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Prediction Of Shrinkage Ratio for 316 L Feedstock With Artificial Neural Networks In Powder Injection Molding

Mehmet SUBAŞI[1a*], Oğuz YILMAZ[2b], Kamran SAMET[2c], Asghar SAFARİAN[3d], Çetin KARATAŞ[2e]

[1]Technical Sciences Vocational School of Higher Education, Gazi University, Ankara, Turkey
[2]Gazi University, Faculty of Technology, Manufacturing Engineering, Ankara, Turkey
[3]Department of Manufacturing Engineering, Maragheh Branch, Islamic Azad University, Maragheh, Iran
[*]msubasi@gazi.edu.tr

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Abstract: Powder injection molding (PIM) has emerged as a production method to overcome some of the mentioned obstacles such as geometric design, multi-step manufacturing process, etc. A final linear decrease in dimensions of components in PIM is known as shrinkage. The primary shrinkage occurs in the last step, sintering, which is intended to be direct. The shrinkage is the ratio of the first dimension of the part to the final dimension. Shrinkage is a significant value to examine the microscopic exchange rates during the sintering. In this study, the shrinkage ratio after the sintering process was investigated for 316 L feedstock depending on the powder loading, particle size distribution (Sw), particle size (D50), and sintering heating rate. The prediction of the shrinkage ratio was carried out by the Matlab Software. Experimental shrinkage ratios for 316L feedstock were compared with the results obtained using Artificial Neural Networks (ANN). As a result of this study, the mathematical formula has been produced for calculation of the shrinkage ratio by performing regression analysis for 316L feedstock. It was is concluded that before carrying out the sintering process in PIM, the shrinkage ratio can be calculated based on parameters such as powder loading, particle size (D50), and size distribution.

Keywords: Artificial neural network, Powder injection molding, Shrinkage ratio, 316 L stainless steel, Regression analysis.

Toz Enjeksiyon Kalıplamada 316 L Besleme Stokunun Çekme Yüzdesinin Yapay Sinir Ağları ile Tahmin Edilmesi

Öz: Toz enjeksiyon kalıplama, bazı engelleri aşmak için (geometrik tasarım, çok adımlı üretim süreci vb.) kullanılabilecek bir üretim yöntemidir. Toz enjeksiyon kalıplamada çekme, doğrusal boyutlarda küçülme olarak tanımlanır. Çekmenin ölçümü genelde doğrusal boyuttaki değişimler ile gerçekleşir. Boyutsal değişim, parça boyutundaki değişikliğin başlangıç ham parça boyutuna bölünmesidir. Çekme, sinterleme esnasındaki mikroskopik değişim hızlarının incelenmesi için önemli bir değerdir. Bu çalışmada, 316 L besleme stokunun toz yüzdesi, toz dağılımı (Sw), besleme stokunun d50 çapı ve sinterleme hızı parametrelerine bağlı olarak sinterleme işlemi sonrasındaki parçada oluşacak çekme oranı yüzdesi tespit edilmiştir. Çekme oranı yüzdesi hesaplaması için Matlab programı kullanılmıştır. 316 L besleme stoku için deneysel çekme yüzdeleri, yapay sinir ağı kullanılarak elde edilen sonuçlar ile karşılaştırılmıştır. Çalışma sonucunda 316 L besleme stoku için regresyon analizi yapılarak çekme yüzdesi değeri için matematiksel formül çıkartılmıştır ve toz enjeksiyon kalıplama prosesinde sinterleme öncesinde besleme stokunun toz yüzdesi, toz dağılımı ve d50 oranı ile çekme yüzdesinin hesaplanabileceği sonucuna varılmıştır.

Anahtar Kelimeler: Yapay sinir ağı, Toz enjeksiyon kalıplama, Çekme oranı, 316 L paslanmaz çelik, Regresyon analizi.

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ORCID: [a] 0000-0003-4826-9175, [b] 0000-0002-8573-7495, [c] 0000-0002-4159-3610, [d] 0000-0001-5938-5206, [e] 0000-0003-0005-3068.

1. Introduction

Powder injection moulding (PIM) is a manufacturing method developed for the production of small, complex, and intricate parts from metal or ceramic powders. This method consists of preparation of the feedstock, injecting into the mold, the binder removal process, and sintering steps [1]. The sintering is the final stage in PIM, which is fundamentally important to have strength components. During sintering because of the bonding mechanism between powders, it is occured a noticeable shrinkage in the final component. This shrinkage depends on the parameters, namely powder loading, powder shape and size, and sintering conditions. The general linear shrinkage in PIM is between 15% and 20%. Fine powders are sintered faster and eliminate the possible defects which could occur during the injection. Besides, it also increases the viscosity of the feedstock and final shrinkage after sintering. However, it increases the needed time for debinding. [2-4]. During sintering, there are some critical phenomena such as polymer (binder) burnout, bonding among the particles, changes in dimension, and a significant amount of the coarsening of microstructure. It could be challenging to have a sintered component with the desired properties and sizes [5]. Shrinkage is an essential factor that should be calculated and controlled to reach the desired dimension. In PIM, the shrinkage occurs during all stages of the process; however, the central part belongs to the final stage, sintering [6]. Dimensional accuracy of the piece would be negatively affected if the amount of shrinkage is not uniform in all sections; it also could deteriorate the quality of shape and geometry of the component. According to shrinkage per cent, the size of the mould cavity is determined, and the mould design is completed. In the cases that the wrong shrinkage is applied, it will need reconstruction of mould (or cavity) and could impose an extra cost on the process. Because of these reasons, the shrinkage should be determined accurately.

In the literature, there are some studys on parameters that affecting the shrinkage in powder injection moulded components with different materials such as 316L [7-10]. Luo and et al. [7] have reported that injection pressure and sintering temperature are the most critical parameters affecting the dimensional accuracy. As a result of the study by using 316 L stainless steel feedstock, Kong et al. [8] have found that geometric and physical properties of powder loading affect the moulding process. Shongwe et al. [9]have reported that shrinkage varies depending on the sintering rate and powder size. Yeh et al. [10] study on alumina revealed that wide powder size distribution results in high green density, and lower shrinkage ratios in sintered samples.

With this study, it has been focused on the prediction of shrinkage percentage that has an essential role in mould design and producing strength components. In this respect, ANN has been established by using the Matlab Software. Data for input layer which was trained for ANN, selected from the literature. Thanks to the ANN application, the effect of different parameters on the shrinkage rate can be estimated from this study. The accuracy of 99% was obtained consequently. Afterwards, mathematical formulas were obtained numerically to calculate shrinkage ratio based on powder loading, particle size (D_{50}), particle size distribution, and heating rate by regression analysis with Minitab 17 program. The study will eliminate the difficulties in mould design by estimating the shrinkage ratio, which is a design parameter of the injection moulding.

2. Artificial Neural Networks (ANN)

The scientific world has been acquainted with artificial neural networks in the 1940s. The first study in this area was done to reveal the function of brain cells, how they communicate with each other. Then, ANNs have developed significantly both in a theoretical and practical sense. Nowadays, neural networks can be established by means of combining many cells in a certain order and using appropriate learning algorithms. These networks can perform very complex tasks successfully[11]. ANNs are data-based systems designed by connecting the layer-shaped neural cells. It is aimed that using human brain talents such as learning and rapid decision change in different conditions, etc. solves complex problems with the help of simplified models [12]. In other words, ANNs are computer programs that simulate biological neural networks [13]. The structure of the ANN has three components, including neurons (artificial neural cells), connections, and learning algorithms. The neuron is the essential operation element of an ANN. Neurons within the network receive one or more inputs, according to factors affecting the problem and release outputs as much as the number of results expected. Neurons come together through a connection with each other to constitute the ANN. In general ANN systems, if the neurons come together in the same direction, create layers [14].

In the ANN, there are three main layers, namely the input layer, an output layer, and the hidden layer to connect nerve cells. The input layer is the first layer receiving the data coming from outside to the ANN. These data correspond to independent variables in the statistics. The input layer consists of the parameters affecting the problem, and the number of neurons in the input layer varies according to the number of parameters. The final layer is named as an output layer, and it transmits the information to outside. Output variables correspond to the dependent variable statistically. Other layers of the model are located between the input and output layers and are called the hidden layers. There is no connection between neurons in the hidden layers and outside. They only receive the signal from the input layer and send it to the output layer. The number of neurons taking place in the hidden layer (or layers), is vital regarding the performance of the established network [15]. ANN examine the example of the events and make their generalizations, then collect the information based on which use these learned patterns toward circumstances never faced before, and finally make decisions [11].

The infrastructure of ANNs is based on the human brain. This is a network system to determine complex and nonlinear relationships between input and output parameters. In recent years, ANN has been utilized widely in the estimation of nonlinear systems, since it is getting more advantages in terms of high accuracy, low cost, and time-saving [16]. Figure 1 illustrates the mathematical model of a neuron. As can be seen in this figure, the neuron inputs are multiplied by the weight of synaptic connections. The result of the multiplication is sent to the collector. The obtained summation is transmitted to the neuron's activation function. Then outputs are calculated. 'S' is the weighting factor sum in equation (1), and 'O' is the calculation of the output neuron in the equation (2).

$$S = w_1.u_1 + w_2.u_2 + w_3.u_3 .... + w_n.u_n + \theta = \sum_{i=0}^{n} w_i.u_i + \theta \qquad (1)$$

$$O = \Psi(S) \qquad (2)$$

where S; Total function - u_i; Input function - w_i; Weighting factor - O; Output function - $\Psi(S)$; Activation function - θ; Threshold value

Any change in each input causes a specific change in the output neuron, whose amplitude is dependent on relationships determining the degree of effective input, collector threshold value, and the type of neuron activation function. The use of the threshold value, the constant input (θ) which, in practice, is (-1) or (+1) is correlated with a weight value, considered as the entry to the collector [17].

ANNs contain different scientific applications; in the aerospace industry with autopilot applications, in the transport industry with orientation systems applications, in defence systems with a moving target tracking, and many other applications. Application fields of ANNs are being developed every day, and new application areas are discovering by the researchers [19-21].

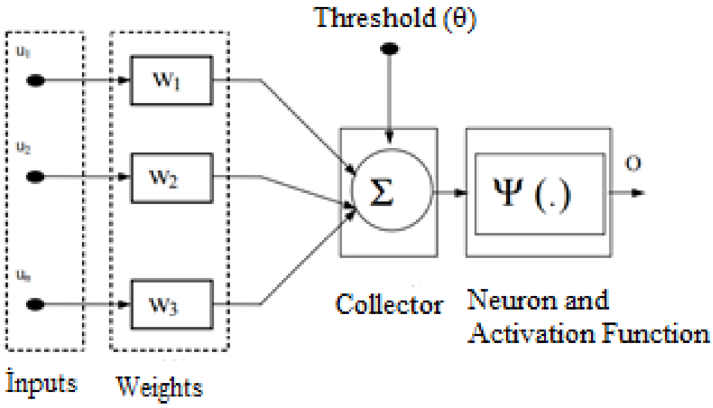


Figure 1. Mathematical modeling of ANN [18]

3. Material and Method

In this study, prediction and regression analysis of the shrinkage ratio of 316 L feedstock were studied. As input parameters, powder loading, particle size D_{50}, particle size distribution, and sintering heating rate were used in experiments. Shrinkage ratios obtained from similar studies in the literature are given in Table 1.

Firstly, the input, that is, feedstock's powder volume loading, particle size D_{50}, powder, particle size distribution, and heating rate and target parameters (shrinkage ratio) were defined into the program as a matrix. Then a network was created to estimate the shrinkage ratio. The established network module is feedforward backpropagation. TRAINGDX was selected as a training function since it shows the best approach to real value and its accuracy. LEARNGDM was also selected as an adaptive learning function, which is preferred with the backpropagation network type and reducing the momentum gradient. Mean square error (MSE) was chosen as the performance function. The reason is, this function provides performance evaluation according to the average of error-decision. In this network, TANSIG (tangent sigmoid function) is the transfer function estimating the optimum result. The schematic view of the defined neural network is shown in Figure 2.

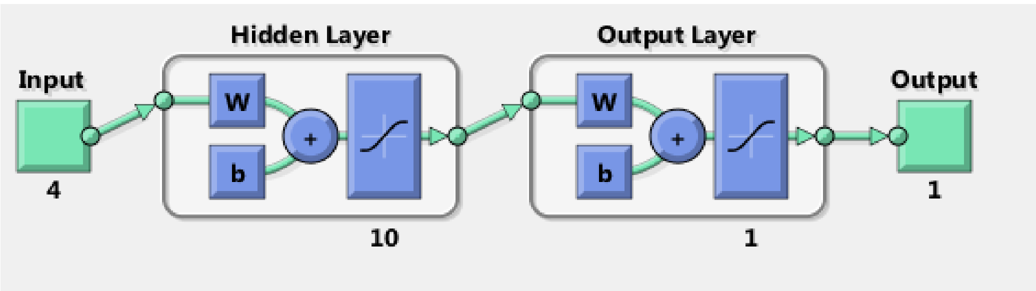


Figure 2. ANN system

In this study, the number of neurons for the data sets was selected to be 10 to establish models. Then, all established models were tested with the allocated data. As the results of the testing process, estimated values were compared with the actual values, therefore the prediction accuracy of ANN models with different structures was evaluated. Input parameters of network were illustrated in Table 2.

Table 1. ANN Input Parameters

316 L Feed Stock Number	Powder Volume Loading (%)	Particle Size D_{50} (µm)	Heating Rate (C°/min)	Particle Size Distribution	Shrinkage Ratio (%)	Reference
1	60	3.4	15	4.89	11.5	[22]
2	60	3.4	10	4.89	9.5	[22]
3	60	3.4	5	4.89	8	[22]
4	57	10	5	3.28	15	[23]
5	56	7	4.5	6.16	15	[23]
6	50	2.37	7	4.89	11.5	[25]
7	64	3.4	5	4.89	13.76	[8]
8	65	4.42	7	4.12	15.7	[26]
9	64	3.4	10	4.89	12.5	[8]
10	60	4.42	7	4.12	16.14	[26]
11	53	8	10	4.33	21	[27]
12	65	10.8	10	4.17	15	[27]
13	60	11	2.5	4.03	15.52	[28]
14	64	3.4	15	4.89	13.06	[8]
15	66	1.8	5	4.97	18	[29]
16	60	3.6	5	5.03	15.8	[30]
17	63	10	10	3.96	15	[31]
18	60	3.4	5	4.89	13.48	[32]
19	60	3.4	8	4.89	14.24	[32]
20	60	3.4	10	4.89	15.04	[32]
21	60	3.4	12	4.89	14.48	[32]

The optimal functions shown in Table 2, were obtained by changing the number of neurons in the hidden layer, learning methods, and network parameters. It was determined that all values resulted from applying input parameters to network, were almost near real ones; errors were also calculated. Matlab Softwares' different models are tested, among which the TRAINGDX function is determined as the most successful one.

Table 2. ANN Input Parameters

Network Type	Feed-Forward Backpropagation
Training Function	Traingdx
Learning Function	Learngdm
Performance Function	MSE
Number of Neurons	10
Activation Function	Tansig

4. Results and Discussion

Minitab 17 program was used to find the mathematical formula of the regression of shrinkage ratio. In the program, the percentage of dust, d50 diameter, powder distribution, sintering speed are defined as input parameters, and the percentage of extraction is defined as the target parameter.

The probability plot was obtained after releasing the mathematical equations for the shrinkage ratio. According to this plot, residual values could be seen based on the shrinkage ratio. As seen in the graph, the deviation of the value is ranging from -5 to +5, regarding the standard curve.

Regression analysis of each 316 L feedstock was carried out. Regression values (R^2) were between 93% and 99%. Figure 3 shows the R^2 value plot for a sample 316L feedstock, using the Matlab Software.

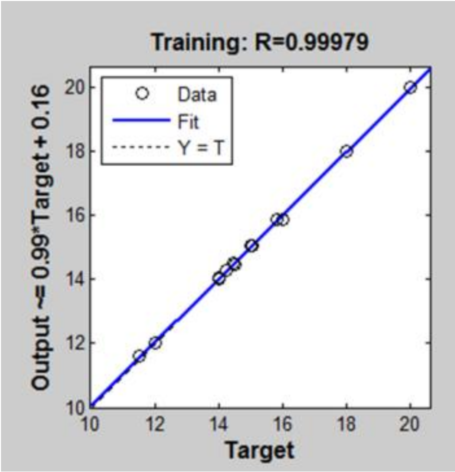


Figure 3. A regression value estimated and plotted for a sample using the Matlab Software

It was determined that the values calculated by ANN were similar to the actual values. ANNs are capable of learning the nonlinear relationships, generalizing them, therefore finding an answer to the problem not encountered before, with acceptable error. Figure 4 shows the MSE value of training, validation, and test data in the learning stage of ANN with different iterations. If the MSE values are renewed for each iteration, the number increases. Iteration continues until reaching the best and acceptable results, which are exported as program output. As shown in Figure 4, the lowest MSE values were obtained in 98 iterations. The best program output is at the end of 98 repetitions with the MSE of 0.0024.

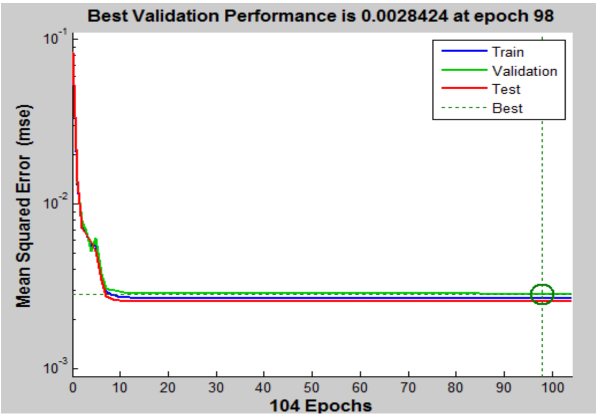


Figure 4. Performance of ANN

The ANN output value to understand better, the deviation percentage was also calculated using the following formula:

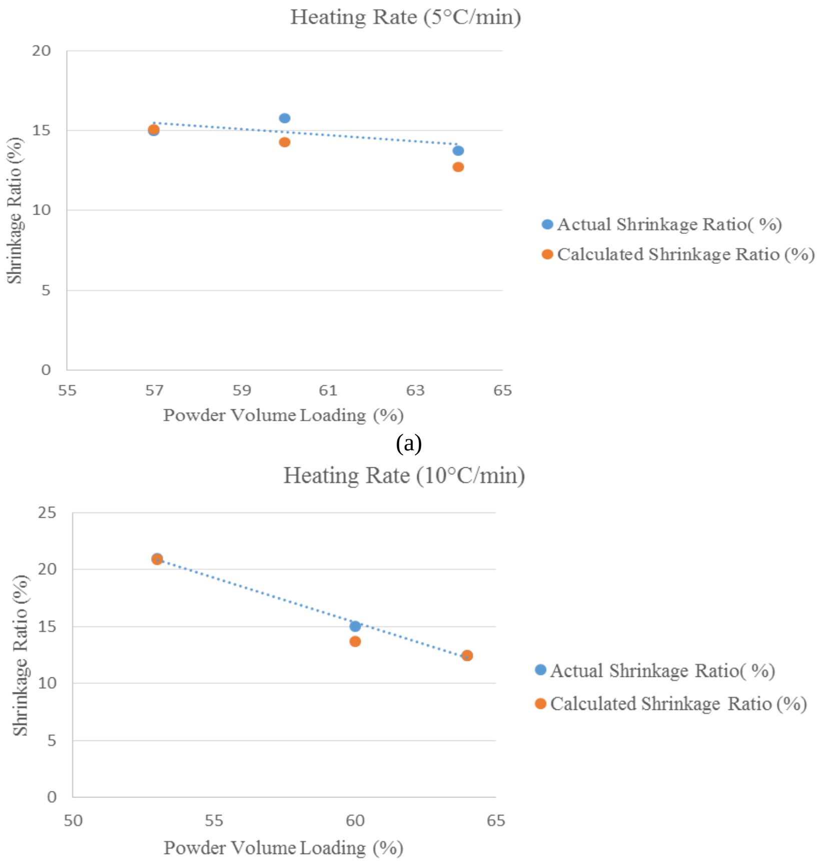
$$Deviation\ percent\ (\%) = \frac{Calculated\ Shinkage\ Ratio - Actual\ Shrinkage\ Raito}{Actual\ Shrinkage\ Raito} \quad (3)$$

The deviation between the experimental data and predicted ones obtained by ANN ranging from 0.0024% to 13%. Table 3 shows 316 L feedstock actual shrinkage ratio, calculated shrinkage ratio, and system error. For example, in the work of Imbaby at al.[29] studying 316L feedstock with 66% powder loading, the particle size of 1.8 μm (D_{50}), the particle size distribution of 4.97 and heating rate of 5 ^{0}C/min, shrinkage ratio was obtained to be 12.5 %. In comparison, it was calculated by ANN to be 12.5003 %.

Table 3. 316 L feedstock actual shrinkage ratio, calculated shrinkage ratio, and error

316 L Feed Stock Number	Actual Shrinkage Ratio(%)	Calculated Shrinkage Ratio (%)	Percentage of Error (%)
1	11.5	11.2226	2.412173913
2	9.5	8.2207	13.46631579
3	8	7.9851	0.18625
4	15	15.0115206	0.076804
5	15	15.01825482	0.1216988
6	11.5	11.58755755	0.76137
7	13.76	12.7201	7.557412791
8	15.7	16.2523	3.517834395
9	12.5	12.5003	0.0024
10	16.14	16.00772737	0.819533024
11	21	20.89850429	0.483312905
12	15	15.13772632	0.918175467
13	15.52	15.52331371	0.021351224
14	13.06	13.1576	0.747320061
15	18	18.01637225	0.090956944
16	15.8	15.69400676	0.670843291
17	15	14.87963301	0.8024466
18	13.48	14.29735589	6.063470994
19	14.24	13.93820396	2.119354213
20	15.04	13.69876934	8.917757048
21	14.48	13.45933472	7.04879337

Figure 5a and Figure 5b shows the comparison of predicted shrinkage ratio and the actual shrinkage ratio. The shrinkage ratio decreases with increasing powder loading [33,34]. There are illustrated in the figures, a decrease of the powder loading causes a shrinkage ratio to increase (Figure 5a, Figure 5b). Also, the effect of the heating rate can be deduced. It is stated in the literature that the shrinkage ratio varies depending on the heating rate and powder size [9,35]. Sanad et al. [35] have reported that the shrinkage ratio increases as the heating rate increases. Kong et al [8] determined that there was a fluctuation in the shrinkage ratio of 316 L parts as a result of experiments conducted at heating rate of 5 °C/min, 10 °C/min and 15 °C/min. In this study, shrinkage rates of the samples with 64 % powder loading for 5 °C/min, 10 °C/min, and 15 °C/min heating rates was detected a fluctuation. The actual shrinkage ratio for these samples' heating rates of 5 °C / min, 10 °C / min, and 15 °C / min was determined as 13.76 %, 12.5 % and 13.15 %, while ANN calculation the shrinkage ratios was 12.72 %, 12.5 % and 13.15 %. The heating rate during the sintering is an important parameter for the control of microstructure formation. As a result of the studies, it was determined that rapid heating damages the brown component. In studies, it is stated that sintering temperature and time are more effective than heating speed on deflection and distortion in components [36-38].



Şekil 5 a. Variation of shrinkage ratio versus powder loading for 5 °C/min heating rate, b. 10 °C/min heating rate

Figure 6 exhibits the comparison of the predicted data and the experimental data. At the end of the study, a result of the ANN model shows proximity with experimental values. Therefore, according to the parameters of powder loading, particle size D_{50}, particle size distribution, and heating rate, this system would be capable of predicting the shrinkage accurately without doing any experiment

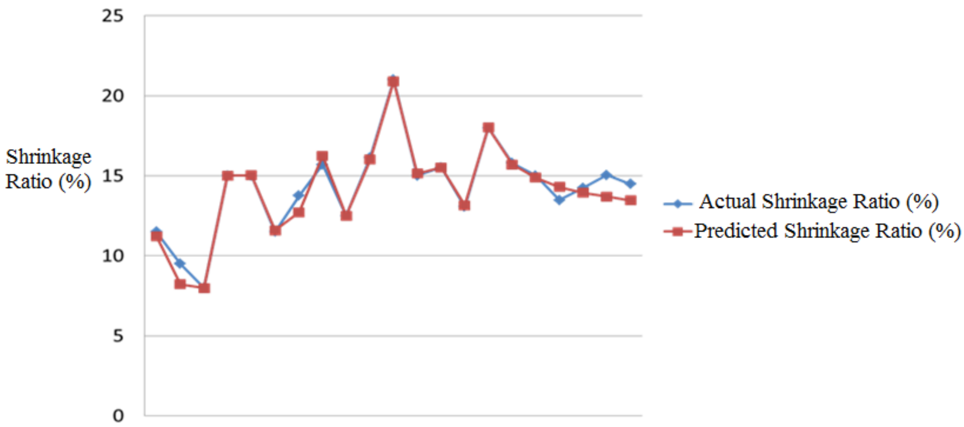


Figure 6. Comparison of the predicted data with the experimental ones

5. Conclusions

In this study, ANN was developed to estimate the shrinkage rates of 316L feed stock without the needing any experiment and the following results were found.

1- At the end of the study, acceptable results were obtained comparing the predicted values with literature.
2- The shrinkage ratio of the sintered specimen could be predicted based on the powder loading, particle size D_{50}, particle size distribution, and heating rate before sintering in PIM.
3- This study shows that ANN and calculated mathematical formula can calculate shrinkage ratio before any process of PIM.
4- This calculation system can be used for predict to shrinkage of different 316L feedstock.

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