MARMARA UNIVERSITY
FACULTY OF ENGINEERING

PREDICTION OF MAXIMUM LOAD AND AVERAGE EFFECTIVE STRAIN BY GENERATING ANN MODEL FOR TMCAP

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by

İbrahim Halil Kızıl

Abdurrahman Eren Bağışlar

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MARMARA UNIVERSITY

Signature of Author..İbrahim Halil Kızıl

Department of Mechanical Engineering

Signature of Author...Abdurrahman Eren Bağışlar

Department of Mechanical Engineering

Certified By...Res.Assist.Dr. Serkan Öğüt

Project Supervisor, Department of Mechanical Engineering

Accepted By .... Prof. Dr. Bülent Ekici

Head of the Department of Mechanical Engineering

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İbrahim Halil Kızıl
Abdurrahman Eren Bağışlar

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ÖZET

TMCAP için YSA Modeli Oluşturarak Maksimum Yük ve Ortalama Etkili Gerinimin Tahmini

Malzemelerin mukavemetini arttırmak için çeşitli yöntemler uygulanarak malzemenin mikro yapısının daha sıkı ve daha homojen bir dağılıma sahip olması sağlanmaktadır. Bu projede aşırı plastik deformasyon (APD) yöntemlerinden yeni bir yöntem olarak önerdiğimiz Bükümlü Çok Kanallı Açısal Presleme (BÇKAP) yöntemi incelenmiştir. BÇKAP yöntemi için yeni bir kalıp tasarımı yapılarak farklı varyasyonlardan oluşan 27 adet sonlu elemanlar analizi yapılmış ve bu analizlerden maksimum yük ve ortalama efektif strain dataları elde edilmiştir. En düşük hata oranıyla tahmin yapmak için elde edilen bu veriler ile yük değerleri arasındaki ilişkiyi modellemek için Matlab programında YSA kullanılmıştır.

ABSTRACT

Prediction of Maximum Load an Average Effective Strain by Generating ANN Model for TMCAP

Various methods are applied to increase the strength of the materials, allowing the microstructure of the material to have a tighter and more homogeneous distribution. In this project, the Twisted Multi-Channel Angular Pressing (TMCAP) method, which we propose as a new method from the severe plastic deformation (SPD) methods, has been examined. A new die design was made for the TMCAP method and 27 finite element analyzes consisting of different variations were made and maximum load and average effective strain data were obtained from these analyses. ANN was used in the Matlab program to model the relationship between these data and load values to make predictions with the lowest error rate.

SYMBOLS

ω : Angular Velocity
β : Beta Angle
γ : Gama Angle
ψ : Psi Angle
φ : Fi Angle
e : Exponent
N : Newton (SI)

ABBREVIATIONS

SPD	: Severe Plastic Deformation
ECAP	: Equal Channel Angular Pressing
HPT	: High Pressure Torsion
TE	: Twisted Extrusion
VF	: Versatile Forging
RCS	: Repeated Corrugation and Straightening
Exp.-ECAP	: Expansion Equal Channel Angular Pressing
TMCAP	: Twisted Multiple Channel Angular Pressing
IECAP	: Incremental Equal-Channel Angular Pressing
TWO-CAP	: Thin-Walled Open-Channel Angular Pressing
AEPS	: Average Effective Plastic Strain
ML	: Maximum Load
ANN	: Artificial Neural Network
FE	: Finite Element
ANNs	: Artificial neural networks
ML-ANN	: Maximum Load- Artificial Neural Network
AEPS-ANN	: Average Effective Plastic Strain- Artificial Neural Network
Fig.	: Figure

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1. INTRODUCTION

In recent years, severe plastic deformation (SPD) methods have been of primary interest to researchers to produce ultrafine grained materials and to achieve a combination of high strength and ductility [1, 2]. The severe plastic deformation method is a material manufacturing process in which microstructure improvement is achieved close to the nano level by exposing the workpiece to high strains. Nanostructured materials offer properties such as high strength, low modulus of elasticity, high toughness, high diffusion activation and high super plasticity at low temperatures. The main reason why excessive plastic deformation attracts the attention of researchers is because of these properties [3]. For this reason, various Severe Plastic Deformation (SPD) methods have been developed. These include Equal Channel Angular Pressing (ECAP) [4], High Pressure Torsion (HPT) [5], Twisted Extrusion (TE) [6], Versatile Forging (VF) [7], Repeated Corrugation and Straightening (RCS) [8]. Although the loss of ductility in the products obtained by these methods is less than the traditional plastic deformation methods, these materials have higher hardness and strength values. Among the mentioned Severe Plastic Deformation (SPD) methods, although ECAP is one of the first SPD processes to be developed, it is still one of the most frequently used SPD technologies. One of the reasons this is the case is that it can be applied relatively effortlessly for a variety of purposes, such as "recycling" waste material. ECAP method is used more than other SPD methods due to its advantages such as no changes in the cross-sections of the sample after the process, localized and homogeneous deformation, and no residual pores, being suitable for other machining processes, and most importantly, not reducing the ductility of the material [4]. The most characteristic feature of this application is that both the desired deformation of the material is achieved and the cross-sectional area remains constant after plastic deformation processes that can be performed multiple times in ECAP applications. In recent years, new modified ECAP methods have been developed, suggesting some changes in the ECAP process in order to increase the efficiency it and expand its application areas. As a result of these studies, many modified ECAP processes such as Expansion Equal Channel Angular Pressing (Exp.-ECAP) [9], Twisted Multi-Channel Angular Pressing (TMCAP) [10], Incremental Equal-Channel Angular Pressing (IECAP) [11], Thin-Walled Open-Channel Angular Pressing (TWO-CAP) [12] have been carried out. In our study, the TMCAP method, which is one of these modified methods, will be used.

Twisted Multi-Channel Angular Pressing (TMCAP) is an important SPD technique that attracts attention due to its ability to produce very fine-grained materials with advanced mechanical properties, the homogeneity of the produced material, and the ability to increase the strength of the material, while not reducing its ductility. This method is a more advanced deformation process used to improve the microstructure of metallic materials. The TMCAP method consists of several steps. In the first step, the metal sample is pressed through channels designed in various shape. In the second step, the workpiece is subjected to a specified pressure so that the workpiece moves through the channel in the direction of the applied force. During this process, the material microstructure changes significantly. A fine-grained structure is formed and its density increases. This process increases the hardness and strength of the material.

The importance of TMCAP is to contribute to the development of more efficient and sustainable engineering practices by increasing the service performance of structural materials such as metals and alloys in various fields. Due to this potential, it is predicted that TMCAP method will be an indispensable production technique in application areas such as aviation, automotive, energy, medicine and defense industry. The image of the die of TMCAP and the different channel angles in the die are given in fig-1.

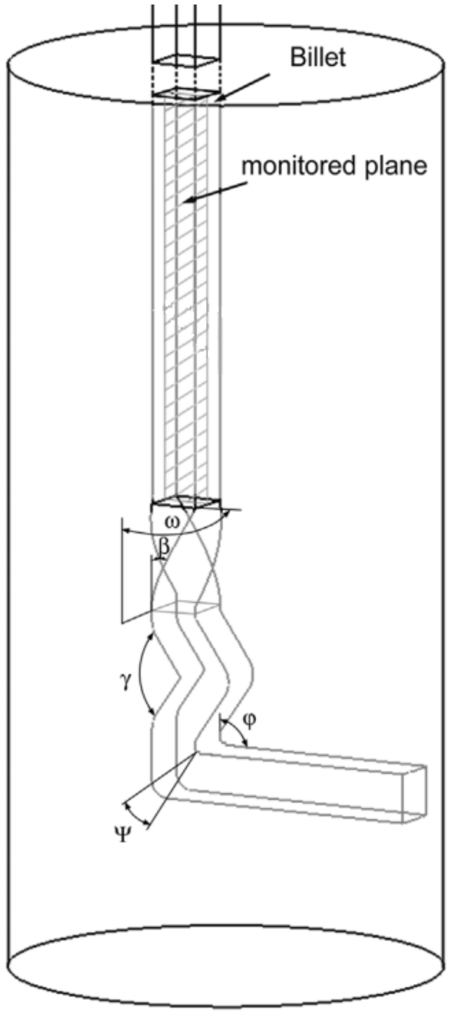

Figure 1. Schemes of the TCMAP. ω – angle of twist rotation, β – twist slope angle, γ – angle between the individual parts of the embedded deformation zone, φ – channel angle, ψ – angle associated with the arc of curvature where the two parts of the channel intersect [13].

According to the studies in the literature, there is a direct correlation between the strain which is exposed to the samples during SPD processes and their mechanical properties. When subjected to higher strain, they have a more homogeneous and smaller-grained microstructure, resulting in increased strength and hardness. Therefore, the average effective plastic strain (AEPS) value is important. Another point is that since dies are exposed to high loads in SPD processes, it is also important to control these loads in terms of die safety. There is no theoretical or empirical equation that gives the AEPS for the TMCAP process. Likewise, there is no equation that gives the maximum load (ML). Therefore, prediction of AEPS and ML by Artificial Neural Network (ANN) is considered.

Within the scope of this study, the effects of beta, phi and gamma angles on the AEPS and the ML applied to the die are investigated, and the AEPS and ML data for different angles are predicted by generated ANN models.

2. METHOD

The methodology applied in this study consists of several steps. In order to perform the Finite Element (FE) analysis, which is the first of these steps, die, workpiece and plunger models were drawn with the Solidworks design program and the assembly of the drawings was made. Images of these models are shown in Fig. 2-5, respectively. In die design, the channel in which the workpiece will be placed is designed 10 mm longer than the sum of the workpiece length and plunger length, and it is designed in this way in order to prevent the workpiece from causing undesirable deformation due to direct pressure by the plunger during the initiation of the analysis. The next stage of the designed die is the twisted-channel, where the workpiece will start to squeeze. In this area, it is aimed to increase the strength of the workpiece by subjecting it to a torsion in the direction of the angles determined during the progress of the workpiece. After passing through this area, the workpiece reaches the twisted area where it will make a final turn. In this area, the metal workpiece is subjected to intense compression again due to the bending of the region, and slides like a liquid. While it finishes its progress in the vertical region here, it reaches the last region where it will turn towards the horizontal channel. In this region, acres are designed with certain angles and radii. In this way, it is aimed to prevent the formation of a dead zone where the workpiece rotates in the lower region between the vertical-horizontal channel. In the upper part of the vertical-horizontal channel's cut point, a radius is placed on the channel turning and it is aimed to rotate the workpiece in a way that has a more homogeneous strain distribution during rotation. The visual of this region is shown in Fig.6.

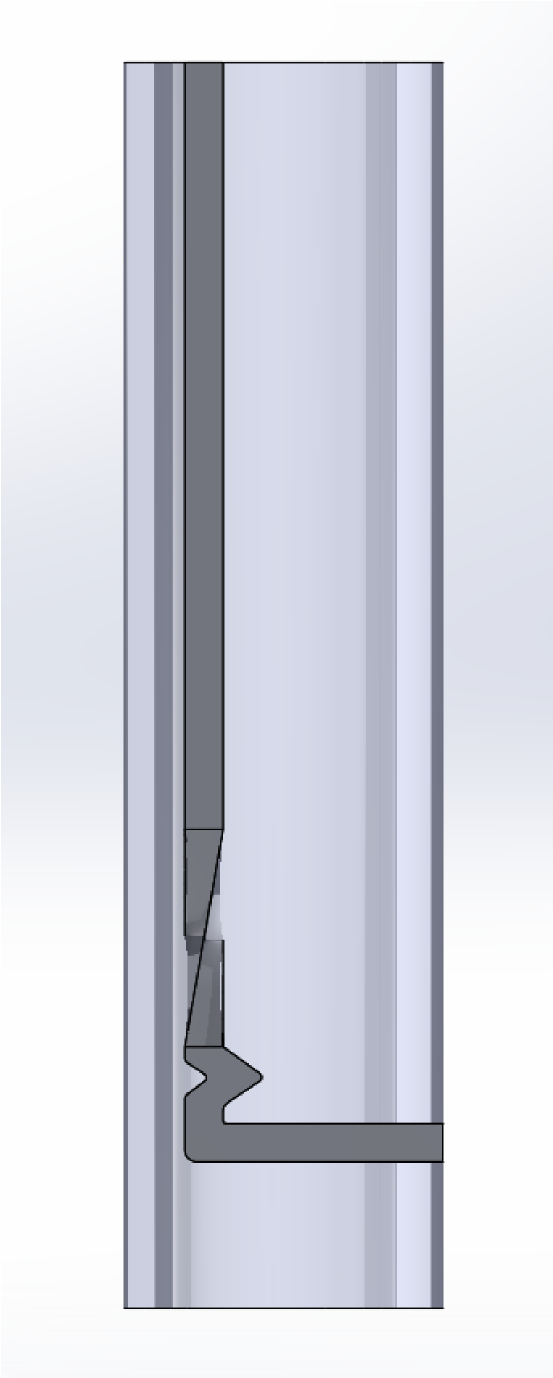

Figure 2. Cross-sectional image of Die design

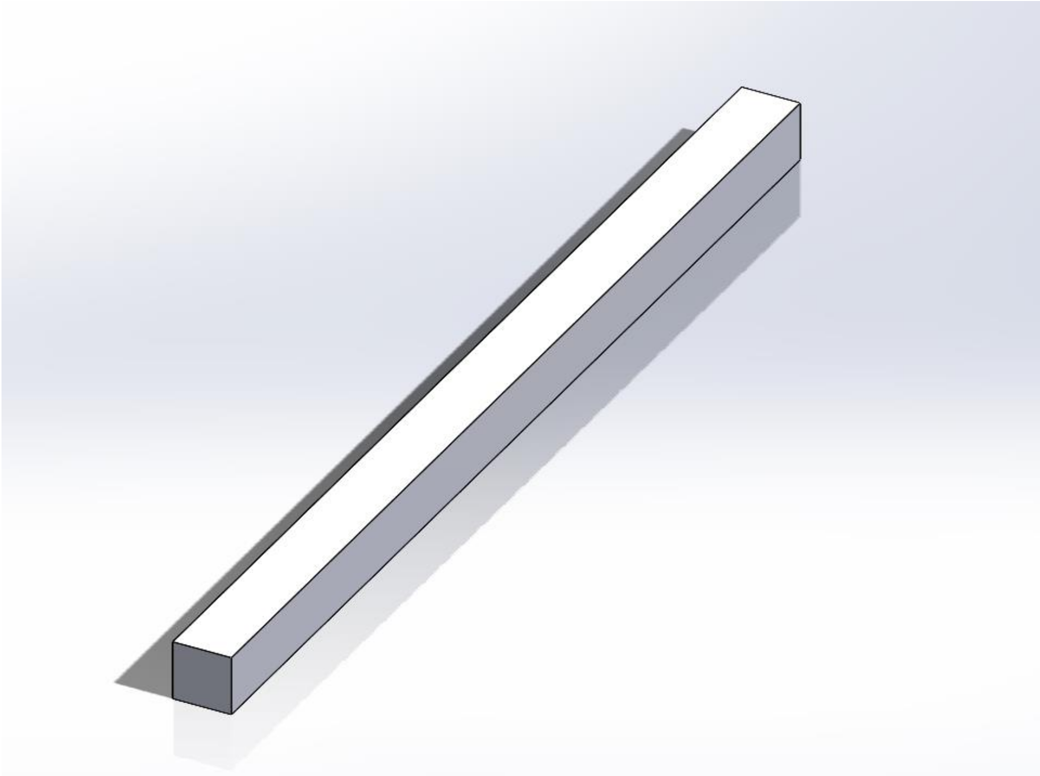

Figure 3. Image of the workpiece

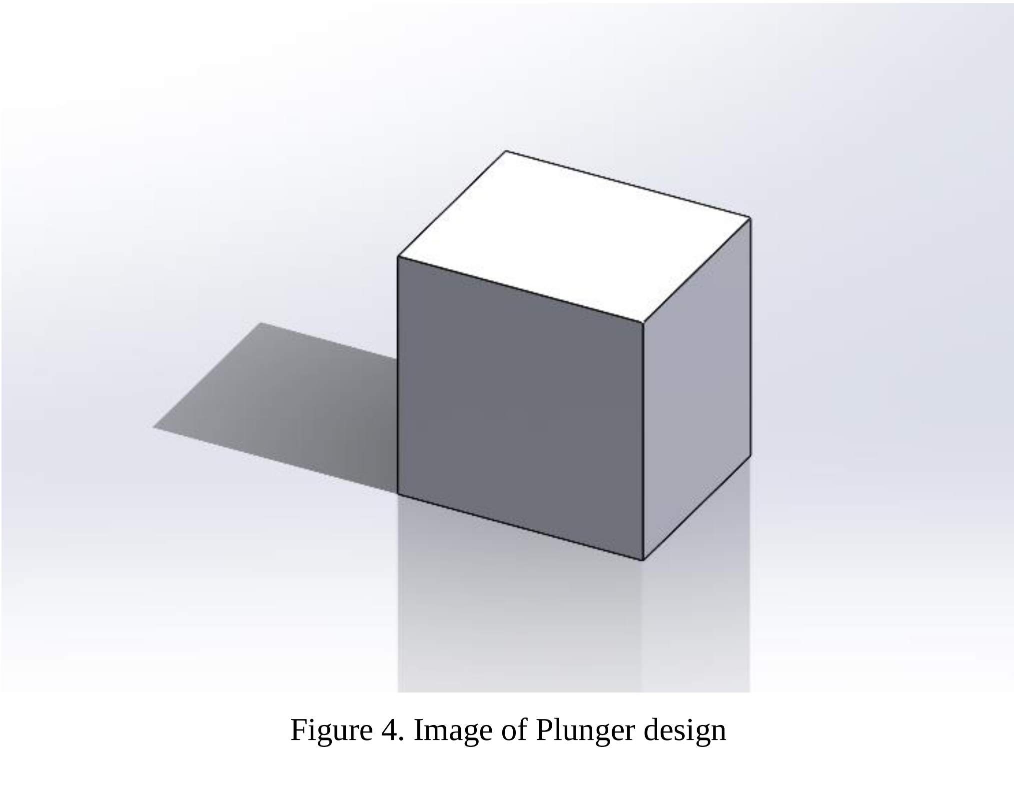

Figure 4. Image of Plunger design

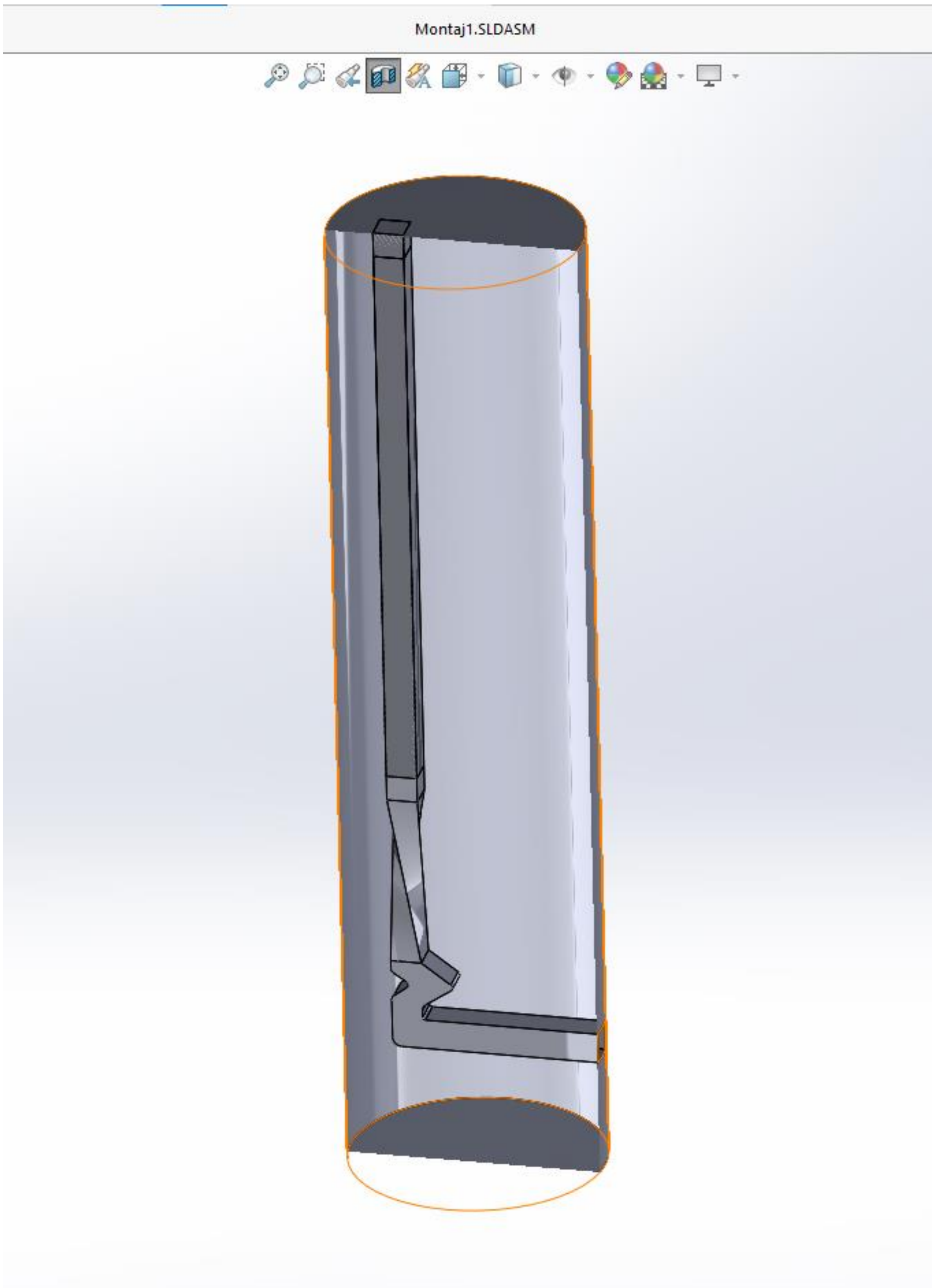

Figure 5. Cross-sectional image of the assembly of Die, Workpiece and Plunger

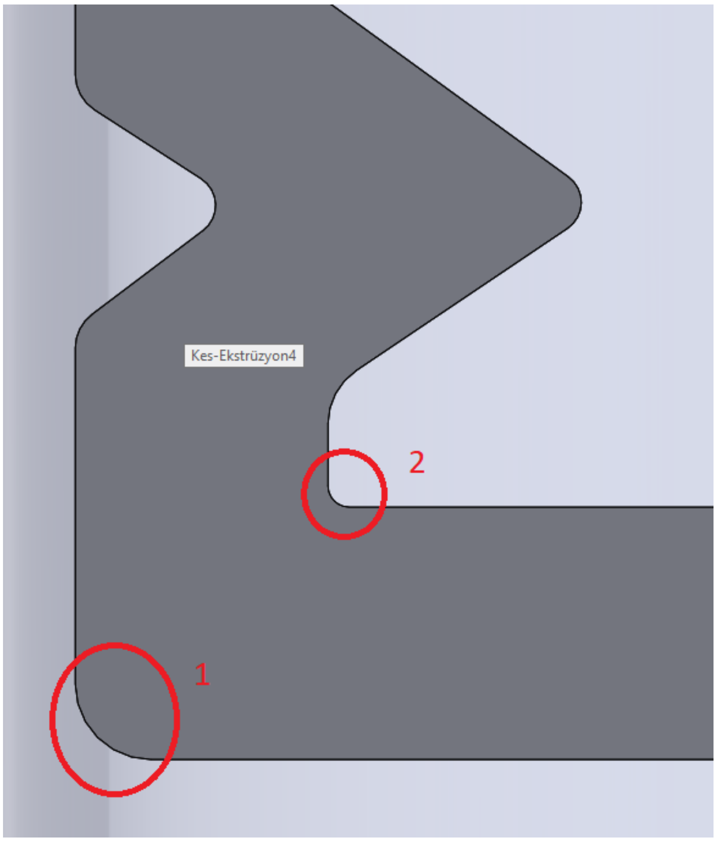

Figure 6. Image showing the turning point between vertical-horizontal regions in die design

Afterwards, for the FE analysis to be carried out within the scope of the TMCAP process, 27 different scenarios were designed in line with the determined angles shown in Table-1 below, and appropriate geometries were modeled in line with these scenarios.

Table-1. Table showing the angles and values determined for the analyzes

No of FEA	Beta (Angle)	Fi (Angle)	Gamma (Angles)
1	10	90	70
2	10	105	70
3	10	120	70
4	10	90	100
5	10	105	100
6	10	120	100
7	10	90	130
8	10	105	130
9	10	120	130
10	30	90	70
11	30	105	70
12	30	120	70
13	30	90	100
14	30	105	100
15	30	120	100
16	30	90	130

17	30	105	130
18	30	120	130
19	50	90	70
20	50	105	70
21	50	120	70
22	50	90	100
23	50	105	100
24	50	120	100
25	50	90	130
26	50	105	130
27	50	120	130

After these stages were completed, some boundary conditions were determined in the Deform program and FE analyzes were applied. Since the process was carried out at room temperature in the reference study [13], FE analysis was also performed at room temperature. Within the scope of the analysis, while rigid material was assigned for die and plunger, plastic material was assigned for workpiece. For this reason, only the workpiece is meshed and a mesh structure containing 30000 elements is created. The network structure of the workpiece is shown in Fig. 7. Pure aluminum used in the reference study was chosen as the material. The mechanical properties of the material were taken from the reference study and entered in the relevant field in the software. Within the scope of the TMCAP process, the feed rate of the plunger and the friction coefficient between the workpiece and the die were determined as 3 mm/s and 0.2 based on the reference study. The advance length of the workpiece in the die was equivalent to the workpiece length and was determined as 220 mm. These limitations were applied to all analyzes and FE analyzes were completed.

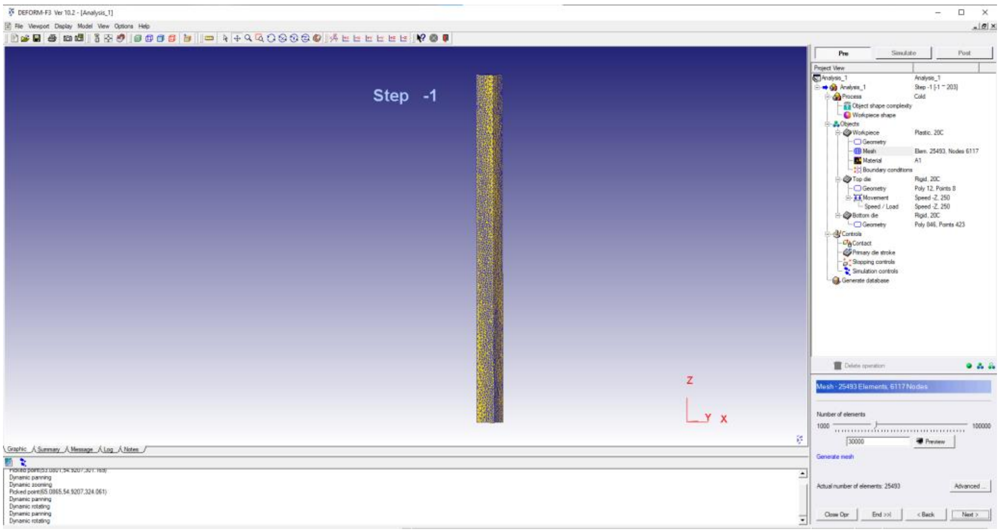

Figure 7. Image of Analysis 1 from the Generate Contact Nodes section.

After the FE analyzes were completed, predictions were made for the development of the die using the ANN method. In order to make these predictions, load data and strain data were taken FE analyzes performed in the Deform software.

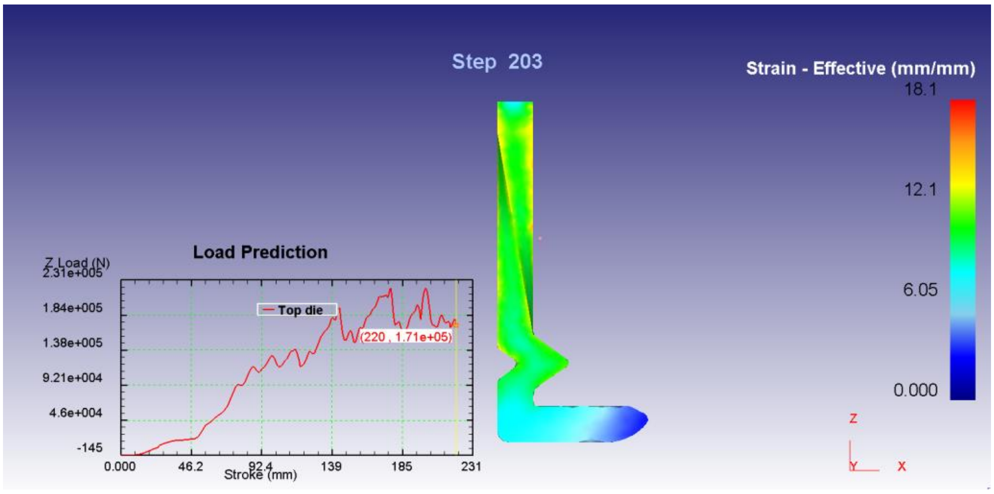

Figure 8. Image showing the Load-Prediction Graph of Analysis 1

The load data are obtained from the same FE analyzes. For this purpose, Load-Stroke graph feature is created in post-processing section. In this section, after setting stroke object as Top die, smoothing option is selected as Second Order. Once the graphic is generated, load and stroke data are exported from the program and saved.

The procedure for obtaining Strain Data is as follows:

After opening the Post section in the program, the feature of the workpiece is selected as "Strain-Effective" from the "State Variables" field and the workpiece is cut from the middle of the last bend point in the die. Thus, it is aimed that the area where the data will be drawn is a homogenized area. Then, 10 different points are selected at equal distance from the middle point of the workpiece displayed on the Y-axis, as shown in Fig.9 below, and the graphic of the selected points is taken from the program.

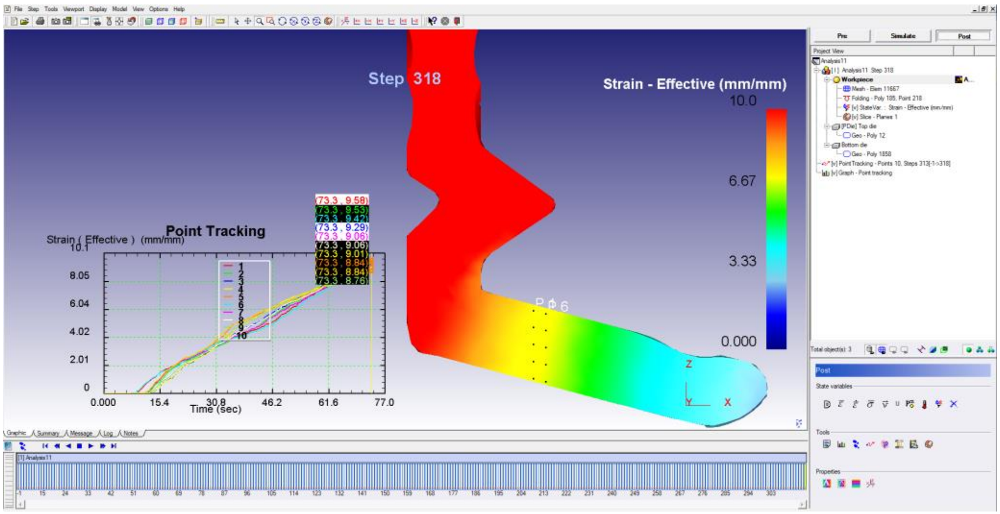

Figure 9. Image showing the Strain-Effective Graph of Analysis 11

3. ARTIFICAL NEURAL NETWORK

Artificial neural networks (ANNs) are a preferred tool over conducting time-consuming experiments and simulations that involve complex repetitions. In this context, ANN method was also used in this research. The method of ANN has emerged as a powerful tool in various fields, including materials science and engineering. In the context of obtaining optimum die design for Twisted Multi-Channel Angular Pressing (TMCAP) process, ANN have been employed to predict material properties and process parameters, providing significant convenience in making these predictions.

In this study, in the Matlab software ANN were used to model the relationship between the angle values of the TMCAP die and the AEPS and ML values obtained from FE analyses. The ANN was trained using a dataset consisting of input features and their corresponding target values. The aim is to predict target values against given inputs with the lowest error rate.

In both generated network files, a matrix containing the input angles Gama, Fi, and Beta was used as the input matrix, while two separate target matrices were created as the target matrix, containing the ML and AEPS obtained from FE analyses. Initially, different numbers of hidden neurons were tried using the "numHiddenNeurons" code, and the best result was obtained with 12 neurons. As shown in Fig. 10, therefore, the number of hidden neurons was set as 12, and the network was initialized using the "newfit" command, which constructs the network based on the provided inputs and targets. Subsequently, training parameters were determined for the network to reach a specific target with a desired error tolerance set at 10^{-6}. To train the ANN, the dataset is divided into two. These are the training set and the test set. 70% of the data was used for the training set, while 30% was used for the test set. During the training process, the "Levenberg-Marquardt" training function was preferred in the network file using the "trainlm" command to minimize the difference between the predicted outputs and targets. In addition, the performance function "mean absolute error" was used to measure how far the predictions of the neural network model were from the real values during the training process. After it was completed, it was tried to create outputs by using the "sim" command as a dependent training on the input values. To evaluate the performance of the trained network, the errors between the generated outputs and the target values were calculated, allowing for further analysis for both the training and test sets. These parameters were decided through multiple trials, selecting the ones with the best performance and the lowest error rate.

```
numHiddenNeurons = 12   ;
net = newfit(inputs,targets,numHiddenNeurons);
net.trainParam.goal=1e-6
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 0/100;
net.divideParam.testRatio = 30/100;


net.trainFcn = 'trainlm';  % Levenberg-Marquardt
net.performFcn = 'mae'; % Mean absolute error

% Train and Apply Network
[net,tr] = train(net,inputs,targets);
outputs = sim(net,inputs);
error=outputs-targets;
trOut = outputs(tr.trainInd);
tsOut = outputs(tr.testInd);
trTarg = targets(tr.trainInd);
tsTarg = targets(tr.testInd);
trerror=trOut-trTarg;
% verror=vOut-vTarg;
tserror=tsOut-tsTarg ;
```

Figure 10. The visual displays the code related to the ANN in the Matlab software.

To evaluate the performance of both the training and test datasets, the process involved plotting graphs. As shown in Fig.11, a regression graph was generated using the "plotregression" command to examine the relationship between the target values and the outputs produced by the trained network. The obtained errors were categorized as training and test errors, and they were written to an Excel file named "Hata" using the "xlswrite" command. This file contains overall errors between the network outputs and target values, as well as the target values and their corresponding values for the training and test sets. The Excel file also includes minimum, maximum, and average error values, allowing for further analysis and evaluations. Additionally, the "plotperf" and "plotfit" commands were used to analyze the performance of the network and visualize the correspondence between the inputs and targets of the ANN.

```
plotregression(trTarg,trOut,'Train',tsTarg,tsOut,'Testing')
xlswrite('Hata',error);
xlswrite('Hata',targets,'A2:V2')
xlswrite('Hata',trerror, 'A10:O10')
xlswrite('Hata',trTarg,'A11:O11')
xlswrite('Hata',tserror, 'A25:G25')
xlswrite('Hata',tsTarg,'A26:G26')
% Plot
plotperf(tr)
plotfit(net,inputs,targets)
plotregression(targets,outputs)
```

Figure 11. The visual displays the code used in the Matlab software to write data to an Excel file and plot graphs.

As a result, several trials were conducted until the best regression values and the lowest error rates were obtained. After finding the best regression values and the least error rates, the graphs were recorded and the error results in the excel file were saved to the file.

4. RESULT & DISCUSSION

The results obtained in the scope of the study are presented under two main headings. First, the results obtained from the FE analysis of the TMCAP process, and the results obtained from 27 FE analyses conducted for the TMCAP process are provided. Second, the results and graphs obtained from the ANN model for max load and AEPS are presented.

4.1. Result of FE

The geometric structure of the TMCAP workpiece obtained from the FE analysis using the Deform program, along with the visual representations related to the FE analysis, is shown in Fig. 12.

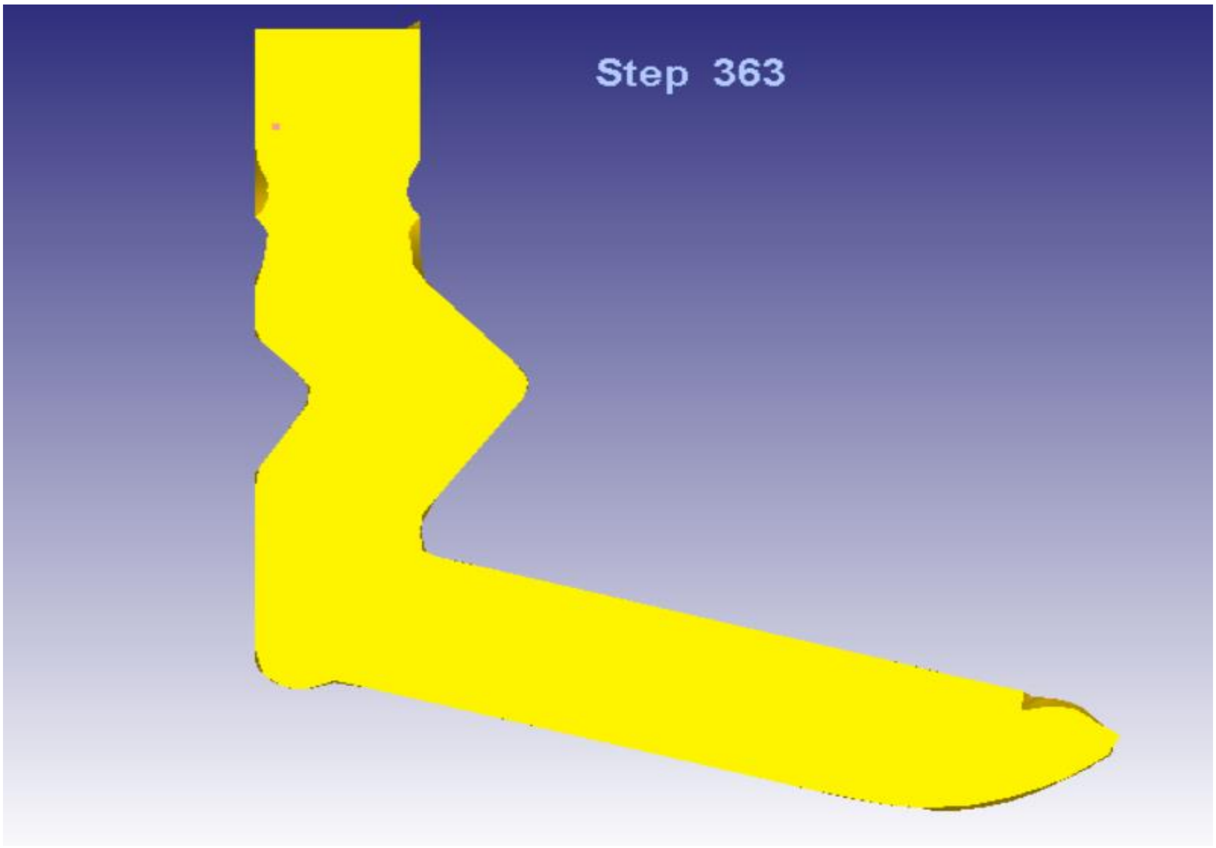

Figure 12. Final state of the workpiece

Additionally, the applied load and stroke values on the die during the TMCAP process are shown in Table 2.

Tablo-2. The table presents the ML values for the load data obtained from the analyses.

ANALYSIS NO	Stroke (mm)	MAX. Load (N)
1	177.244	219543.419
2	210.869	119784.385

3	220.544	115679.401
4	208.232	117551.422
5	219.189	116798.630
6	216.704	116030.559
7	205.956	104934.713
8	217.988	97906.114
9	71.378	35589.266
10	210.581	148973.234
11	215.493	146692.026
12	217.842	140930.594
13	214.725	160488.624
14	218.638	138554.634
15	215.345	134890.068
16	216.964	123475.243
17	218.823	92806.800
18	173.362	40572.703
19	216.959	150567.287
20	203.459	149941.163
21	205.083	149189.734
22	215.426	143711.926
23	218.428	145526.577
24	205.852	143248.076
25	218.741	127906.753
26	215.232	108056.059
27	210.271	52251.702

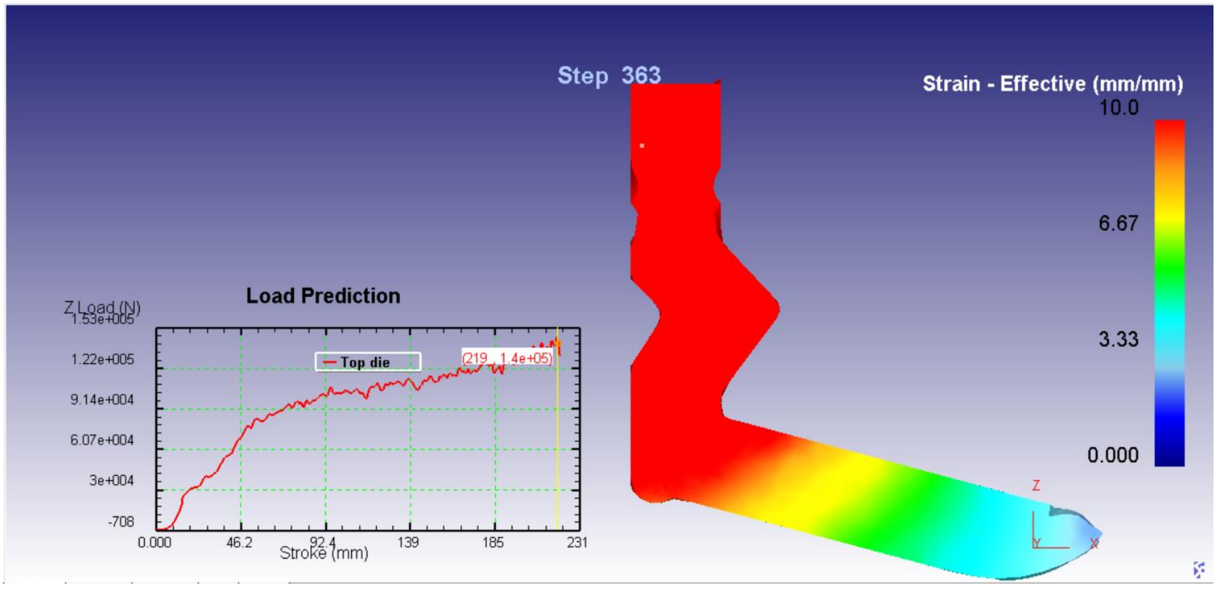

Figure 13. The graph shows the load data, and displays the workpiece resulting from the 23rd analysis.

The effective strain distribution for the TMCAP process is shown in Fig.14.

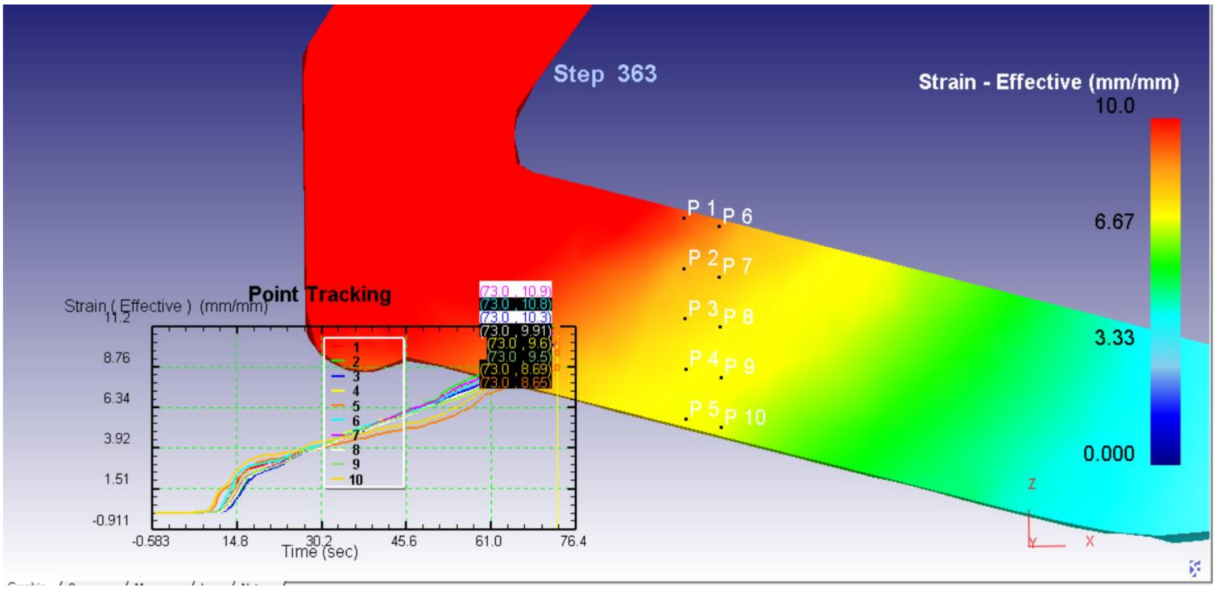

Figure 14. 10 points determined for the strain data of the 23rd analysis and the strain graph of the analysis

For the effective strain value, min. Max. Std. and their mean values are shown in Table 3. The average strain values for the workpiece were obtained by calculating the average of the differences from 10 points on the cross-section.

Tablo-3. The table displays the strain data.

ANALYSIS NO	MIN	MAX	AVERAGE	STD
1	2.71	15.4	9.18	2.43
2	2.37	17.8	8.59	3.10
3	2.15	15.4	8.38	2.84
4	1.97	16.7	8.68	2.91
5	1.81	15.8	8.55	2.77
6	1.73	14.9	8.5	2.6
7	1.18	12.6	6.6	2.24
8	1.12	11.5	5.3	1.85
9	0.145	4.66	1.86	0.69
10	3.72	25	13.4	5.49
11	2.41	22.4	12	5.33
12	2.39	22.1	11.9	5.54
13	1.78	35.5	15.8	7.72
14	2.11	21.3	11.8	4.93
15	1.83	21.7	11.8	4.93
16	1.36	17.9	10.2	3.88
17	1.41	10	3.94	1.33
18	0.689	6.26	2.73	0.70
19	3.87	24.4	12.8	5.9

20	3.72	20.9	12.3	4.46
21	3.24	21.5	12.8	4.87
22	2.07	19.6	11.3	4.34
23	2.2	20	11.6	4.71
24	1.51	19.3	9.71	4.17
25	1.29	14.1	7.06	2.91
26	1.06	10	5.05	1.67
27	1.27	7.75	3.94	0.94

4.2. Result of ANN

The ANN was used based on 27 analyses conducted in the prediction process, along with 22 analysis data. The reason for this is to observe the adverse effects on the performance of the neural network. These effects lead to higher errors and inaccurate predictions. Also, the regression and test values yield results much lower than expected. The impact of these extracted analyses on the workpiece can be seen in Fig.15, where the workpiece has deviated from the pattern and reached an undesirable length, resulting in bending as the workpiece elongates.

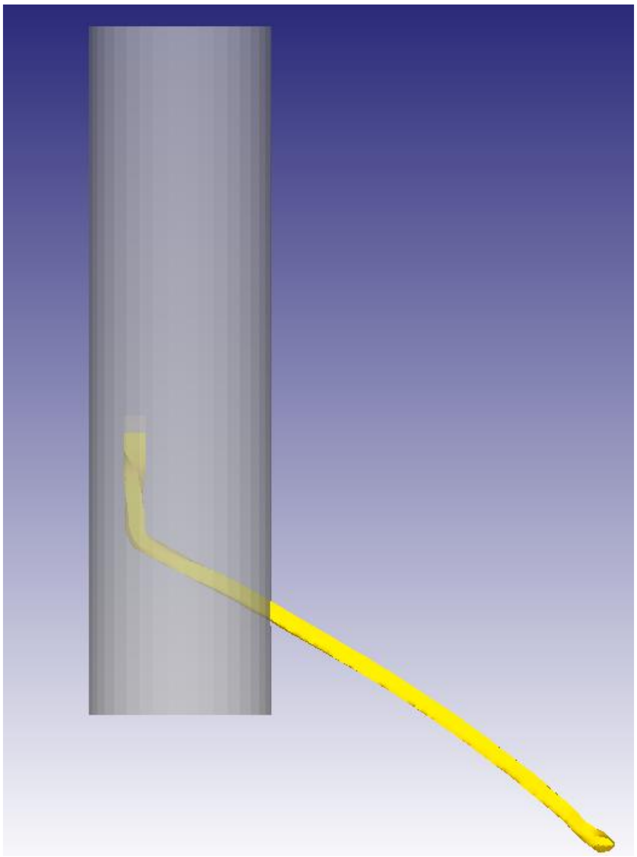

Figure 15. Image of analysis-18 added as an example to the workpiece overflowing from the die

To obtain higher regression values and make accurate predictions in ML and AEPS analyses using the ANN, as shown in Table 4-5 the 1st, 9th, 13th, 18th, and 27th analyses have been removed.

Table-4. 22 strain data used for ANN

ANALYSIS NO	MIN	MAX	AVERAGE	STD
2	2.37	17.8	8.59	3.10
3	2.15	15.4	8.38	2.84
4	1.97	16.7	8.68	2.91
5	1.81	15.8	8.55	2.77
6	1.73	14.9	8.5	2.6
7	1.18	12.6	6.6	2.24
8	1.12	11.5	5.3	1.85
10	3.72	25	13.4	5.49
11	2.41	22.4	12	5.33
12	2.39	22.1	11.9	5.54
14	2.11	21.3	11.8	4.93
15	1.83	21.7	11.8	4.93
16	1.36	17.9	10.2	3.88
17	1.41	10	3.94	1.33
19	3.87	24.4	12.8	5.9
20	3.72	20.9	12.3	4.46
21	3.24	21.5	12.8	4.87
22	2.07	19.6	11.3	4.34
23	2.2	20	11.6	4.71
24	1.51	19.3	9.71	4.17
25	1.29	14.1	7.06	2.91
26	1.06	10	5.05	1.67

Table-5. 22 load data used for ANN

ANALYSIS NO	**Stroke (mm)**	**MAX. Load (N)**
2	210.869	119784.385
3	220.544	115679.401
4	208.231	117551.422
5	219.189	116798.630
6	216.704	116030.559
7	205.955	104934.713
8	217.987	97906.114
10	210.581	148973.234
11	215.492	146692.026
12	217.842	140930.594
14	218.638	138554.634
15	215.345	134890.068
16	216.964	123475.243
17	218.823	92806.800

19	216.959	1505670.287
20	203.459	149941.163
21	205.083	149189.734
22	215.426	143711.926
23	218.428	145526.577
24	205.852	143248.076
25	218.741	127906.753
26	215.232	108056.059

Angle values of the die geometry, which are effective in the behavior of the workpiece, are shown in Table 6 below.

Table-6. Angle values of analyzes that were not used in Ann

No of FEA	Beta (Angle)	Fi (Angle)	Gamma (Angles)
1	10	90	70
9	10	120	130
13	30	90	100
18	30	120	130
27	50	120	130

Fig. 16 and Table 7 show the performance of the ANN files used in the prediction process for ML calculations for any parameter set (Φ, β, and γ). Based on the conducted tests, the training and testing performance of the maximum load data is provided in Fig. 16.

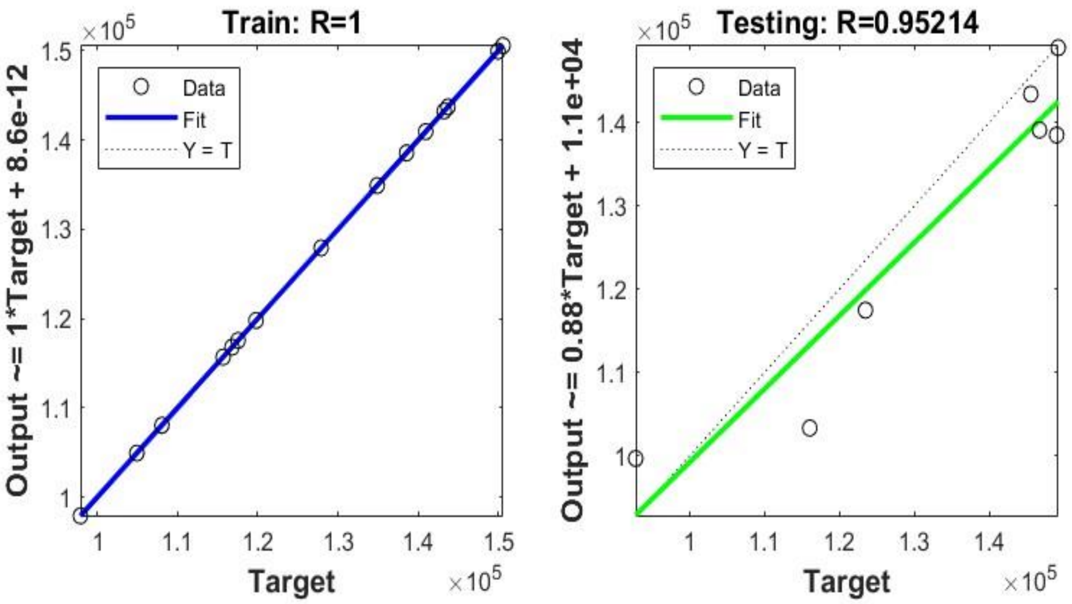

Figure 16. Predicted values vs FE analysis values for training data of ML neural network, and test data of maximum neural network.

The regression values for the training and testing data sets of the ML neural network are given as 1 and 0.95214, respectively, in Table 7. These regression values indicate highly positive results. Additionally, the mean absolute error values calculated on the training and testing data for the ML neural network are 1.763e-15% and 5.302%, respectively. Also, the maximum absolute error is also calculated. As shown in Table 7, the maximum absolute error values for the training and testing data of the ML neural network are 1.386e-14% and 10.938%, respectively.

Furthermore, Fig. 17 shows the performance of the AEPS neural network on the training and testing data. The regression values calculated for the training and testing data are determined as 1 and 0.8099, respectively, as shown in Table 7. Although the regression value for the AEPS test data is lower than that of the ML data, it is still considered acceptable. Moreover, the mean absolute error values calculated on the training and testing data for the AEPS neural network are obtained as 2.645e-14% and 9.358%, respectively. Also, as shown in Table 7, the maximum absolute error values for the training and testing data of the AEPS neural network are calculated as 6.139e-14% and 20.329%, respectively.

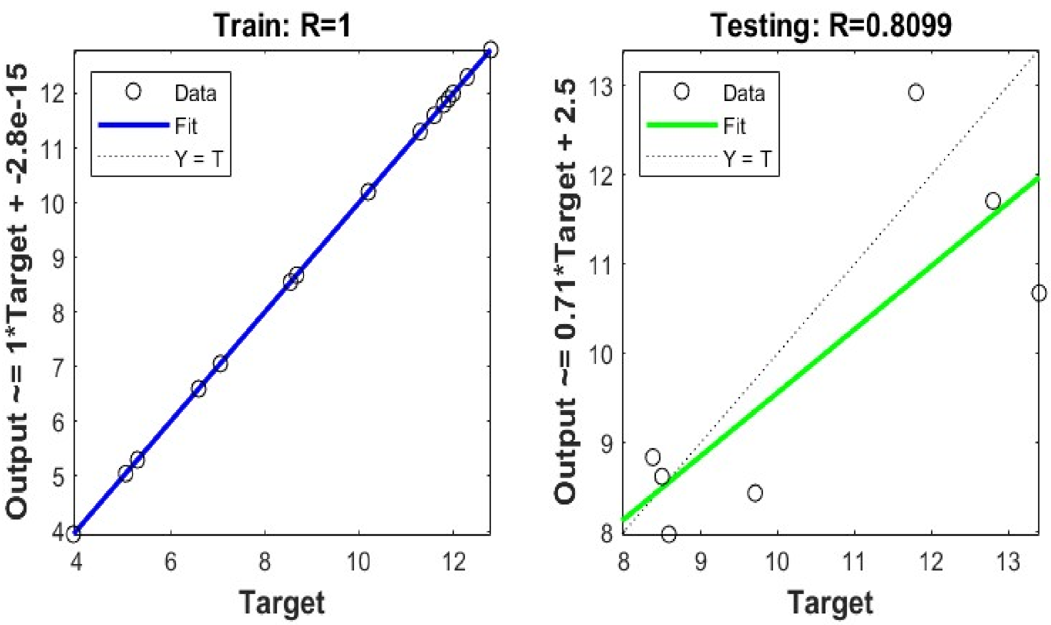

Figure 17. Training data of AEPS and test data of AEPS.

Table-7. Results for the performance of ML and AEPS neural networks

	MAKSIMUM LOAD		AVERAGE EFFECTIVE PLASTIC STRAIN	
	Training Data	Test Data	Training Data	Test Data
Average Absolute Error %	$1{,}763e-15$	5.302	$2.645e-14$	9.358
Maximum Absolute Error %	$1.386e-14$	10.938	$6.139e-14$	20.329
Regression	1	0.952	1	0.8099

4.3. DISCUSSION

When the regression, average absolute and maximum absolute error values for the two ANN models, it is seen that regression of the training data of the two ANN models are quite satisfactory. Same can be said for the ML-ANN test data with a regression value of 0.952. On the other hand, regression value of AEPS -ANN test data is relatively low. This can be attributed to the process of strain data extraction. Since it is dependent on the point selection, locations of the selected points are affecting AEPS values and it causes to a non-standardization. Due to this non-standardization, low regression value may be obtained as result. If average and maximum absolute error values are taken into consideration, it is seen that both error type are quite low for training data of the two ANN models. However, the decisive errors are the ones obtained for the test datas. When they are taken into consideration, average absolute error values for ML and AEPS-ANN models are 5,302 % and 9,358%, respectively. These error values are satisfactory. Additionally, maximum error value for ML-ANN model is 10,938 % it is acceptable. Lastly, maximum error value for AEPS-ANN model is 20,329 which is slightly beyond of the acceptable error rate.

5. CONCLUSION

In this study, ML and AEPS values with minimum values were found with the results obtained from the analyzes made with the TMCAP process and a series of predictions made using the ANN method. The most suitable die design was determined according to the results obtained from the analyzes made with some dies designed first. Die designs were made for 27 different scenarios with different angle values (Φ, γ, β) determined by making necessary adjustments on this design.

Afterwards, FE analysis of 27 different die designs was performed to examine the load and effective strain data from the Deform software. As a result of the analysis made, load and effective strain data were obtained. The maximum load values of the analyzes were determined from the load data obtained for each analysis. While the mean ML value obtained for the data was 123763 N, the largest and smallest load values of the analyzes were 219543,418N and 35589,265 N, respectively. In addition, minimum, maximum and average effective strain data were obtained for the effective strain values, and then ANN operations were applied in Matlab software. Angles were taken as input matrix for ANN operations, and ML and AEPS data obtained from Deform program were taken as target matrices. Very high value errors were obtained when ANN operations were applied for 27 different scenarios. When the data were checked, in consecutive analyzes, decreases of 30% or 100% were observed in the ML results when the β and γ angles were constant and the value of the Φ angle increased. In addition, 1200% increases were observed for the AEPS value. In some cases where the γ angle was variable, irregular increases and decreases were observed for AEPS. Due to this situation, it has been observed that the error rates in ANN operations are very high and the regression values are very low. Since the average error of 145%, the maximum error of 520% and the regression value of 0.4235 were observed in the ANN operations, the analyzes 1,9,13,18 and 27 that caused the mentioned changes were excluded from the target matrices to be used in the ANN operations. After this process, the average error rates for ML and AEPS were found to be 5.302 and 9.358, respectively, as a result of repeated ANN applications. In addition, the regression values of ML and AEPS for all data were obtained as 0.97332 and 0.9644, respectively.

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