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Comparative analysis of artificial neural network model and analysis of variance for predicting defect formation in plastic injection moulding processes

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Abstract. This study investigates the impact of plastic injection moulding process parameters on overflow defect formation. Experiments were conducted using a Taguchi L27 orthogonal array design. Multilayer Perceptron (MLP) artificial neural networks is explored and compared with ANOVA predictions. To assess model performance, the Root Mean Squared Error (RMSE) and the coefficient of determination (R2) is applied. The study considered temperature, speed, pressure, and packing force when constructing the MLP model using the back-propagation algorithm in Python. Results show that among the configured MLP neural networks, the 3-layer MLP architecture with sigmoid activation functions in hidden layers and a linear function in the output layer exhibited the lowest prediction error and the highest coefficient of determination. Comparative analysis reveals that the MLP neural network outperforms the ANOVA model, indicating superior prediction accuracy. The predicted outcomes from the ANN align well with experimental values, demonstrating the effectiveness of the ANN model in forecasting defect formation under specific process conditions. This research sheds light on the significance of process parameters and showcases the potential of MLP neural networks as a valuable tool in predicting and mitigating overflow defects in plastic injection moulding.

Keywords: Analysis of variance, Artificial neural network, Multilayer perceptron, injection moulding, defects.

1. Introduction

Plastic Injection moulding (PIM) is a technique that involves heating a polymer to a highly plastic state and forcing it to flow at high pressure into a mold cavity, in which it hardens [1–3]**.** After that, the molded portion is withdrawn from the hollow as shown in Figure 1. The technique yields discrete components that are close to the net form or near-net shapes. PIM is applied to produce complex features and intricate shapes. They are less expensive than other methods like 3D printing [4, 5]. By using the PIM method, a variety of thermoplastics, including ABS, Nylon, PLA, Polycarbonate, PEEK, Polyethylene, Polypropylene, Polystyrene, and Polyvinyl Chloride, are frequently utilized [6]. Fast-moving consumer goods, of which half are produced using plastic, are in high demand in this rapidly

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developing global economy [6, 7]. According to Maarif *et al*. [8], PIM now accounts for around 30% of the global production of products or components made of plastic. PVC is the most widely produced and reasonably priced polymer with the necessary chemical properties as well as mechanical and thermal stability [9–11]. Plastic Industries mold PVC to varieties of shapes according to the desired functions i.e., shoe sole is one of the applications.

Filling, holding, and cooling are the three fundamental stages of the injection moulding procedure. First, the cavity is filled with molten plastic material to form the product's desired shape. The pressure on the holding stage is then increased by packing additional material into the cavity. To solidify the molten materials, the temperature will be greatly reduced during the cooling phase. The last step ensures that the finished product of the moulding process is stable enough for ejection. If there are no flaws, the outcome of the injection moulding process is deemed satisfactory [12, 13].

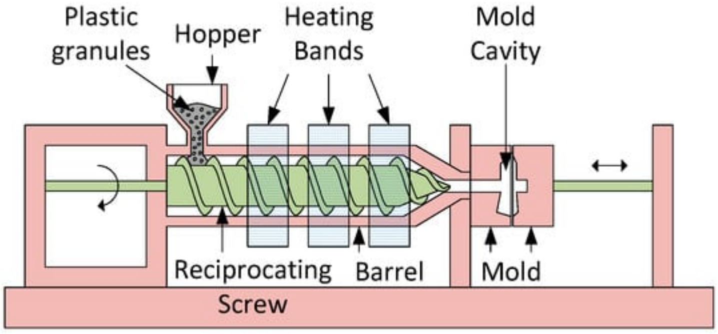

Figure 1. Plastic injection moulding machine in a simplified form [12].

Final products with defects are frequently the result of unforeseen behavioural changes in injection moulding parameters [14]. The common flaws detected on the final products of PIM are shrinkage and warpage, short-shot, and sink mark. This research addressed several defects in the process of shole sole injection moulding process as short-shot, weight variation, overflow, warpage, shrinkage, swelling, sink mark and black dot. However, based on the frequency and effects on the defects; this research addresses the overflow in the PIM. The different sorts of flaws are caused by different factors which influence the injection moulding process. An overflow defect due to different control process parameters involving in different stages PIM and causes incomplete parts or often causes weight variations. In PIM, process parameters need be managed to get the desired shape and minimum defects that may arise from different sources, including skills (man), machine, measurement, material, mold design, system parameters, and surroundings [11].

The process parameters such as flow velocity, melt temperature, heat input, metering length, hold pressure and holding duration are vital variables observed in this research. From the trends of scholars there have been several attempts to formulate the cause and effect of independent variables and the desired quality PIM final products. For instance, independent factors analysed to discuss the impacts on the microscopic moulding process and part quality of micro gears [15, 16]. Huang *et al.* [17], investigated the impacts of gate size, mold heat temperature, melting time, packing pressure, injection pressure and packing time to find the ideal warpage outcome of a molded plastic part on the quality characteristics. According to Aditya *et al*. [18], the mechanical and physical properties, dimensional or quantifiable features are the attributes of PIM quality characteristics.

The source of defects can be related to material, filling, packing, and cooling. Material-related defects are black specks and splays; filling-related are short fills, overflow, while packing and cooling associated defects such as sink mark voids, warpage, deformations, and others [11]. The cause effect analysis are the techniques used to identify the responsible factors for the formation of defects [19, 20] Except material-related flaws, the defects stated earlier are primarily formed due to poor selection of processing parameters. Massive research has been conducted from several angles to examine the effect of the PIM process parameters on the on the mechanical characteristics of molded parts and the incidence of moulding flaws [15]. The optimization of the involving process parameters is common in the current research to get better quality results of final components. Plastic pipe flaws were optimized to improve to the level of defects occurring in the process [21]. Similar techniques are followed to determine the influence of temperature on the tensile and flexural strengths of bidirectional kenaf/PLA composites and the optimal temperature. These demonstrates that including independent factors in PIM influences defect formation [22–24].

Numerous model-based and experimental research has been conducted on the impacts process parameters on the formation of several defects. Taguchi Method and Response Surface Method are generally preferred in experimental studies due to their effective combination of factors and cost. Predicting the impacts of process parameters on the quality characteristics of PIM are vital aspects of current research. For instance, the barrel temperature, holding time, mold temperature, holding pressure, and cooling time effects on the warpage formation are predicted by using machine learning, while their significancy performed by using Analysis of Variance (ANOVA) [25, 26]. Moreover, the correlation between PIM process parameters and particle size of kaolin clay affects strength, shrinkage and warpage polymer composite executed by ANOVA. In Chen *et al*. [27] study, the Taguchi technique and ANOVA are employed to identify the most important parameters to cause warpage during the moulding process. Then a numerical strategy with SolidWorks Plastics is used to optimize the process variables to lessen warpage. Analysis of the impacts of machine process parameters is vital to plan and design PIM process. The majority of current parameter analysis research, however, is focused on computer-aided engineering (CAE) or simulation, which has been shown to be insufficient for assessing complicated behavioural changes in the actual PIM process [8].

Artificial Intelligence (AI) has found diverse applications across various domains, encompassing tasks like calculating cutting forces, estimating tool lifespan, discovery new materials, implementing predictive maintenance, and forecasting process quality. Within the realm of AI techniques, Artificial Neural Networks (ANNs) stand out as one of the earliest and most widely adopted methods [28, 29]. ANNs, alongside other advanced machine learning approaches, have exhibited remarkable success in enhancing prediction accuracy [30]. In this study, we exploited the power of ANN to forecast the influence of crucial process parameters on the occurrence of overflow incidents in PIM processes. To achieve the experimental data was collected, and applied ANOVA and construct an ANN-based predictive model.

2. Experimentation and setups

2.1 Parameters selection

Among several defects the overflow was one of the significant challenges in the injection moulding process. The responsible process parameters were selected as an independent variable based on the cause-and-effect analysis conducted followed by 5-why. The independent variables are identified as temperature, injection pressure, injection speed and packing pressure. The dependent variable is overflow or flash out molten from the cavity. Melt temperature (T), injection velocity (S), injection pressure (P), and packing pressure (Pf) are recognized as the fundamental reasons for overflowing. These process parameters are independent variables and are responsible for the occurrence of overflows (R). The relationship between overflow and underweight is studied, and overflow becomes the cause of underweight.

2.2 Design of experiments

The Taguchi method orthogonal array L27 was used to conduct experiments. The level of temperature (160, 170, and 180 ^{O} C), injection speed (10, 15, and 20 cm/s), injection pressure (0.2, 0.4, and 0.6 bar) and packing pressure (0.1, 0.3 and 0.4 bar) based on the ranges of operating conditions stated by the manufacturer. The weight results are measured while the signal to noise ratio (S/N) is calculated as shown on Table 1. As measuring the overflow is challenging, the opposite measurement of the part left inside the mold weight is measured. The "Larger-is-better" method as shown on Equation (1) is used, and the S/N ratio methodology was used to reduce the overflows or increase the weight of the final part.

$$S / N = -10 \times Log10(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y^2}) \quad (1)$$

Table 1. Taguchi design of experimentation and response

Run	T(ºC)	S (cm/s)	P (bar)	Pf (bar)	y(Kg)	S/N (dB)
1	160.0	10.0	0.20	0.10	0.200	-13.980
2	160.0	10.0	0.20	0.10	0.210	-13.560
3	160.0	10.0	0.20	0.10	0.220	-13.1530
4	160.0	15.0	0.40	0.30	0.240	-12.400
5	160.0	15.0	0.40	0.30	0.230	-12.770
6	160.0	15.0	0.40	0.30	0.260	-11.700
7	160.0	20.0	0.60	0.40	0.290	-10.7520
8	160.0	20.0	0.60	0.40	0.280	-11.060
9	160.0	20.0	0.60	0.40	0.270	-11.3730
10	170.0	10.0	0.40	0.40	0.280	-11.060
11	170.0	10.0	0.40	0.40	0.280	-11.060
12	170.0	10.0	0.40	0.40	0.270	-11.380
13	170.0	15.0	0.60	0.10	0.110	-19.1720
14	170.0	15.0	0.60	0.10	0.130	-17.7210
15	170.0	15.0	0.60	0.10	0.150	-16.480
16	170.0	20.0	0.20	0.30	0.170	-15.410
17	170.0	20.0	0.20	0.30	0.190	-14.430
18	170.0	20.0	0.20	0.30	0.180	-14.900
19	180.0	10.0	0.60	0.30	0.250	-12.0410
20	180.0	10.0	0.60	0.30	0.260	-11.7010
21	180.0	10.0	0.60	0.30	0.250	-12.0410
22	180.0	15.0	0.20	0.40	0.240	-12.370
23	180.0	15.0	0.20	0.40	0.250	-12.0410
24	180.0	15.0	0.20	0.40	0.230	-12.770
25	180.0	20.0	0.40	0.10	0.150	-16.490
26	180.0	20.0	0.40	0.10	0.160	-15.920
27	180.0	20.0	0.40	0.10	0.140	-17.080

As indicated on Table 2 and in Figure 2, the S/N is calculated, and these ratios offer valuable insights into the significance of each parameter for the formation of overflow are ranked.

Table 2. Response signal to noise ratios

Level	T	S	P	Pf
1	-12.32	-12.22	-13.64	-16.01
2	-14.67	-14.22	-13.33	-13.05
3	-13.62	-14.17	-13.64	-11.55
Delta	2.35	1.99	0.31	4.46

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Rank	2	3	4	1

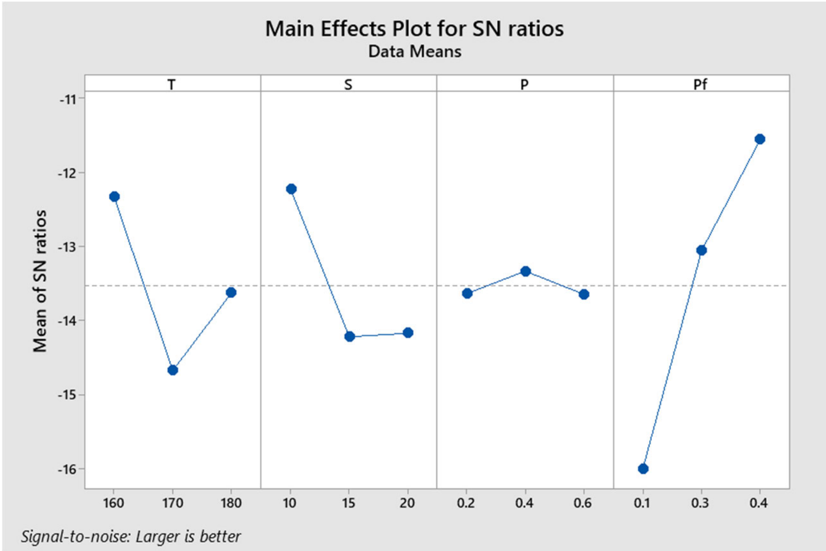

Figure 2. Signal- to- noise ratio: Larger is better result.

3. Results and discussions

3.1 Analysis of variance.

Based on the study of the experimental data, the ANOVA statistical approach is used to propose significant contribution of selected process parameters. ANOVA was used to assess the model's fit, indicating the effects of the model that were statistically significant at a 95% level of confidence (p-value < 0.05). The results of the multiple regression analysis used to fit the models to the experimental data, along with the values of the coefficients and the model summary statistics L27 designs, are displayed in Tables 3. The key selected parameters have statistically significant contribution for the formation of overflows. Moreover, it can be deduced that among the effective input parameters, the one with the higher F-value has a greater influence than the other parameters [31, 32]. Therefore, pressure is the most significant while temperature and packing pressure have slightly similar effects, and relatively speed has less contribution. Furthermore, as shown on Table 4, the computed regression coefficients R-sq. and R-sq. adjusted for overflow is 85.99% and 78.18% respectively. The result ensures a good match for the link between the process parameters and the examined quality requirements. The mathematical relationship for linking the overflow and the key process parameters was established as given in Equation (2).

Table 3. ANOVA results

Source	DF	Adj. SS	Adj. MS	F-Value	P-Value
T	2	0.015496	0.007748	23.77	0.000
S	2	0.007385	0.003693	11.33	0.001
P	2	0.016719	0.008359	25.65	0.000
Pf	2	0.015030	0.007515	23.06	0.000
Error	18	0.005867	0.000326		
Total	26	0.060496			

Table 4. The model summary

Residual std. deviation	R-sq.	R-sq. (adj.)	R-sq.(pred.)
0.0180534	90.30%	85.99%	78.18%

$$\text{Response (R)} = 0.21963 + 0.02593 \times T_{160} - 0.03185 \times T_{170} + 0.00593 \times T_{180} - 0.02185 \times S_{10} + 0.00370 \times S_{15} + 0.01815 \times S_{20} + 0.01815 \times P_{0.2} - 0.03519 \times P_{0.4} + 0.01704 \times P_{0.6} - 0.02852 \times PF_{0.1} + 0.02926 \times PF_{0.3} - 0.00074 \times PF_{0.4} \quad (2)$$

3.2 ANN model for response prediction.

In the present study, an ANN is composed of a few neurons connected by links. The feed forward neural network based on back-propagation is the best all-purpose model out of the different neural network types [33]. The network includes one response output, and four inputs: temperature, speed, pressure, and packing force. The TensorFlow library of python software package used for writing the programming code. To train and test the model; the data are partitioned by 70 and 30 % respectively. To identify the ideal architecture, several model iterations were conducted with different numbers of hidden layers, neurons, and activation functions for best training and testing developed models. Root mean square error (RMSE) is used in prediction, and R^2 values of the trained models as a primary selection criterion. The algorithm was trained using adaptive moment estimation (Adam) technique which combines the advantages of gradient descent (GD) and Stochastic gradient descent (SGD). The three layers as input layer, hidden layer, and output layer make up the usual type of ANN. An input unit layer is connected to a hidden unit layer, which is coupled to an output unit layer. The sigmoid activation function for hidden layer and linear function is chosen for output for training, and the MSE objective was set at 0.0001 to ensure that the MSE would not exceed this threshold. The selection of several hidden layers is executed by trial and error.

Several models are built, and some of the significant data are shown on Table 5. Equations (3)-(7) represent the feed-forward mechanism used by the MLP technique to estimate the output parameters based on the input parameters. The number of layers (i), sigmoid activation function S(X), input parameter (x), target value (y), output of the prediction ($y_{pred.}$), weight (w), bias (b), and error function (Ɛ). The input value for the n^{th} layer is multiplied by the weight value, and the bias value is added. The resulting value is entered into a sigmoid activation function, which computes a new value and transmits it to the next output layer. This method of training the model is continued until the computer error function between the output of the prediction model and the target value reduces to an acceptable level. Throughout the iterations 70/30 %, 15 second running time for each, 1000 epochs, 10 batch size and mse is utilized as metrics. So, that one hidden layer with 17 neurons provided minimum rmse, high R^2 value with demanded range of loss which is 0.00000612.

$$X = (x_1, x_2, x_3, x_4) = (T, S, P, Pf) \quad (3)$$

$$y_{train} = W_{i-1}X_{i-1} + W_i X_i + b \quad (4)$$

$$S(X) = \frac{1}{(1+e^{-x})} \quad (5)$$

$$y_{pred} = f(X_{test}) \quad (6)$$

$$\varepsilon = f(y_{test}, y_{pred}) = mse \quad (7)$$

$$R2 = r2\_score(y_{test}, y_{pred}) \quad (8)$$

The outputs of the hidden layer are used to construct the error function at the end of each feed-forward loop of the prediction model. When this error function returns a result, the weight values of the earlier layers are updated.

Table 5. The selection of neurons and hidden layer iterations

1st hidden	2nd hidden	RMSE	R^2	Loss (MSE)
7	0	0.02	0.82	0.00051462
8	0	0.02	0.83	0.00048113
9	0	0.01	0.96	0.00011662
10	0	0.02	0.87	0.00037283
11	0	0.02	0.90	0.00027857

12	0	0.02	0.87	0.00035588
13	0	0.02	0.88	0.00034911
14	0	0.02	0.82	0.00051478
15	0	0.02	0.86	0.00038781
16	0	0.01	0.97	0.00000975
17	0	0.01	**0.98***	0.00000612
18	0	0.01	0.94	0.000163909
19	0	0.01	0.95	0.000143263
20	0	0.01	0.94	0.000179964
21	0	0.01	0.94	0.000182297
9	1	0.05	0.03	0.002733573
	2	0.03	0.75	0.000704302
	3	0.01	0.96	0.000704302
	4	0.02	0.83	0.00038281

MLP artificial neural network model was used to predict the results, and the architecture is shown on Figure 3, which is built by using an online tool [34]. Three statistical performance evaluation metrics are utilized to evaluate the performance of the models: mean square error (mse), coefficient of determination (R^2) and root mean square error (rmse). The experimental results show that the 3-layer MLP architecture with sigmoid activation functions in each hidden layer and a linear function in the output layer has the lowest prediction error and the highest coefficient of determination among the configured MLP neural networks. Comparative analysis of performance findings shows that the MLP neural network has a lesser prediction error than the ANOVA model.

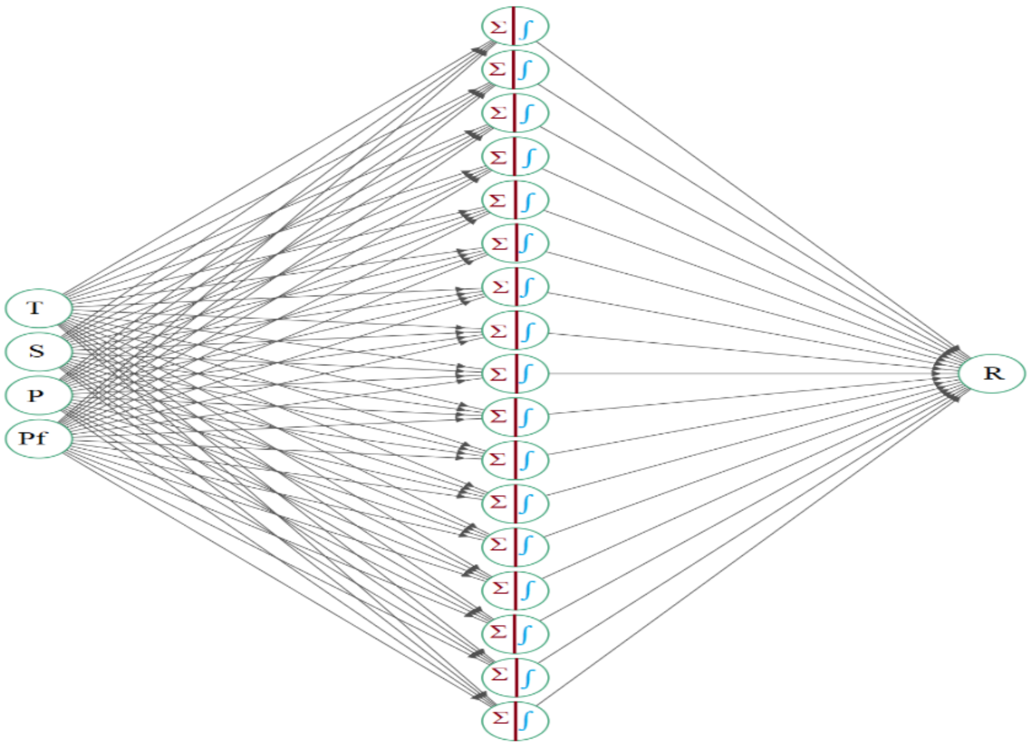

Figure 3. Multi-Layer Neural network architecture

The validation data set's regression coefficient (R^2), which was discovered to be 0.9693 and nearly one, shows a significant correlation between the experimental output and network predicted output. The result is given on Table 6, with the testing data.

Table 6. Experimental and ANN predicted results.

Run	T (ºC)	S (cm/s)	P (bar)	Pf (bar)	Actual	Predicted	% Error
9	160	20	0.6	0.4	0.27	0.281	0.0407
17	170	20	0.2	0.3	0.19	0.171	0.0100
1	160	10	0.2	0.1	0.20	0.217	0.0850
25	180	20	0.4	0.1	0.15	0.157	0.0466
12	170	10	0.4	0.4	0.27	0.278	0.0296
10	170	10	0.4	0.4	0.28	0.278	0.0071
14	170	15	0.6	0.1	0.13	0.128	0.0154
2	160	10	0.2	0.1	0.21	0.217	0.0333

4. Conclusion

In this study the effects of plastic injection moulding process parameters on the formation of defect particularly overflow is studied. The study focused on the impacts of process parameters on overflow via comparison of ANN and ANOVA prediction and based on the findings; the following conclusion is observed.

- According to the ANOVA result, the selected factors temperature, speed, pressure, and packing force are vital process parameters with different levels of impacts on the formation of overflow or incomplete injection.
- ANOVA is better to assess the influence of each process on the formation of defects.
- The built MLP with 3 layers indicates better predicting capacity compared to ANOVA. The R^2 value of both ANOVA and ANN is 78.18 and 96.93% respectively.
- The ANN model has been demonstrated to be effective at predicting defect formation under process conditions.
- The drawback of ANN is that it needs more data to train the model compared to ANOVA prediction model.

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References

[1]. Attia U M, Marson S and Alcock J R 2009, Micro-injection moulding of polymer microfluidic devices, *Microfluidics and nanofluidics*. **7**, 1-28.
[2]. Groover MP 2020, Fundamentals of modern manufacturing: materials, processes, and systems. *John Wiley & Sons*. **53**.
[3]. Fernandes C, Pontes A J, Viana JC and Gaspar-Cunha A 2018, Modeling and Optimization of the Injection-Molding Process: A Review. *Adv. Polym. Technol.* **37**(2), 429-449.
[4]. Khosravani M R, Nasiri S and Reinicke T 2022, Intelligent knowledge-based system to improve injection molding process, *J. Ind. Inf. Integr.* **25**, 100275.
[5]. Subramanyam B, Vineeta T V, Garre P, Bharadwaj V N and Shashank P S 2018, Comparative analysis of additive manufacturing over conventional manufacturing. In *IOP Conf. Ser. Mater. Sci. Eng.* **455**(1), 012102.
[6]. Ravikiran B, Pradhan D K, Jeet S, Bagal D K, Barua A and Nayak S 2022, Parametric optimization of plastic injection moulding for FMCG polymer moulding (PMMA) using hybrid Taguchi-WASPAS-Ant Lion optimization algorithm. *Mater. Today Proc.* **56**, 2411-2420.

[7]. Cooper T A 2013, Developments in plastic materials and recycling systems for packaging food, beverages, and other fast-moving consumer goods. *Trends in Packaging of Food, Beverages, and Other Fast-Moving Consumer Goods. (FMCG). Woodhead Publishing*. 58-107.
[8]. Maarif M R, Listyanda R F, Kang Y S and Syafrudin M 2022, Artificial Neural Network Training Using Structural Learning with Forgetting for Parameter Analysis of Injection Molding Quality Prediction. *Inf.* **13**(10), 488.
[9]. Lieberzeit P, Bekchanov D, and Mukhamediev M 2022, Polyvinyl chloride modifications, properties, and applications. *Polym. Adv. Technol.* **33**(6), 1809-1820.
[10]. Al-Oqla F M, Hayajneh M T and Fares O 2019, Investigating the mechanical thermal and polymer interfacial characteristics of Jordanian lignocellulosic fibers to demonstrate their capabilities for sustainable green materials. *Clean. Prod.* **241**, 118256.
[11]. Dejene N D and Gopal M 2021, The Hybrid Pareto Chart and FMEA methodology to Reduce Various Defects in Injection Molding Process. *Solid State Technol.* **64**(2), 3541-3555.
[12]. Khomenko M, Veligorskyi O, Chakirov R and Vagapov Y 2019, An ANN-based temperature controller for a plastic injection moulding system. *Electronics*. **8**(11), 1272.
[13]. Zhou H 2013, Computer modeling for injection molding. *Comput. Model. Inject. Molding Simulation, Optim. Contro*. doi: 10.1002/9781118444887.
[14]. Moayyedian M, Abhary K and Marian R 2016, The analysis of defects prediction in injection molding, *Int. J. Mech. Mechatronics Eng.* ***10***(12), 1883-1886.
[15]. Fei N C, Mehat N M and Kamaruddin S 2013, Practical applications of Taguchi method for optimization of processing parameters for plastic injection moulding: a retrospective review. *ISRN Ind. Eng.* **2013**, 1-11.
[16]. Zhao J, Mayes R H, Chen G E, Xie H and Chan P S 2003, Effects of process parameters on the micro molding process. *Polym. Eng. Sci.* **43**(9), 1542-1554.
[17]. Huang M C and Tai C C 2001, The effective factors in the warpage problem of an injection-molded part with a thin shell feature. *J. Mater. Process. Technol.* **110**(1), 1-9.
[18]. Darekar A M, Venkatesh T S, Patil B T and Yazad N 2015, Review of Optimization Aspects for Plastic Injection Molding Process. *An Int. J.: ESTIJ.* **5***,* 2250–3498.
[19]. Sunadi S, Purba H H and Paulina E 2021, Overall Equipment Effectiveness to Increase Productivity of Injection Molding Machine: A Case Study in Plastic Manufacturing Industry. *ComTech Comput. Math. Eng. Appl.* **12**(1), 53-64.
[20]. Farahani S, Khade V, Basu S and Pilla, S 2022, A data-driven predictive maintenance framework for injection molding process. *J. Manuf. Process.* **80**, 887-897.
[21]. Tharazi I, Sulong A B, Muhamad N, Haron C H C, Tholibon, D, Ismail N F and Razak Z 2017, Optimization of hot press parameters on tensile strength for unidirectional long kenaf fiber reinforced polylactic-acid composite. *Procedia Eng.* **184**, 478-485.
[22]. Kumar B S and Balachandar S 2014, A study on the influence of hot press forming process parameters on Flexural Property of Glass/PP Based Thermoplastic Composites Using Box-Behnken Experimental Design. *Int. sch. res. notices*. **2014**.
[23]. Rathore A and Ujjainwala F 2017, Defects analysis and optimization of process parameters using Taguchi DoE technique for sand casting. Int. Res. J. Eng. Technol. **4**, 432-437.
[24]. Shahbudin S N A, Othman M H, Amin S Y M and Ibrahim M H I 2017, A review of metal injection molding-process, optimization, defects, and microwave sintering on WC-Co cemented carbide. *IOP Conf. Ser. Mater. Sci. Eng.* **226**(1), 012162.
[25]. Ahmed T, Sharma P, Karmaker C L and Nasir S 2022, Warpage prediction of Injection-molded PVC part using ensemble machine learning algorithm. *Mater. Today Proc.* **50**, 565-569.
[26]. Kowalczyk M 2014, Application of Taguchi, and ANOVA methods in selection of process parameters for surface roughness in precision turning of titanium. *Adv. Manuf. Sci.* **38**(2), 22–35, 2014.
[27]. Chen J, Cui Y, Liu Y and Cui J 2023, Design and parametric optimization of the injection molding process using statistical analysis and numerical simulation. *Processes*, **11**(2), 414.

[28]. Serin G, Sener B, Gudelek M U, Ozbayoglu A M and Unver H O 2020, Deep multi-layer perceptron-based prediction of energy efficiency and surface quality for milling in the era of sustainability and big data. *Procedia Manuf.* **51**, 1166-1177.

[29]. Wardah W, Khan M G, Sharma A and Rashid M A 2019, Protein secondary structure prediction using neural networks and deep learning: A review. *Comput. Biol. Chem*. **81**, 1-8.

[30]. Ahmed A N, Othman F B, Afan H A, Ibrahim R K, Fai C M, Hossain M S and Elshafie A 2019, Machine learning methods for better water quality prediction. *Introd. to Eng.* **578**, 124084.

[31]. Lillian S K, Charles E G 2008, Analysis of Variance: Is there a Difference in Means and What Does It Mean?," *J. Surg. Res.***144**(1), 158–170.

[32]. Eren B, Yaqub M and Eyupoglu V 2019, A comparative study of artificial neural network models for the prediction of Cd removal efficiency of polymer inclusion membranes. *Desalin. Water Treat.* **143**, 48-58.

[33]. Choraś, M and Pawlicki M 2021, Intrusion detection approach based on optimized artificial neural network. *Neurocomputing*. **452**, 705-715.

[34]. LeNail, A 2019, NN-SVG: Publication-Ready Neural Network Architecture Schematics. J. Open Source Softw. **4**(33), 747.