Research Article

Integration of Artificial Neural Network and Taguchi Method for Prediction and Minimisation of Thick-Walled Polypropylene Gear Shrinkage

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ABSTRACT

The main aim of this research is to optimize the injection molding process parameters in order to mitigate the shrinkage of polypropylene (*PP*) spur gears. The methodology used integrated experimental approaches with artificial neural networks (ANN), and Taguchi methods to determine the optimal combination of injection molding parameters. The experimental data was used to create an ANN model using Matlab software that accurately predicts unseen data with a variation of less than 5%. The trained ANN model was further used to predict gear shrinkage in the context of Taguchi-based design of experiments. The investigation involved the use of Taguchi and analysis of variance techniques, determining that cooling time is the most important and relevant parameter. This is followed by packing time and melt temperature. The analysis revealed that the gears saw the least amount of shrinkage when the molding was carried out using the optimal combination of injection molding parameters.

1. Introduction

The performance of engineering components has been sustainably improved in recent decades by making use of advanced and environmentally friendly materials, efficient production techniques, and optimized component thickness [1,2]. The mechanical performance of plastic components increases as wall thickness increases. However, manufacturing thick-walled plastic parts is a challenge because, as thickness increases, maintaining a uniform melt pressure throughout the wall thickness is very difficult, which results in density and shrinkage variation throughout the wall thickness of the part [3,4]. The IM process often uses artificial neural networks (ANN) to predict outcomes because this process offers high prediction accuracy and saves time and material consumption in real-time manufacturing. A developed model predicts the behavior of independent variables, such as input parameters, on dependent quality characteristics, such as target. The ANN model consists of layers and neurons, whose combination mainly determines the accuracy of prediction. Additionally, it also depends on the amount of input and target data used in model development [5,6]. Meiabadi et al. [7] carried out polymer IM process parameter optimization using ANN and genetic algorithm (GA) methods. The developed ANN model consisted of one input layer, two hidden layers, and one output layer. These three layers each have four, ten, and three neurons. Using Moldflow, ANN, and experimental investigation, it was observed that at injection pressures of 10.9 MPa, 10.8 MPa, and 11.0 MPa; the component weights of 16.6 g, 16.1 g, and 16.3 g; and process cycle times of 32.0 s, 31.6 s, and 32.7 s were observed, accordingly. Abdul et al. [8] predicted shrinkage of HDPE parts using the ANN and Taguchi methods. The ANN input layer, hidden layer, and output layer contain three, four, and two neurons, respectively. The developed ANN model had a prediction error of 0.08% and 0.69% with experimental outcomes for part length and width, respectively. Lockner et al. [5] tried to reduce the sample size requirement for training an ANN model using the transfer learning method. This method used existing data from other processes as training data. The developed ANN model was based on a transfer

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learning approach that showed superior features to the base approach. Xu et al. [9] optimized IM process parameters to enhance the quality of plastic parts by integrating ANN with particle sworn optimization (PSO). The developed ANN model consisted of one input layer, two hidden layers, and one output layer. The Taguchi method has been applied in the IM process to optimize process parameters to achieve the best quality characteristics of molded components [10,11]. Moayyedian et al. [10] optimized thin-walled PP parts by integrating ANN with the Taguchi method. The Taguchi L_{18} *OA* array was used to design the experiments using parameters such as gate design, filling time, cooling time, pressure holding time, and melt temperature. The observation was made to minimize short shots, shrinkage rate, and warpage. They found a 1.5% margin of error between the normalized outcomes of both methods. Wang et al. [12] used Taguchi L_{18} OA to reduce micro gear shrinkage. It was reported that the minimum shrinkage of 0.06% was found using a mold temperature of 80 ^{o}C, injection speed of 300 mm/s, a packing speed of 20 mm/s, a packing time of 1 s, and a melt temperature of 190 ^{o}C. In addition to this, the ANOVA method revealed that packing time was the most significant parameter for reducing gear shrinkage. This was followed by injection speed and mold temperature. Mehat et al. [13] optimized IM process parameters to minimize PP gear shrinkage by incorporating Taguchi, grey relational analysis (GRA), and principal component analysis (PCA). The Taguchi L_9 *OA* was used to design the experiment by optimizing melt temperature, packing pressure, packing time, and cooling time. The minimum shrinkage of 1.8%, 1.53%, and 2.42% were found in tooth thickness, addendum circle diameter, and dedendum circle diameter, respectively. The melt temperature was found to be the most significant factor for gear shrinkage reduction, with a contribution of 71.47%. Hao et al. [14] analyzed the quality of plastic gear by integrating the CAE method with ANN based on MATLAB. The maximum error of 0.077% was reported between simulation and ANN prediction. Hakimian et al. [15] reduced the warpage and shrinkage of micro gear using the simulation-based Taguchi method. They found that amorphous polymers shrink and warp less than crystalline polymers at the same IM parameter.

This literature review showed that the vast majority of models of neural networks were developed through simulation studies. This may be due to the fact that experimentation requires more time and money. However, the simulation technique cannot implicate all constraints involved in the IM experiment and its accuracy further declines if the product to be molded has a higher wall thickness and complex shape. Thus, experiments were carried out to gather sufficient input and target data to construct an accurate neural network model. This model was used to predict the outcomes of the Taguchi experiment to reduce gear shrinkage. In addition to this, a conformation test was performed to validate the findings, and regression analysis was applied to examine each factor's impact on gear shrinkage.

2. Methodology

Figure 1 shows the workflow scheme followed in the present work. There were two methods adopted to minimize gear shrinkage, namely ANN and Taguchi methods, which were performed using Matlab and Minitab software. The steps involved in formulation of the methodology include the:

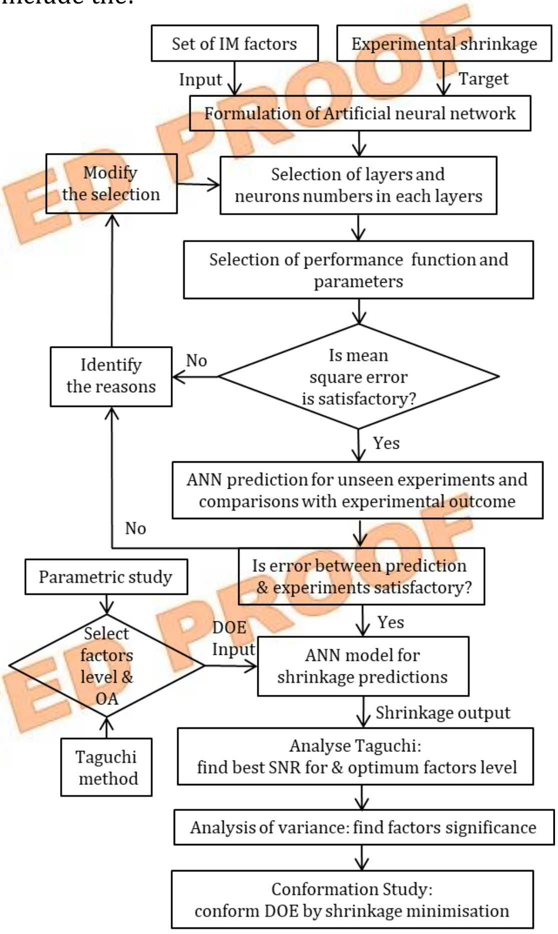

Fig. 1. Workflow scheme

2.1 Experimental Setup

The IM process is used to produce useful parts from plastic granules. The solid granules are heated through band heaters to melt the plastic to be injected into the mold cavity. The IM process mainly contains four stages, specifically filling, packing, cooling, and ejection. The prominent process parameters are injection pressure, packing pressure, melt temperature, mold temperature, injection time, packing time, and cooling time. The chosen feature is gear shrinkage, which is significantly influenced by the aforementioned factors. In the present work, an experimental investigation was performed to minimize the spur gear diametric shrinkage. The expression used to calculate shrinkage is shown in eq. 1 [16]. The measured diameter was the addendum circle diameter of the spur gear (D_G) and mold cavity (D_C). The designed spur gear has a module of 3 mm, a pressure angle of 20°, *and a* tooth count of 12. Figure 2 shows a 2D CAD model of spur gear, where all linear dimensions are measured in mm [4].

The selected polymer was polypropylene (PP) homopolymers having a density of 0.91 g/cm³, melt flow index of 8 g/10 min, tensile strength of 30 MPa, barrel temperature, and mold temperature should be in the range of 180 °C to 260 °C and 30 °C to 40 °C, respectively [17]. The IM parameters were varied in such a way that at a time one factor was changed while other factors were fixed at a medium level. The range of each factor used in the generation of data is given in Table 1. The Milacron servo IM machine was used for experiments (Fig. 3). This machine has a maximum hydraulic pressure of 17.5 MPa, maximum melt pressure of 248 MPa, maximum screw speed of 320 rpm, and maximum flow rate of 116 cm³/s.

$$\text{hrinkag } (\%) = \left\{\frac{D_C - D_G}{D_C}\right\} \text{X } 100 \qquad (1)$$

Table 1 Range of IM processing factors

Parameter	Unit	Range	
		Min	Max
Injection Pressure (IP)	MPa	100	180
Packing pressure (PaP)	MPa	125	160
Packing time (PT)	s	5	30
Cooling time (CT)	s	5	25
Injection time (IT)	s	0.5	1.75
Melt temperature (MT)	°C	170	205
Mold temperature (MoT)	°C	30	52

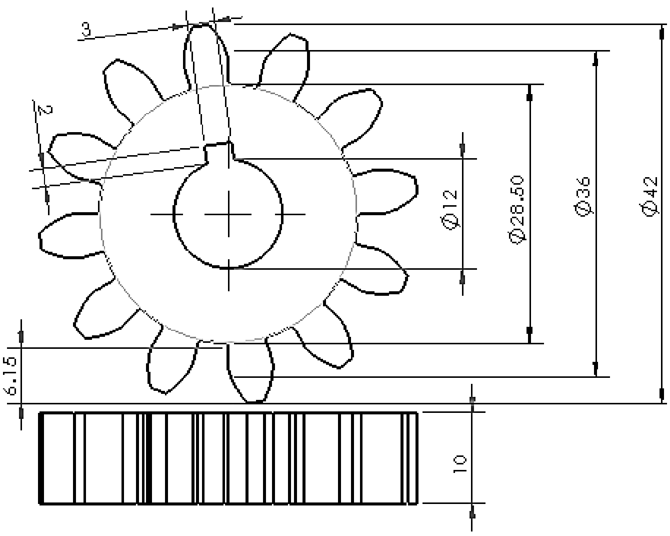

Fig. 2. Generated 2D model of spur gear

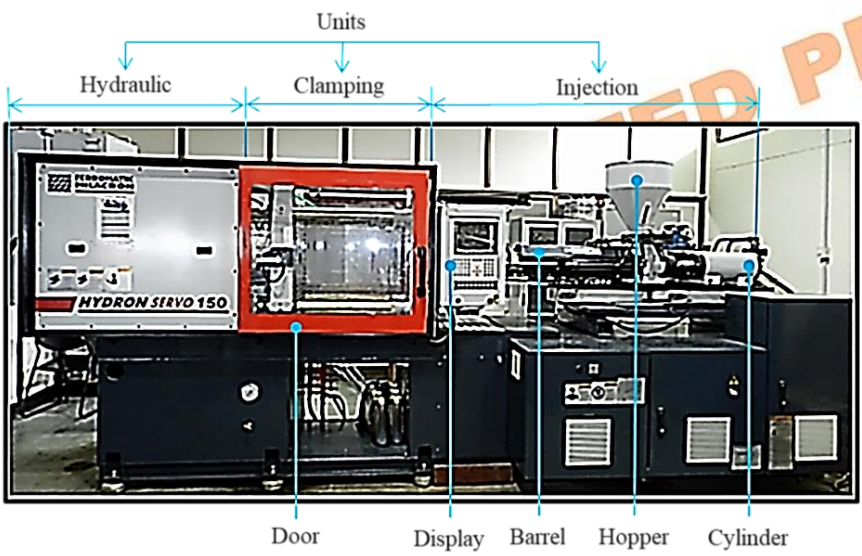

Fig. 3. Schematic of in-house available injection molding machine

2.2 Artificial Neural Network Design

MATLAB software was used to conduct the ANN analysis, and the generated structure is shown in Fig. 4. The developed ANN model has one input layer, one hidden layer, and one output layer. The input layer has seven IM factors: injection pressure, packing pressure, packing time, injection time, cooling time, melt temperature, and mold temperature. One neuron was assigned in place of each factor; hence, the input layer contains seven neurons. Using trial-and-error methodology, the neurons in the hidden layers were chosen, and a minimum error value of 64 neurons was obtained. Similarly, the neuron counts in the output layer are the same as the output variables. Since an investigation was made for shrinkage as an output variable; the output layer contains only one neuron. The inputs and hidden layers were activated using the "Tansig" activation function, while the hidden and output layers were activated using the "Purelin" activation function. The performance function was taken as a mean square error (MSE) for minimization of network errors on the training data, and the learning approach was dependent on the Levenberg Marquardt process. The set of control variables and target variables were then utilized as input-output data for the training and verification of neural networks. The 36 datasets that composed the samples included in this investigation have been used for training, validation, and testing, respectively, in percentages of 68%, 16%, and 16%. Additionally, an ANN simulation was performed with 10 unknown data points, and the results were compared to the results of the experiment. The response variable was obtained using eq. 2.

$$Y = \text{FFANN}[x_1 \ldots \ldots \ldots x_7] \quad (2)$$

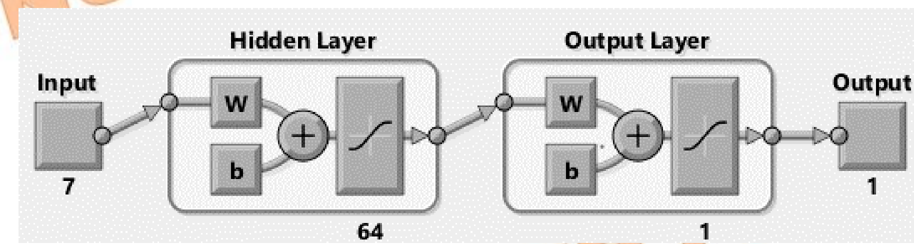

Fig. 4. Construction of ANN

Table 2 Set of IM process parameters and shrinkage

S. No.	MT	MoT	IP	PaP	IT	PT	CT	Shrinkage (%)
1	175	40	100	125	0.5	20	20	1.453
2	175	40	120	125	0.5	20	20	1.432
3	175	40	160	125	0.5	20	20	1.410
4	175	40	180	125	0.5	20	20	1.391
5	175	40	140	130	0.5	20	20	1.327
6	175	40	140	140	0.5	20	20	1.295
7	175	40	140	160	0.5	20	20	1.124
8	175	40	180	160	0.5	20	20	1.120
9	175	46	125	150	0.5	20	20	1.222
10	175	40	180	160	0.5	5	20	1.174
11	175	40	180	160	0.5	15	20	1.104
12	175	40	180	160	0.5	25	20	1.145

13	175	40	180	160	0.5	30	20	1.150
14	175	40	180	150	0.5	5	20	1.220
15	175	40	180	150	0.5	10	20	1.216
16	175	40	180	150	0.5	20	20	1.178
17	175	40	180	160	1.5	15	20	1.388
18	175	40	180	160	2	15	20	1.567
19	175	40	180	160	0.5	15	10	1.251
20	185	40	180	160	0.5	15	20	1.131
21	195	40	180	160	0.5	15	20	1.168
22	205	40	180	160	0.5	15	20	1.649
23	175	52	180	160	0.5	15	20	1.157
24	185	34	135	135	1.75	25	25	1.269
25	170	40	150	150	0.5	20	20	1.251
26	170	34	140	140	0.5	20	20	1.420
27	170	34	150	150	0.5	20	20	1.444
28	170	40	150	150	0.5	20	15	1.228
29	170	40	150	150	0.5	15	15	1.283
30	170	46	150	150	0.5	15	15	1.230
31	175	30	100	100	0.5	5	20	1.497
32	175	30	100	100	0.5	10	20	1.439
33	175	30	100	100	1	15	20	1.405
34	175	30	100	100	1.5	15	20	1.396
35	175	30	100	100	1.5	15	5	1.114
36	175	30	100	100	0.5	15	10	1.186

2.3 Steps in the Taguchi Method

The Taguchi method is used for the robust design of experiments. This is done by collecting important data to obtain the significant factors that influence the performance of the part by reducing the number of experiments. This minimizes the requirement for resources and computational and experimental time.

2.3.1Selection of Quality Characteristics

The Taguchi methodology is an effective method for enhancing the level of usefulness, cost, and performance. This technique creates a distinct set of process parameters for experiments using the concept of an orthogonal array (OA). Compared to complete or fractional factorial designs of experiments, the method has been found to be more effective. A signal-to-noise ratio (SNR) technique is used to determine the data set's performance parameters. The data is categorized into three groups, namely nominal is better, larger is better, and smaller is better, and the corresponding SNR is calculated using equations 3-6. Additionally, the regression analysis-based analysis of variance approach is used to conduct relevant analyses of independent variables or combinations of numerous factors on quality characteristics [18–25].

minal is better $\frac{S}{N} - 10\log\left(\frac{1}{nS}\sum_{i=1}^{n} y_i^2\right)$ (3)

Larger is better $\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$ (4)

Smaller is better $\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$ (5)

Mean square deviation $= \left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$ (6)

2.3.2Selection of Control Factors and Levels

The selection of a control factor for the optimization study was based on a parametric study conducted to generate the shrinkage data for ANN training, validation, and testing. The significant control factors were melt temperature, packing pressure, injection time, packing time, and cooling time. The levels of these factors were chosen by considering their effect on shrinkage and machine constraints. The combinations of selected factors were made to search out the optimum combination of factors to further minimize the gear shrinkage. Table 3 shows selected factors and their levels.

Table 3 Selected factors and their levels

Factors	Unit	Level			
		1	2	3	4
MT	°C	176	179	182	185
PaP	MPa	153	157	161	165
IT	s	0.2	0.4	0.6	0.8
PT	s	8	11	14	17
CT	s	13	16	19	22

2.3.3Selection of Orthogonal Array

The Minitab software was used to perform Taguchi analysis. The selected number of factors was five, and their levels were four. Based on selected factors and their levels, L_{16} OA was available in the design of the experiment (DOE). The obtained DOE set is shown in Table 4.

Table 4 Layout of L_{16} *OA*

Experiments	MT	PaP	IT	PT	CT
1	176	153	0.2	8	13
2	176	157	0.4	11	16
3	176	161	0.6	14	19
4	176	165	0.8	17	22
5	179	153	0.4	14	22
6	179	157	0.2	17	19
7	179	161	0.8	8	16
8	179	165	0.6	11	13
9	182	153	0.6	17	16
10	182	157	0.8	14	13
11	182	161	0.2	11	22
12	182	165	0.4	8	19
13	185	153	0.8	11	19
14	185	157	0.6	8	22
15	185	161	0.4	17	13
16	185	165	0.2	14	16

2.3.4Analysis of Variance

The selected factors in the study were numeric variables. Hence, regression analysis was carried out using Minitab software to obtain an analysis of the variance table for identifying the relative contribution of each factor in gear shrinkage. This technique determines significant factors based on a confidence interval of 95% and their relative contribution. However, limitations like factor instability, public awareness of certain relationships, and assumption violations can all have an impact on the analysis's ability to determine the relative contribution.

3 Result and Discussion

The minimization of spur gear shrinkage is carried out by integrating ANN with the Taguchi method.

3.1 Artificial Neural Network

The regression graph for training, validation, and testing data for gear shrinkage is shown in Fig. 5. It was clear from the graph that the degrees of fit for training, validation, testing, and all together were 0.99018, 0.98539, 0.99445, and 0.99004, which were very close to each other. This demonstrates that the model successfully captured the behavior contained in the training data set, while the high correlation coefficient (R) for the test set of data indicated that the suggested model had adapted efficiently without over-fitting. Figure 6 displays the error curve for shrinkage of ANN predictions with an experimentally produced unknown data set. It was observed that the experimental shrinkage values and the ANN simulated shrinkage values agreed through each run, and the trend lines for both exhibited a close similarity. In the entire set of unobserved shrinkage data, the error was found to be within 4.478%. Thus, it was claimed that the produced ANN model was verified by the results of the experiments.

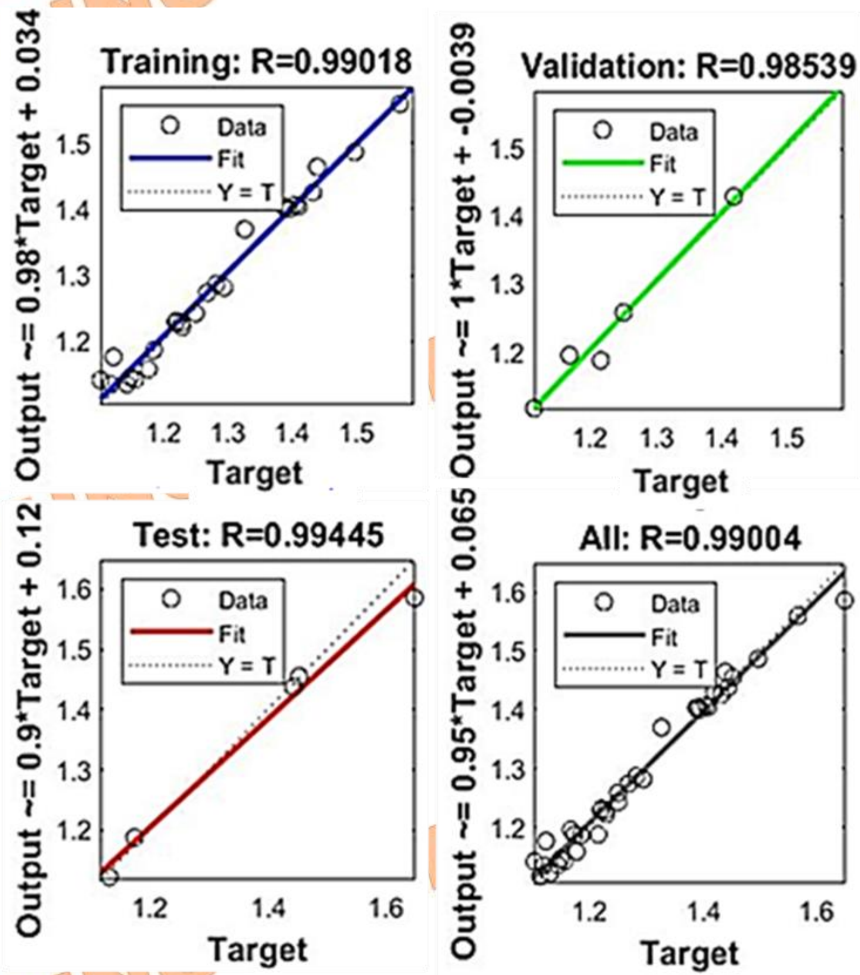

Fig. 5 Regression plot of ANN

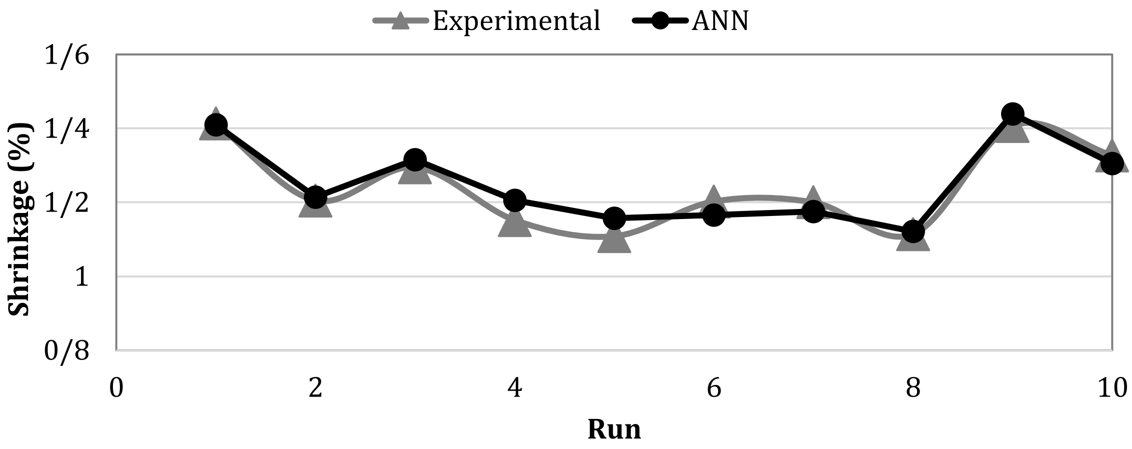

Fig. 6. Error plot for shrinkage of unseen data set

3.2 Optimisation of IM Parameters

A trained ANN model was used to predict the gear shrinkage for the Taguchi L_{16} *OA*. The predicted shrinkage was used to perform Taguchi analysis to obtain SNR corresponding to L_{16} OA, SNR table for each level of IM process parameters, and main effect plot. The simulated shrinkage value and SNR are displayed in Table 5

Table 5 Results of the L_{16} OA

Experiment	Shrinkage (%)	S/N Value
1	1.218	-1.71132
2	1.170	-1.36092
3	1.143	-1.16185
4	1.135	-1.09751
5	1.136	-1.10692
6	1.133	-1.08351
7	1.215	-1.68874
8	1.181	-1.44251
9	1.136	-1.10632
10	1.176	-1.41098
11	1.128	-1.04739
12	1.125	-1.02546
13	1.143	-1.16038
14	1.138	-1.12321
15	1.135	-1.09619
16	1.127	-1.04135

3.2.1Estimation of Signal-to-Noise Ratio

In this study, smaller is better SNR criteria were used for identifying the optimal set of process parameters. The eq. 5 was used to determine the SNR for each experiment and factor level. Figure 7 shows the main effect plot for the SN ratio. This plot represents the relationship between each parameter and SNR. It was noticeable seen that with an increase in the melt temperature, packing time, and cooling time, the SNR value increases and approaches zero. This indicates that boosting these parameters will increase the signal and decrease the noise. However, as packing pressure increases, SNR first rises, then falls, and finally rises instead to its highest value. Likewise, as injection time is increased, SNR first rises before falling to its lowest value. The maximum SNR and the associated level of factors are thus optimal for minimizing gear shrinkage. As observed, the highest SNR for the factors specifically melt temperature, packing pressure, injection time, packing time, and cooling time was determined to be at levels 4, 4, 2, 4, and 4, respectively. The respective optimum combination of the parameters included a melt temperature of 185 °C, packing pressure of 165 MPa, injection time of 0.4 s, packing time of 17 s, and cooling time of 22 s. Table 6 shows the SNR value of factors at each level and their rank on gear shrinkage. The maximum difference in SNR is called Delta, and the factor having the maximum Delta is ranked 1. As a result, it is clear that cooling time has come out on top. This was followed by packing time, melt temperature, injection time packing pressure, and associated ranks of 2, 3, 4, and 5.

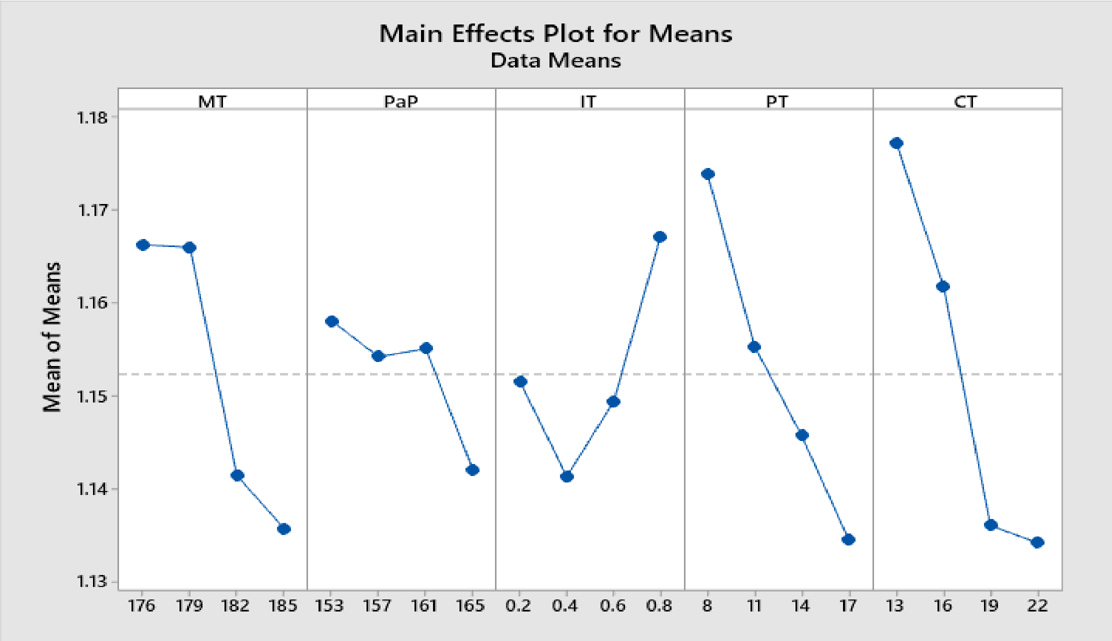

Fig. 7. Main effect plot for SN ratios

Table 6 Signal to Noise Ratios

Level	MT	PaP	IT	PT	CT
1	-1.333	-1.271	-1.221	-1.387	-1.415
2	-1.33	-1.245	-1.147	-1.253	-1.299
3	-1.148	-1.249	-1.208	-1.18	-1.108
4	-1.105	-1.152	-1.339	-1.096	-1.094
Delta	0.228	0.12	0.192	0.291	0.321
Rank	3	5	4	2	1

3.2.2Analysis of Variance

Table 7 shows an analysis of variance for gear shrinkage. It can be clearly seen that the model P value is less than 0.05; which denotes the significance of the applied regression model with a confidence interval of 95%. Additionally, the P value of cooling time, packing time, and melt temperature are less than 0.05; hence, these parameters are significant parameters for minimizing gear shrinkage. The corresponding contribution of these factors on shrinkage was found to be 40.633%, 27.65%, and 22.836%, respectively. However, the P value of injection time and packing pressure is higher than 0.05; hence, these parameters are insignificant for shrinkage minimization. The corresponding contribution of these factors on shrinkage was found to be 5.085% and 3.790%.

Table 7 Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Contribution (%)
Model	5	0.011856	0.002371	12.82	0	
MT	1	0.002707	0.002707	14.64	0.003	22.836
PaP	1	0.00045	0.00045	2.43	0.15	3.790

IT	1	0.000603	0.000603	3.26	0.101	5.085
PT	1	0.003278	0.003278	17.73	0.002	27.656
CT	1	0.004817	0.004817	26.05	0	40.633
Error	10	0.001849	0.000185			
Total	15	0.013706				

Figure 8 shows the interaction plot of the IM factor for shrinkage. In this plot, parallel lines do not indicate interaction; nevertheless, non-parallel lines and intersecting lines indicate the significant connection between the factors. It can be observed that parallel lines are not present in the interaction plot between the factors which denotes a single factor does not significantly influence the shrinkage. However, the majority of the lines intersect, and their slopes also vary, indicating the strong mutual interaction of factors affecting gear shrinkage. Hence, gear shrinkage is a cumulative effect of all factors that have been taken into account. At the lowest melt temperature of 176 °C, shrinkage significantly reduces with an increase in packing pressure, injection, packing, and cooling time; however, at the highest melt temperature of 185 °C, it is not affected by another factor significantly. Fig. 9 shows a contour plot for gear shrinkage. It is clear from plots that the cooling time has a dominant role in shrinkage, if the packing time is more than 21 seconds, shrinkage lies within 1.14%. However, if it is essential to reduce the cooling time to reduce overall cycle time without increasing the shrinkage by more than 1.14%, the remaining factors level, namely melt temperature must be between 181 °C to 184 °C, packing time must be greater than 14 s (Fig. 9 (a-b)). But packing pressure and injection time are found to be the least significant parameters for shrinkage minimization (Fig. 9 (c-d). Therefore, contour plots consolidate the findings obtained from Taguchi and the analysis of variance.

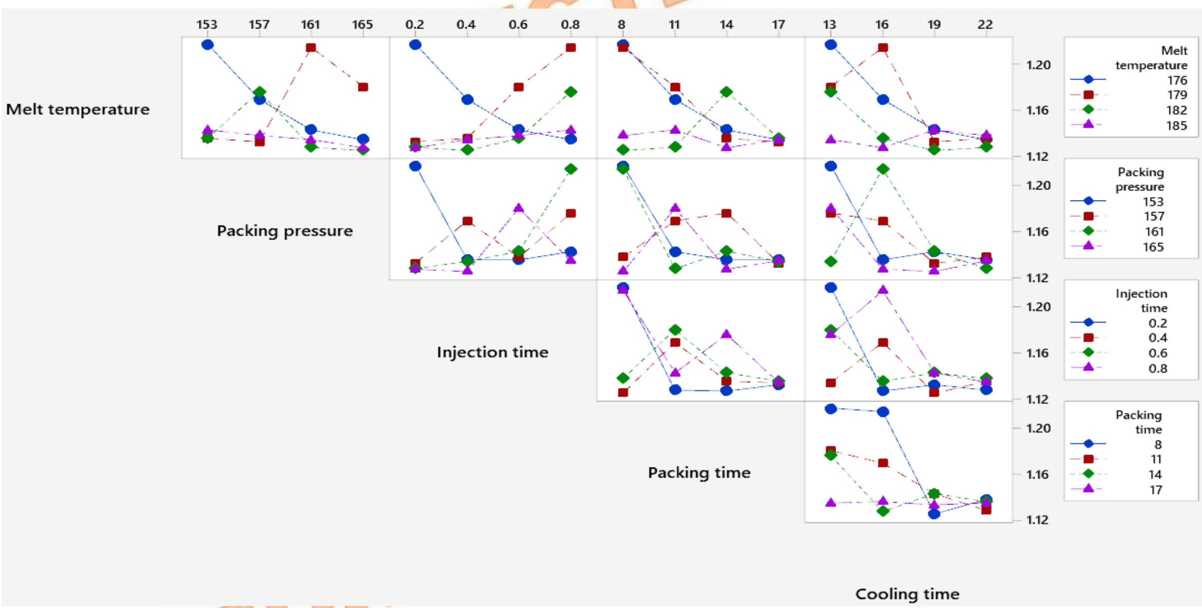

Fig. 8. Interaction plot for gear shrinkage

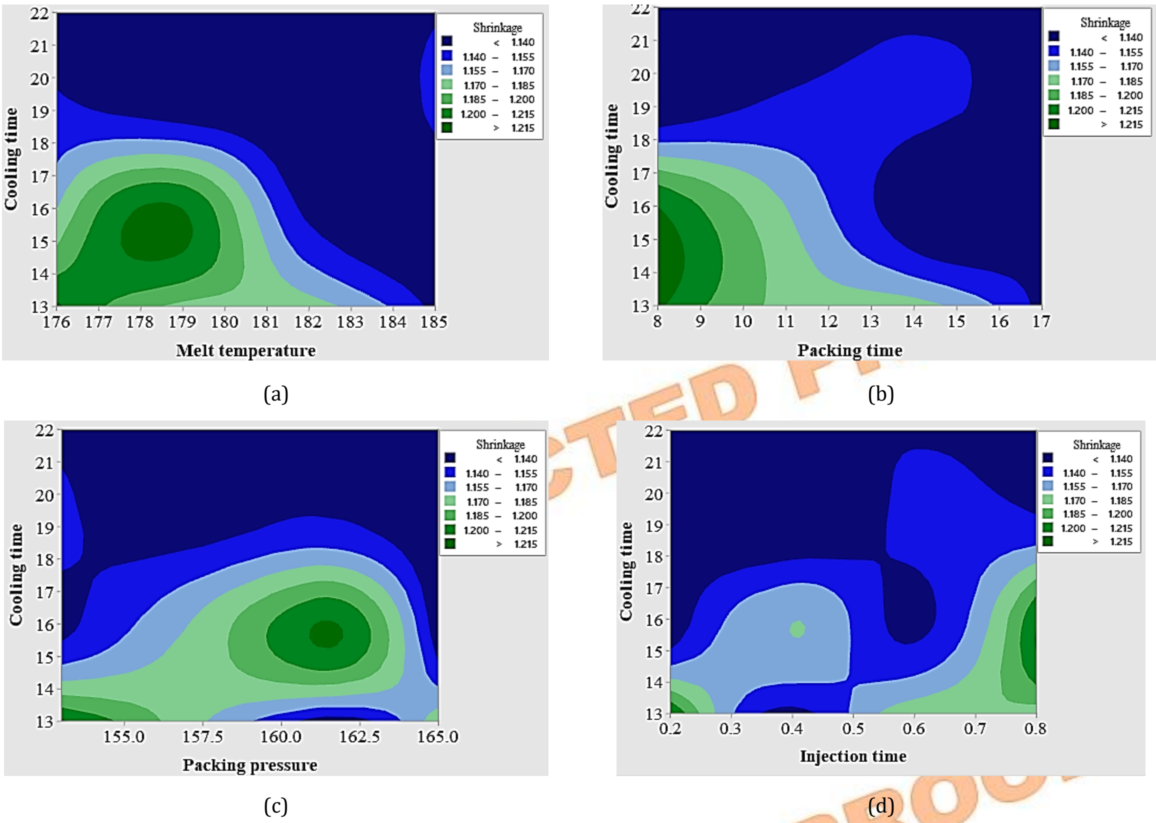

Fig. 9. Contour plot for shrinkage (a) Cooling time versus Melt temperature (b) Cooling time versus Packing time (c) Cooling time versus Packing pressure, and (d) Cooling time versus Injection time

3.2.3Conformation Test

The conformation test was carried out to minimize the gear shrinkage using an optimum combination of process parameters, namely melt temperature of 185 °C, packing pressure of 165 MPa, injection time of 0.4 s, packing time of 17 s, and cooling time of 22 s. The ANN prediction was made using these parameters and the corresponding shrinkage was found to be 1.121%. Similarly, experimental analysis was also conducted using the same parameters, and the corresponding shrinkage was found to be 1.127%. Hence, it can be deduced that the developed ANN model had high prediction accuracy as the produced shrinkage was found to be in good agreement with experimental findings, and the corresponding error was found to be 0.535%.

The minimum shrinkage of PP gear in the current investigation was determined to be 1.127%, which is significantly less than the 1.606% and 1.656% shrinkage reported by Solanki et al.[16,26], resulting in a 42.502% improvement. The most significant factor in minimizing gear shrinkage was found to be cooling time, which was similar to the findings of Mehat et al. [27].

Conclusion

In the present study, the optimization of IM process parameters was carried out with the aim of minimizing the shrinkage of PP gear. This was conducted by integrating an artificial neural network and the Taguchi method. The IM factors selected for optimization were melt temperature, packing pressure, injection time, packing time, and cooling time. Additionally, analysis of variance was carried out to determine the contribution of selected parameters on gear shrinkage. Based on the findings, the following conclusions could be drawn:

- The designed ANN for shrinkage of PP gear shows a degree of fit greater than 0.99 in training, validation, and testing.
- The predicted shrinkage for the unseen set of experiments was found to be in good agreement with experimental outcomes, and the maximum error was within 5.0%.
- The Taguchi analysis depicted the optimum IM parameter as a melt temperature of 185 °C, packing pressure of 165 MPa, injection time of 0.4 s, packing time of 17 s, and cooling time of 22 s.
- The analysis of variance advocated that the cooling time, packing time, and melt temperature were found to be significant IM

factors with contributions of 40.633%, 27.656%, and 22.836%, respectively.
- The conformation test revealed minimum gear shrinkage was obtained at optimum parameters via ANN and experimental analysis.

Application

The PP gears are widely used in lightweight power transmission and underwater applications.

Future Scope

The present study has the following limitations, which need more comprehensive work on fabrication and analysis.
- Fillers such as glass fiber, carbon fiber, etc. can be added with PP to further reduce the gear shrinkage.
- Wear and fatigue analysis of PP gear can be conducted using a gear test rig.

Nomenclature

PP	Polypropylene
ANN	Artificial neural network
ANOVA	Analysis of variance
GRA	Grey relational analysis
PCA	Principal component analysis
OA	Orthogonal array
CAE	Computer-aided engineering
IM	Injection molding
PSO	Particle sworn optimization
IP	Injection pressure
PaP	Packing pressure
PT	Packing time
CT	Cooling time
IT	Injection time
MT	Melt temperature
MoT	Mold temperature
Dc	Addendum circle diameter of mold cavity
DG	Addendum circle diameter of spur gear
MSE	Mean square error
DOE	Design of experiment
SNR	Signal-to-noise ratio
R	correlation coefficient
SS	Sum of squares
MS	Mean square
DF	Degree of freedom

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Conflicts of Interest

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