysis program were compatible with the experimental stress-strain curves obtained in light of these results.

The effect of design parameters on quality characteristics in fiber-reinforced composite material injection molding was studied using the ANOVA method based on the experiment design and Moldflow (MPI) numerical simulation. The RSM was used in the determination of optimum design parameter values. The experiment confirmed that the results obtained by the proposed method are better than those obtained by GWO. It was shown that the residual stress on the test specimens decreased according to the numerical values obtained by the optimization of design parameters using both methods. Finally, the test specimen produced in the injection machine based on the optimized design parameter values was subjected to tensile testing, and it was concluded that according to the results obtained experimentally, both optimization methods could improve the tensile modulus of the polymer.

References

[1]. Zhang X., Yu S., Gong Y., Li Y., Optimization design for turbodrill blades based on response surface method, Advanced Mechanical Engineering, 2016, 8(2), 1–12.

[2]. Ihesiulor O.K., Shankar K., Zhang Z., Ray T., Validation of algorithms for delamination detection in composite structures using experimental data, J Compos Mater, 2014, 48(8), 969–983.

[3]. Shen C., Wang L., Li Q., Optimization of injection molding process parameters using a combination of artificial neural network and genetic algorithm method, J Mater Process Technol, 2007, 183(2), 412–418.

[4]. Barghash M.A., Alkaabneh F.A., Shrinkage, and warpage detailed analysis and optimization for the injection molding process using multistage experimental design, Qual Eng, 2014, 26(3), 319–34.
[5]. Guo W., Mao HJ., Xu Q., Warpage and structural analysis of automotive trim based on FFD and CAE in plastic injection molding, Adv Mater Res, 2011, 1282(6), 314– 316.
[6]. Kuram E., Tasci E., Altan A.I., Medar M.M., Yilmaz F., Ozcelik B., Investigating the effects of recycling number and injection parameters on the mechanical properties of glass-fiber reinforced nylon 6 using Taguchi method, Mater Des, 2013, 49(5), 139–150.
[7]. Pei J.W., Multi-objective optimization scheme for quality control in injection molding, Intell. Transp Syst J, 2002, 6(4), 331–342.
[8]. Myers R.H., Montgomery D.C., Anderson-Cook C.M., Response Surface Methodology: Process and Product Optimization Using Designed Experiments, John Wiley & Sons, 2016.
[9]. Zhang X., Yu S., Gong Y., Li Y., Optimization design for turbodrill blades based on the response surface method, Adv Mech Eng, 2016, 8(2), 1–12.
[10]. Mirjalili S., Lewis A., Grey wolf optimizer, Adv Eng Software, 2014, 69, 46–61.
[11]. Haj Ali RKH., Nonlinear constitutive models for FRP composites using artificial neural networks, Mech Mater, 2007, 39(12), 1035–42.
[12]. Megat-Yusoff PSM., Abdul Latif MR., Ramli MS., Optimizing injection molding processing parameters for the enhanced mechanical performance of oil palm empty fruit bunch high-density polyethylene composites, J Appl Sci, 2011, 11(9), 1618–1623.
[13]. Imihezri S., Sapuan S.M., Sulaiman S. et al., Mould flow and component design analysis of polymeric based composite automotive clutch pedals, J of Mater Process Technol, 2006, 171, 358–365.
[14]. Kurtaran H., Erzurumlu T., Efficient warpage optimization of thin shell plastic parts using response surface methodology and genetic algorithm, Int J Adv Manuf Technol, 2006, 27(5), 468–472.
[15]. Chen W.C., Nguyen M.H., Chiu W.H., Chen T.N.,. Tai P.H., Optimization of the plastic injection molding process using the Taguchi method, RSM, and hybrid GAPSO, Int J Adv Manuf Technol, 2016, 83(9), 1–14.
[16]. Yin F., Mao H., Hua L., A hybrid of backpropagation neural network and genetic algorithm for optimization of injection molding process parameters, Mater Des, 2011, 32(6), 3457–3464.
[17]. Sadabadi H., Ghasemi M., Effects of some injection molding process parameters on fiber orientation tensor of short glass fiber polystyrene composites (SGF/PS), Journal of Reinforced Plastics and Composites, 2007, 26(17), 1729–1741.
[18]. Nagahanumaiah BR., Effects of injection molding parameters on shrinkage and weight of plastic part produced by DMLS mold, Rapid Prototyp J, 2009, 15(3), 179–86.
[19]. Kang GJ., Process factor optimization for reducing warpage and shrinkage in injection molding using design of experiments, Appl Mech Mater, 2014, 359(62), 541-542.
[20]. Xu G., Yang Z.T., Long G.D., Multi-objective optimization of MIMO plastic injection molding process conditions based on particle swarm optimization, Int J Adv Manuf Technol, 2012, 58(5), 521–531.
[21]. Rong Y., Zhou Q., Huang Y., Chang Y., Zhang G., Shao X., Multi-objective optimization of laser brazing with the crimping joint using ANN and NSGA-II, Int J Adv Manuf Technol, 2016, 85(5), 1239–1247.