A COMPARISON OF ARTIFICIAL NEURAL NETWORKS AND MULTIPLE LINEAR REGRESSION MODELS AS PREDICTORS OF DISCARD RATES IN PLASTIC INJECTION MOLDING

Vesile Sinem ARIKAN KARGI *

Dr., Research Assistant, Economics and Administrative Sciences Faculty, Econometrics Department, Uludağ University, Bursa

Abstract

In today's global competitive environment, it is important to be able to evaluate the efficient use of a firms' resources. The aim of this study is to predict the discard rate for headlight frames before the project of an automotive sub-industry firm in Bursa. For this prediction, the multilayer perceptron model, the radial basis function network model and multiple linear regression models were used. Matlab R2010b software was used for the multilayer perceptron model and radial basis function network solutions, and SPSS 13 packet software was used to solve the multiple linear regressions. Comparing the three models, the multilayer perceptron model was identified as the best predictive model.

Keywords: Artificial neural network, Multilayer perceptron model, Radial basis function network model, Multiple linear regression model, Discard rate
Jel Code: C13, C45

PLASTİK ENJEKSİYON KALIPLAMADA ISKARTA ORANI TAHMİNİNDE YAPAY SİNİR AĞLARI VE ÇOKLU DOĞRUSAL REGRESYON MODELLERİN KARŞILAŞTIRILMASI

Özet

Günümüz küresel rekabet koşullarında firmaların kaynakları etkin kullanarak değerlendirmesi oldukça önemli bir konudur. Bu çalışmanın amacı Bursa'da bir otomotiv yan sanayi firmasının proje öncesinde far çerçeve parçasının ıskarta oranını tahmin etmektir. Bu tahmin için yapay sinir ağ modellerinden çok katmanlı algılayıcı model, radyal tabanlı fonksiyon ağ modeli ve çoklu doğrusal regresyon model teknikleri kullanılmıştır. Çalışmada çok katmanlı algılayıcı model ve radyal tabanlı fonksiyon ağ model çözümleri için Matlab R2010b programı, çoklu doğrusal regresyon model çözümü için SPSS 13 paket programı kullanılmıştır. Firmanın ıskarta oranı tahmininde bu üç model kıyaslanmış ve en uygun modelin çok katmanlı algılayıcı model olduğu belirlenmiştir.

Anahtar Kelimeler : Yapay sinir ağları, Çok katmanlı algılayıcı model, Radyal tabanlı fonksiyon ağ modeli, Çoklu doğrusal regresyon model, Iskarta oranı
Jel Kodu : C13, C45

1. INTRODUCTION

Aggressive competition in demand-driven global markets forces firms to produce fewer faulty products. To achieve this firms use methods such as lean production, Six Sigma, benchmarking, total quality management, and just-in-time production (Arıkan Kargı, 2015).

As with every industry, the plastics industry aims to produce quality products in the shortest possible time and with lowest possible cost. The project firm for this study in Bursa employs a lean production system. Lean production is defined as a system in which wastage with

* vesa@uludag.edu.tr (Corresponding author)

no added value, such as faults, costs, inventory, labour, development processes, prodution area wastage, or customer dissatisfaction is minimised (Womack et al, 1990). The quality of production is an essential condition for a firm applying lean principles. In lean production "product quality" requires a discard rate of 3,4 per million to 0.

Plastic goods such as toys, automobile parts, various electronic parts, or the home appliances we encounter in daily life, are mostly produced by using injection molding techniques. Plastic injection molding is a process for producing parts by injecting molten thermoplastic material into a mold and removing the part after it has hardened on cooling (Özek and Çelik, 2011). Thermoplastics materials are used in the injection molding process. Thermoplastics structurally become soft and fluent under heat, and harden when cooled down only undergo physical change. For this reason injection molding is used for shaping thermoplastics (Chang et al, 2007).

2. LITERATURE REVIEW

One of the prediction tools used for plastic injection molding is artificial neural networks. In the literature Rewal and Toncich (1998) used artificial neural networks to predict part weights and improve part quality. Lau et al. (1999) used artificial neural networks and fuzzy logic for mold manufacturing for plastic injection molding. Artificial neural networks were used to study the effect of input parameters such as injection time, cooling time, clamping time and clamping pressure on parts that are molded. Sadeghi (2000) used back-propagation techniques for predicting ideal injection pressure and injection time for high density polyethylene materials. Zhu and Chen (2006) predicted flashes (excess material attached to the finished product) in injection molding operations by analyzing data with a fuzzy neural network algorithm, using injection speed, melting temperature and clamping pressure as input parameters, to create a multiple regression model. Öktem et al. (2006) used neural networks and genetic algorithms to determine cutting parameters, such as cutting speed, feeding amount, axial and radial cutting depths, and machining tolerances, for the minimization of surface hardness. The genetic algorithm and the neural network were able to determine the optimal cutting parameters for minimum surface hardness without any constraints. It can be seen that the values from this technique and measurements done for the experiments are very close to each other. Changyu et al. (2007) examined how injection molded parts are affected by process conditions. They indicated that a combination of artificial networks and genetic algorithms for optimization of injection molding processes produced satisfactory results. Karataş et al. (2007) using artificial neural networks, devised a new formula that is based on various injection parameters, for determining flow length in injection molding of commonly used commercial plastics. Tsai and Luo (2015) used artificial neural networks and response surface methodology to obtain a prediction model for lens form correctness.

Our study is applied in a automotive sub-industry company which manufactures headlight frame parts by plastic injection molding in Bursa. In conclusion of the meeting which was held with the executives, it was stated that a new project will be started. In this new project, we were demanded that determining optimal parameters of headlight frame production for minimizing discard rates. To solve the problem faced by this automotive sub-industry firm, it was decided that using a multiple linear regression model, artificial neural network types multilayer perceptron model and radial basis function networks would be the most suitable due to the knowledge we attained. The main purpose of our study is predicting the discard rate before the project for headlight frames that are produced by plastic injection molding and determine which one of the three models that was used for the prediction is the most effective.

3. DATA AND METHOD

Data used in the study consist of 205 data points that were collected at the automotive sub-industry firm in January 2015. The data was used for determine the discard rate of headlight frame products and the parameters that lead to discards. Input parameters that cause discards are: injection pressure, mold temperature, injection speed, clamping pressure, counter-pressure, clamping time and screw-barrel unit temperature. The output parameter is the headlight frame discard rate.

This study used a multilayer perceptron model, a radial basis function network model, and a multiple linear regression model to predict the headlight frame discard rate.

3.1. Artificial Neural Network Models

Artificial neural networks (ANN), are information processing structures inspired by the human brain. They are parallelly distributed computer programs consisting of computing elements that are related to each other with weighted relations and that each have their own memory. In other words, ANNs are computer programs which mimic biological neural Networks (Elmas,2011).

ANNs simulating the performance of human brain have many features such as learning from data, generalizing, tolerating errors and working with unlimited number of variables. The smallest units forming the basis of ANN are called artificial neurons or computing elements. As in Figure 1, the simplest artificial neuron consists of five main components including inputs, weights, combination function, transfer function and output.
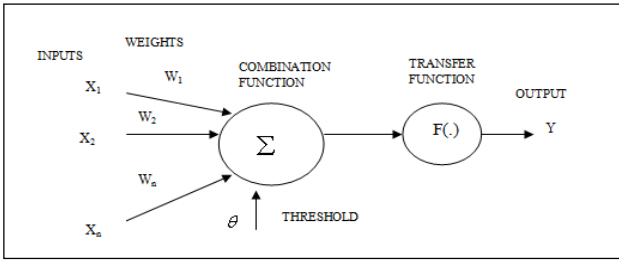
Alphanumeric Journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
htttp://www.alphanumericjournal.com/

Figure 1. Functional Structure of an Artificial Neuron

Figure 1 shows that inputs (x1,x2,.., xn) are obtained from outside the artificial neuron. These data can be provided by samples which the network will use to learn from – by another neuron or by the neuron itself. Weights (w1,w2,..wn) are values indicating the effects on sets of inputs or a computing element of previous layers. Each input is combined with a combination function through multiplication with weights, connecting input to computing element. The output (y) is determined by passing the result of the combination function through linear or nonlinear derivative transfer functions.

$$y = f\left(\sum_{i}^{n} x_i w_i + \theta \right) \qquad (1)$$

To date, many artificial neural network models have been developed. The most commonly used, and the ones that were used in this study, are the multilayer perceptron (MLP) model and radial basis function network (RBFN) model.

3.1.1. Multilayer Perceptron Model

Multilayer perceptron (MLP) is a type of artificial neural network which uses at least one layer between the input and output layers. Contrary to single layer perceptron, MLP can produce solutions to non-linear problems, making MLPs the most popular type of artificial neural network, with widespread usage. The structure of an artificial neural network using one hidden layer between input and output layers is given below in Figure 2 (Lippmann, 1987).
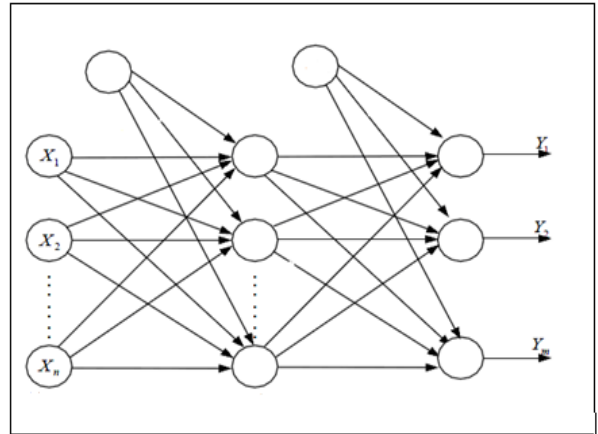

Figure 2. Structure of the Multilayer Perceptron Artificial Neural Network Model

An artificial neural network learns from training samples and acquires the ability to make generalizations. The power of a neural network is closely dependent on how well it can make generalizations using sample data sets. The learning process of an artificial neural network takes place with the calculation of link weights between layers. Weights are altered with the selected learning algorithm. In the learning phase of MLP networks, a back-propagation algorithm is generally chosen which aims to reduce and distribute errors from output to input layers. This is the most common type of algorithm in practice and has a supervised learning structure where a sample data set consisting of input and target values is given to train the network. In the learning phase of this supervised learning algorithm, weights are updated with the equation given below and a minimization of error function (Öztemel, 2003).

$$Total\ Error = TE = \frac{1}{2} \sum_{m=1}^{n} (B_m - y_m)^2 \qquad (2)$$

In Equation 2, Bm represents the output produced by the network, ym represents real output value. To minimize the total error, link weights are recalculated and updated, making the network produce values closest to the real values. When the weights are updated correctly, the neural network correctly predicts the results for the newly input data.

3.1.2. Radial Basis Function Network Model

Radial basis function networks (RBFN) consist of three layers – one input layer, a single hidden layer used as transfer function and giving a name to the network, and one output layer [16]. Inputs of the network are non-linear, while the output is linear.

Alphanumeric Journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
httt://www.alphanumericjournal.com/

RBFNs were initially applied to the solution of multivariate interpolation [†] problems. The first RBF studies were carried out by Powell (1985) and then by Light (1992). At present, RBF is one of the principal fields of numeric analysis research. On the other hand, Broomhead and Lowe (1988) were the first researchers who used RBF for neural network design (Haykin,1999). RBF networks take a shorter period of time in training compared to MLP and they can approach the best solution without getting stuck on local minimums. Therefore, RBF networks have started to be used in applications involving prediction, curve fitting and function approximation as an alternative neural network to MLP (Kaynar et al, 2010). The structure of radial basis function network is given in Figure 3.
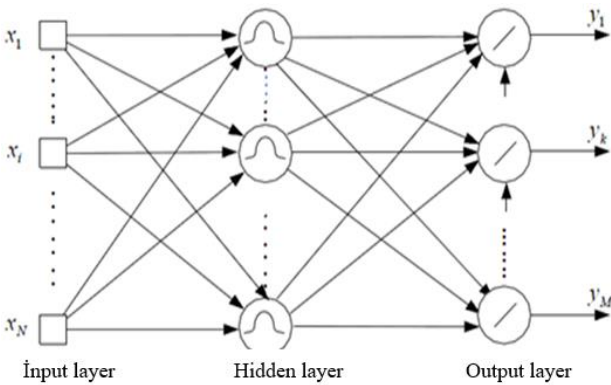

Figure 3. Structure of Radial Basis Function Artificial Neural Network

In this network type, inputs are directly transferred to a hidden layer without multiplication with weights, unlike MLPs. Then, as shown in the equation below, an output ( ) is produced based on the distance between input vector and the reference vectors (uj) indicating the center of radial functions in the hidden layer. Although many distance measures are defined, generally the Euclidian distance, measuring the linear distance between two points, is used as the distance measure. And, although there are many radial basis functions suggested for hidden layers, Gauss function, as shown below, is the most preferred.

$$\phi_j = \exp\left(-\frac{\|x_i - u_j\|^2}{2\sigma_j^2}\right) \tag{3}$$

In Equation 3, x_i signifies the input vector given to the network and u_j represent the central (reference) vector, while $\|.\|$ is the distance function and σ_j indicates the spread of Gauss function. Then, φ_j values obtained in the hidden layers are multiplied with weights and totalled to give the output of the network, as is shown in the below equation.

$$y_k = \sum_{j=1}^{L} w_{kj}\phi_j + b_k \tag{4}$$

In equation 4, L is the number of nodes in the hidden layer, y_k is the output (w_{kj}) for k^{th} input of jth node, b_k is the weight between kth RBF unit and j^{th} output node and threshold of kth node.

In designing an RBF network, many different training approaches are proposed in the literature for determining the radial basis functions' central vector. Some of these approaches are: fixed centres selected at random, self-organised selection of centres, and supervised selection of centres (Haykin, 1999).

3.2. Multiple Linear Regression Model

The multiple linear regression method is used to investigate the linear relation between one dependent variable and two or more independent variables. It is generally shown as a model demonstrating the relation between dependent variable (output) and n-independent variables (input) (Tso and Yau, 2007).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ...\beta_n x_n + u \tag{5}$$

In Equation 5, y is the output variable, x_i (i=1,2..n) are the input variables, parameter is the regression coefficient, coefficients of x which are β_i (i=1,2..n) are partial regression coefficients, and u is the random error term. Multiple linear regression analysis makes use of least squares method. This method minimizes the sum of the differences between real and predicted y values.

Comparing artificial neural networks and the multiple regression model, the criteria are: determination coefficient (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE). According to these criteria, the better fitted model with higher R^2 and lower MSE, RMSE ve MAE values is chosen. The equations of subject and terms used in these equations are given below.

$$\bar{R}^2 = 1 - \left(1 - R^2\right)\frac{n-1}{n-k} \tag{6}$$

[†] "Interpolation" is a general method of predicting possible values at different and unknown points or in the range of these points based on existent (known) data points.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \qquad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \qquad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \qquad (9)$$

In the equation y_i is the target (actual) output value, $\hat{y}_i$ is the output value produced by the network (predicted), n is the number of data and k is the numbers of variables used in the model.

4. COMPARISON OF THE MODELS AND RESULTS

In this section, the models used to predict the factory's headlight frame discard rates and the results are discussed.

4.1. Multilayer Perceptron Model and Results

The data that is used in the study consists of 205 items that is collected on January 2015. Matlab R2010b program has been used in order to construct and solve the model. The data is divided such that 80% is the training data and 20% is the test data. 25% of the training data is separated as the verification data, thus, The whole dataset is divided randomly into three parts so that 60% of data is for training (123 items), 20% verification (41 items), and the remaining 20% is for the test (41 items).

The multilayer perceptron model constructed for training had an input layer consisting of 7 neurons (injection pressure, mold temperature, injection speed, clamping pressure, counter-pressure, clamping time and screw design unit temperature), and a single neuron at the output layer represented the discard rate for plastic headlight frame production. The hidden layer architecture was determined by trial and error and there was only one hidden layer in the model used in this study. In order to determine the number of neurons in the hidden unit, cases from 1 neuron to 50 neurons were tried so that each model was tested 10 times to determine the best model for our study. The hyperbolic tangent sigmoid (tansig) transfer function was used between the input and hidden layers in the model. A linear (pureline) transfer function was used between the hidden and output layers. While searching for the most suitable model, a Levenberg-Marquardt (LM) back-propagation algorithm was used for training. The maximum number of iterations (epoch) during training in the program was 1000. The performance criteria were MSE, RMSE and MAE. The program sets the learning rate

as 0.001 in the beginning and changes it automatically by increasing or decreasing as the performance degrades.

After a model suitable for the parameters was constructed and trained, the most suitable variant was determined by testing the results. The lowest MSE, RMSE and MAE values and the highest R^2 value was obtained with the model having 8 hidden neurons. Therefore, a 7-8-1 network model is the most suitable having 7.30 MSE, 2.70 RMSE, 2.12 MAE and 0.75 R^2 values. The high determination coefficient, R^2, demonstrates that the prediction is correct.

The change of the error values for training, verification and test sets for each iteration is given in Figure 4. Best performance was obtained on iteration (epoch) 11.
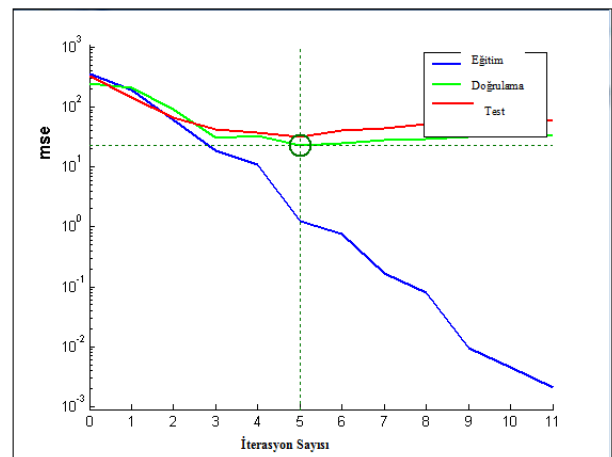

Figure 4. MSE of training, verification and test sets

4.2. Radial Basis Function Network Model and Results

As in the multilayer perceptron model, the dataset for the radial basis function network model was divided into 60% training data, 20% verification data, and 20% test data. The RBF network model had 7 neurons in its input layer and a single neuron in its output layer. Spread and center-value parameters that needed to be determined for this network structure were found by trial and error. The spread parameter was determined as 8. The values for these parameters are 1, 10, 100, 1000, 10,000, 100,000, 1,000,000, 10,000,000. Trials were made for the number of neurons from 50 to 250 by increasing by 50. Therefore, in this study the neuron numbers were taken as 50, 100, 150, 200 and 250. The transfer function between the input layer and the hidden layer is a radial based Gaussian function. The transfer function between the hidden layer and the output layer is a linear (pureline) function. The performance criteria is MSE, RMSE and MAE values as in the MLP model.

After the model suitable for the parameters was constructed and trained, the most suitable variant is determined by testing the results. Using the Matlab R2010b program the results determined a 50-1 network

Alphanumeric Journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
htttt://www.alphanumericjournal.com/

structure model as the most suitable. The factors affecting the choice of this model were the least values of MSE, 7.38, RMSE, 2.72, MAE, 2.12, and highest value of R^2 which is 0.73.

The change of the error values of training, verification and test sets after training is given in Figure 5. As seen in Figure 5, training of the network reached an optimum value at iteration (epoch) 164.
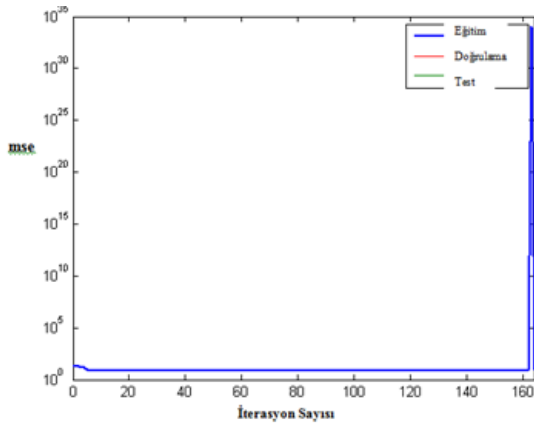

Figure 5. MSE of training set

4.3. Multiple Linear Regression Model and Results

After determining that the distribution of the data obtained from the company is normal, and there are no multicollinearity problems among the independent variables, a multiple linear regression model was applied to the abovementioned discard rate problem. More than half (61%) of the company's discard rate is explained through independent variables such that injection pressure, mold temperature, injection rate, clamping pressure, counter-pressure, clamping time and screw-barrel unit temperature. F table values obtained from the variance analysis table demonstrated that the model is meaningful as a whole. Then, coefficients of independent values were found by predictions about the model and a t test was conducted to determine whether each variable affected the discard rate on its own. A significance level of 0.05 was used and 3 of 7 independent variables were found as significant in the analysis. Therefore, the multiple linear regression model for the firm included in the study was determined to be equation 10.

$$\hat{Y} = 16,082 - 0,110x_1 + 0,034x_3 - 0,645x_5 \quad (10)$$

This concluded that injection pressure (X_1), injection speed (X_3) and counter-pressure (X_5) variables affect the discard rate with 1 bar of increase in injection pressure resulting in a 0.11 decrease in the discard rate, and a 1 second increase in injection speed resulting in a 0.034 decrease in the discard rate. An increase of 1 bar in counter-pressure results in a decrease of 0.645 in the discard rate.

Comparing the prediction performances of the MLP, RBF and MLR models, this study demonstrates that MLP is the best model for the company as it achieves the highest coefficient of determination (R^2) and lowest error performance criteria as seen in Table 1. Therefore, the company will be 75% successful in predicting the discard rates of the headlight frame piece if the MLP model is used before the project.

Table 1. Comparison of MLP, RBF and MLR Models

Model	R^2	MSE	RMSE	MAE
MLP	0,75	7,30	2,70	2,12
RBF	0,73	7,38	2,72	2,12
MLR	0,61	8,21	2,86	1,91

5. CONCLUSION

This study demonstrates that when managers use artificial neural network models, it is possible to produce a minimum quantity of defective items by determining the properties of the product before producing orders requested by the customer. Moreover, by taking measures based on information obtained from the model, the company can channel its resources better by making the right decisions and providing the supply of raw materials needed for production in advance. This also enables the company to deliver customer orders on time, with fast, high-quality production by reducing scrap costs resulting from production and supply delays.

This study developed three models that help determine what percentage of items are going to be discarded on average by changing some of the input variables of the headlight frame parts to be produced. Comparing three models, this study concluded that the MLP model is the best for predicting headlight frame part discard rates. As such, this study is expected to contribute to the company's production quality and efficiency, a reduction of "safety stock" needed to be held in reserve, and an increase in the company's revenue.

Alphanumeric Journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
htttp://www.alphanumericjournal.com/

References

Arıkan Kargı, V.S.(2015). Yapay Sinir Ağ Modelleri ve Bir Tekstil Firmasında Uygulama. Bursa: Ekin Yayınevi.

Chang, P., Hwang, S., Lee, H. and Huang, D.(2007). Development of an External-Type Microinjection Molding Module for Thermoplastic Polymer. Journal of Materials Processing Technology, 184(1-3), 163-172.

Changyu, S., Lixia, W. and Qian, L.(2007). Optimization of Injection Molding Process Parameters Using Combination of Artificial Neural Network and Genetic Algorithm Method. Journal of Materials Processing Technology, 183(1), 412-418.

Elmas, Ç.(2011). Yapay Zeka Uygulamaları, Seçkin yayınevi, Ankara.

Haykın, S.(1999). Neural Networks: A Comprehensive Foundation, New Jersey.

Karataş, Ç., Sözen, A., Arcaklıoğlu and E., Ergüney, S.(2007). Modelling of Yield Length in The Mould of Commercial Plastics Using Artificial Neural Networks. Materials and Design, 28(1), 278-286.

Kaynar, O.,Taştan, S. and Demirkoparan, F.(2010). "Ham Petrol Fiyatlarının Yapay Sinir Ağları ile Tahmini", Ege Academic Review, 10(2), 575-596.

Kim, K. B. and Kim, C. K.(2004). "Performance Improvement of RBF Network Using ART2 Algorithm and Fuzzy Logic System" , Australia Conference on Artificial Intelligence.

Kuo-Ming T. and Hao-Jhih L.(2015). "Comparison of Injection Molding Process Windows for Plastic Lens Established By Artificial Neural Network and Response Surface Methodology", International Journal of Advanced Manufacturing Technology, 77(9), 1599-1611.

Lau, H.C.W., Wong, T.T. and Pun, K.F. (1999). Neural-Fuzzy Modeling of Plastic Injection Molding Machine for Intelligent Control. Expert System with Applications, 17(1), 33–43.

Lippmann, R. P.(1987). An Introduction to Computing with Neural Nets, IEEE ASSP Magazine, 4(2), 4-22.

Öktem, H., Erzurumlu, T. and Erzincanlı, F.(2006). Prediction of Minimum Surface Roughness in End Milling Mold Parts Using Neural Network and Genetic Algorithm. Materials and Design, 27(1), 735-744.

Özek ,C. and Çelik, Y. H.(2011). Plastik Enjeksiyon Kalıplarında Enjeksiyon Sürelerinin Yapay Sinir Ağları ile Modellenmesi. Fırat Üniv. Mühendislik Bilimleri Dergisi, 23(1), 35-42.

Öztemel, E.(2003). Yapay Sinir Ağları, Papatya Yayıncılık, İstanbul.

Rewal,N. and Toncich,D.(1998). Predicting Part Quality In Injection Molding Using Artificial Neural Networks. Journal of Injection Molding Technology, 4(2), 109-119.

Sadeghi, B.H.M.(2000). A BP- Neural Network Predictor Model for Plastic Injection Molding Process. Journal of Materials Processing Technology,103(3), 411–416.

Tso GK and Yau KK.(2007). "Predicting Electricity Energy Consumption: A Comparision of Regression Analysis, Decision Tree and Neural Networks", Energy, 32(9), 1761-1768.

Womack, P.J., Daniel J.,T. and Ross, D.(1990). Dünyayı Değiştiren Makine, Çeviri Osman Kabak. İstanbul: Panel Matbaacılık.

Zhu, J. and Chen, J.C.(2006). Fuzzy Neural Network Based in Process Mixed Material Caused Flash Prediction (FNN-IPMFP) in Injection Molding Operations. International Journal of Advanced Manufacturing Technology, 29(1), 308-316.

Appendixes

App 1. Determining the Most Appropriate MLP Model

Hidden Layer Neurons Number	R	R^2	MSE	RMSE	MAE
1	0,8532	0,7280	7,8275	2,7978	2,0012
2	0,8562	0,7331	7,7500	2,7839	1,9204
3	0,8497	0,7220	8,0761	2,8419	2,2266
4	0,8546	0,7304	7,6992	2,7747	2,0287
5	0,8527	0,7270	8,1588	2,8564	2,3534
6	0,8325	0,6931	8,7674	2,9610	2,4162
7	0,8354	0,6978	8,6475	2,9407	2,1481
8	0,8505	0,7233	9,2089	3,0346	2,3858
9	0,8366	0,6998	8,5773	2,9287	2,2066
10	0,8688	0,7549	7,3021	2,7053	2,1215
11	0,8024	0,6439	10,2615	3,2034	2,5273
12	0,8126	0,6603	10,9568	3,3101	2,7907
13	0,8455	0,7148	8,4040	2,8990	2,2431
14	0,8210	0,6740	9,9539	3,1550	2,7632
15	0,8198	0,6721	10,2984	3,2091	2,6622
16	0,8138	0,6623	10,8372	3,2920	2,7283
17	0,8042	0,6468	10,2487	3,2014	2,5657
18	0,7909	0,6255	11,3112	3,3632	2,7468
19	0,8032	0,6451	11,0665	3,3266	2,9328
20	0,8132	0,6612	12,2284	3,4969	2,7786
21	0,8095	0,6553	11,8901	3,4482	2,6975
22	0,8165	0,6666	9,8235	3,1343	2,6293
23	0,8010	0,6416	11,2669	3,3566	2,6867
24	0,7899	0,6240	11,1468	3,3387	2,3877
25	0,7829	0,6129	11,7594	3,4292	2,6940
26	0,7376	0,5441	17,6229	4,1980	3,5541
27	0,7685	0,5906	14,6171	3,8232	3,2345
28	0,7155	0,5120	15,9091	3,9886	3,2660
29	0,8068	0,6509	10,2968	3,2089	2,6651
30	0,7231	0,5229	15,5896	3,9484	3,2965
31	0,7454	0,5556	14,0067	3,7426	3,0577
32	0,7998	0,6397	13,7264	3,7049	3,0690
33	0,7956	0,6330	12,9592	3,5999	3,3047
34	0,7602	0,5779	15,4935	3,9362	3,2383
35	0,6755	0,4563	18,2181	4,2683	3,4603
36	0,7449	0,5548	14,5766	3,8179	3,2552
37	0,7684	0,5904	13,8562	3,7224	3,0509
38	0,7392	0,5463	18,0386	4,2472	3,6326
39	0,4894	0,2396	26,5439	5,1521	4,2567
40	0,6008	0,3610	27,0933	5,2051	4,3843
41	0,6750	0,4556	18,1257	4,2574	3,5739
42	0,6827	0,4661	17,0325	4,1270	3,5823
43	0,7348	0,5399	20,5398	4,5321	3,5720
44	0,5837	0,3408	24,8558	4,9856	4,0338

Alphanumeric Journal

The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
htttp://www.alphanumericjournal.com/

Hidden Layer Neurons Number	R	R²	MSE	RMSE	MAE
45	0,6382	0,4074	20,3158	4,5073	3,4869
46	0,5818	0,3385	22,8085	4,7758	3,8513
47	0,5075	0,2576	25,8248	5,0818	4,2802
48	0,5713	0,3263	27,4861	5,2427	4,3890
49	0,6075	0,3691	36,9688	6,0802	5,0571
50	0,6175	0,3814	25,1545	5,0154	4,5201

AS	Hidden Layer Neurons Number	R	R²	MSE	RMSE	MAE
S=10000000	50	0,7170	0,5141	13,7110	3,7028	2,9994
	100	0,7699	0,5927	11,7919	3,4339	2,8904
	150	0,7821	0,6117	10,5994	3,2557	2,6208
	200	0,7807	0,6095	10,5104	3,2420	2,9511
	250	0,7995	0,6392	10,0213	3,1656	2,8252

AS : Appropriate Spread

App 2. Determining the Most Appropriate RBFN Model

AS	Hidden Layer Neurons Number	R	R²	MSE	RMSE	MAE
S=1	50	0,7989	0,6383	9,9855	3,1600	2,4433
	100	0,8233	0,6777	8,9138	2,9856	2,1982
	150	0,8400	0,7056	8,2819	2,8778	2,0698
	200	0,8474	0,7180	8,2065	2,8647	2,0548
	250	0,8199	0,6722	8,8600	2,9766	2,3080
S=10	50	0,8513	0,7247	8,0936	2,8449	2,1575
	100	0,8297	0,6884	9,0348	3,0058	2,2965
	150	0,8585	0,7370	7,3859	2,7177	2,1195
	200	0,8500	0,7226	7,8544	2,8026	2,4648
	250	0,8415	0,7082	7,7320	2,7806	2,1574
S=100	50	0,8426	0,7100	7,8360	2,7993	2,2717
	100	0,8204	0,6731	9,3284	3,0542	2,1022
	150	0,8254	0,6814	9,5250	3,0863	2,2380
	200	0,8189	0,6706	8,6790	2,9460	2,3971
	250	0,8536	0,7287	7,1610	2,6760	2,2451
S=1000	50	0,8278	0,6853	8,8174	2,9694	2,4387
	100	0,8473	0,7178	8,1686	2,8581	2,1210
	150	0,8485	0,7200	7,4002	2,7203	2,5174
	200	0,8239	0,6789	9,7657	3,1250	2,3966
	250	0,7920	0,6273	10,2602	3,2032	2,6689
S=10000	50	0,7912	0,6260	10,4473	3,2322	2,8650
	100	0,8248	0,6803	10,0047	3,1630	2,9858
	150	0,8055	0,6489	9,7022	3,1148	2,4976
	200	0,8252	0,6810	8,9947	2,9991	2,3007
	250	0,7815	0,6107	10,9942	3,3158	2,8167
S=100000	50	0,7771	0,6039	10,6460	3,2628	2,7007
	100	0,8264	0,6829	9,4598	3,0757	2,5181
	150	0,7885	0,6218	12,5899	3,5482	2,6120
	200	0,7625	0,5814	11,6205	3,4089	2,5253
	250	0,7903	0,6245	10,4660	3,2351	2,5672
S=1000000	50	0,8062	0,6500	9,8731	3,1421	2,6242
	100	0,8459	0,7155	8,6097	2,9342	2,5241
	150	0,7789	0,6066	10,7940	3,2854	2,7113
	200	0,7531	0,5672	11,7469	3,4274	2,9254
	250	0,8163	0,6663	12,8995	3,5916	3,0020

Alphanumeric Journal
The Journal of Operations Research, Statistics, Econometrics and Management Information Systems
ISSN 2148-2225
htttt://www.alphanumericjournal.com/