Scientific Research and Essays Vol. 5 (11), pp. 1274-1283, 4 June, 2010
Available online at http://www.academicjournals.org/SRE
ISSN 1992-2248 © 2010 Academic Journals

Full Length Research Paper

The use of artificial neural network for prediction of grain size of 17-4 pH stainless steel powders

Tayfun Fındık[1], Şakir Taşdemir[2*] and İsmail Şahin[1]

[1]Faculty of Technology, Gazi University, 06500 Ankara, Turkey.
[2]Technical Science College, Selcuk University, Campus, 42075, Konya, Turkey.

Accepted 16 March, 2010

This study is aimed to deals with artificial neural network (ANN) approach for prediction grain size (GS) of 17 - 4 pH stainless steel powders. Experimental data which were obtained from experimental studies in a laboratory environment have been used for this modeling. Using some of the experimental data for training and testing an ANN for GS was developed. In these systems, output parameters GS has been determined using input parameters including environment, time, speed, ball diameter, ball ratio, and material. When experimental data and results obtained from ANN were compared by regression analysis in Matlab, it was determined that both groups of data are consistent. The correlation coefficient between estimated GS values and experimental data obtained are 0.99 for traing and 0.98 for testing respectively. The correlation coefficient is closely to 1. This coefficient shows that there is a strong relationship between these data. Also, the accuracy rate was 98.97% for GS. As a result, it has been shown that designed ANN can be used reliably in powder metallurgic industry and engineering.

Keywords*:* Artificial neural network, mechanical milling, garin size.

INTRODUCTION

One of the problems encountered in modern technology is to obtain some of the metal alloys. For instance, it is very difficult to get an alloy by mixing a low melting and a high melting point metals through traditional alloying techniques. Although, the two metals that have these aspects help in the making of liquid solution, while they are solidifying, the component which is the lower melting point separated (Benjamin, 1988). In addition, though the new materials are harder, tougher and lighter than the materials produced by means of traditional techniques, there is a demand for the designing and development of the new materials (Suryanarayana, 2001). These demands have led to the improvement of a new tech-niques in the recent years. One of these techniques is Mechanical Alloying (MA). With this method, it is possible to produce new alloys that are impossible to be produced with traditional methods. MA is a powder proccessing technique. By using this technique, homo-genous materials from the element powder mixture is obtained. This technique was developed by John Benjamin and his fellows Paul D. Menica Research Laboratory of the Inter-national Nickel Company (NCO) in 1966. Here, with the help of the heat resistance and the mixture of the oxide dispersal and the resistance of high heat, the Ni-based super alloys were produced. These alloys with their corrosion resistance were suitable in the making of gas tribune engines (Benjamin, 1976; Benjamin, 1989; Benjamin, 1990). MA is high energetical and dry ball milling method which is used for interesting and com-mercial materials. After ball milling of Ni–Nb system in 1983 and Y–Co intermetalic in 1981, the method has been termed as unstable milling technique (Ermakov, 1981; Koch et al., 1983). In mechanical alloying/milling process, various mills are used. These mills have various sizes and one can select one of them according to their needs.

For this type of experimental work, experts and special

*Corresponding author. E-mail address: stasdemir@selcuk.edu.tr. Tel: +90 332 2232380 fax: +90 332 2410185.

Table 1. Chemical compositions of 17-4 precipitate hardened stainless steel powders.

	Cr	Ni	Cu	Nb	Si	C(ppm)	Balance
Gas atomized (p101)	15.4	4.7	3.2	0.02	0.4	23	Fe
Water atomized (p104)	16.1	4.9	4.1	0.05	0.3	32	Fe

equipment are needed. Also, this type of work causes loss of cost, time and labour force. Artificial intelligence methods to eliminate the disadvantages and drawbacks of this type of methods can be used. Nowadays, computers are used in a wide variety of fields in engineering fields especially metallurgy sector. ANNs are information processing systems and since their inception, they have been used in several areas of engineering application. The researchers have used neural network techniques to develop prediction models for mechanical properties of materials. ANNs have been trained to solve non-linear and complex problems that are not exactly modeled mathematically.

ANNs eliminate the limitations of the classical approaches by extracting the desired infor-mation using the input data. Applying ANN to a system needs sufficient input and output data instead of a mathematical equation. Furthermore, it can continuously re-train for new data during in operation, thus, it can adapt to changing of the system (Dincer et al., 2008; Taşdemir et al., 2008; Kalogirou, 2003).

There have been many investigations with ANN in metallurgy, some are briefly mentioned below. Predictions of the process parameters of metal powder perform forging using artificial neural network (Ohdar and Pahsa, 2003), an artificial neural network model for toughness properties in microalloyed steel in consideration of industrial production conditions (Çöl et al., 2007), determination of residual stresses based on heat treatment conditions and densities on a hybrid (FLN2-4405) powder metallurgy steel using artificial neural network (Kafkas et al., 2006), a neural network approach for solution of the inverse problem for selection of powder metallurgy materials (Smith et al., 2002), a neural network approach for selection of powder metallurgy materials and process parameters (Cherian et al., 2000), analysis of stress ratio effects on fatigue propagation in a sintered duplex steel by experimentation and artificial neural network approaches (Iacoviello et al., 2004), mapping the input–output relationship in HSLA steels through expert neural network (Datta et al., 2006), prediction of the amount of PCA for mechanical milling (Zhang et al., 1999), application of artificial neural networks for modeling correlations in titanium alloys (Malinov and Sha, 2004), failure of carbon/epoxy composite tubes under combined axial and torsional loading 1. Experimental results and prediction of biaxial strength by the use of neural networks (Lee et al., 1999) are some examples were ANN is used.

The purpose of this article is to provide a methodology for predicting the GS. To acquire data for training and testing the proposed ANN as a mechanical alloying/ milling attritor was used. By using this attritor, optimum processing parameters such as milling time, milling speed, diameter and the amount of the milling balls, milling atmosphere and raw material properties were determined when mechanical milling of gas and water atomized 17 - 4 pH stainless steel powders. After milling, powder size analyses and microscopic studies were carried out for the characterization of received and milled powders. It was observed from the results of the present investigation that for 17 - 4 pH stainless steel powders, optimum properties were obtained for milling at 500 rpm in an inert atmosphere by using 250 g of 10 mm diameter balls. In the modeling, Experimental data, which were obtained from experimental studies, have been used. This study was aimed to deal with ANN approach for the prediction of GS.

EXPERIMENTAL PROCEDURE AND DATA

In this study, 17 - 4 precipitates hardened stainless steel powders that are produced with water and gas atomization were used for mechanical milling process. These powders were obtained from Mannessmann Demag GmbH Company in Germany. The chemical compositions of 17 - 4 precipitate hardened stainless steel powders are given in Table 1.

The Experimental study was performed by using mechanical alloying/milling mill (Figure 1). The devices show chamber mixing arms and a two-dimensional figure of mechanical alloying/milling system, respectively. This system was designed and constructed at the Laboratories of Technology Faculty of Gazi University. The mechanical alloying mill has a variator that has 50 Hz power of rounding. This variator also has control over the speed of mill and can stop the mill. The mill has a motor that include a power of 50 Hz and control the milling options. To determine the velocity of the shaft that turns around the milling arms, a digital photo tachometer with a capacity of 25 - 2500 rpm angular velocity was used. Alloying chamber and mixture arms were made of stainless steel and the cooling tank was made of cast aluminum. However, to prevent friction during running and the over-heat on milling chamber, a water input/output system between the milling chamber and the cooling tank was installed.

The alloying mill with a charge rate of 20:1 for balls and powders that are weighed in 1:1000 sensitive scales and this charge rate was kept fixed for all the experiments. After running the attritor, the balls and milling powders were put from the cover of cooling unit into the chamber and the mechanical milling process was started. The Experimental studies were carried out using six different parameter and their coded as A (Enviromental: Ar, Speed: 500 rpm, Ball diameter: 10 mm, Ball ratio: 250, Material: 17 - 4 pH gas atomized), B (Enviromental: Air, Speed: 500 rpm, Ball diameter: 10 mm, Ball ratio: 250, Material: 17 - 4 pH gas atomized), C (Enviromental: Ar, Speed: 500 rpm, Ball diameter: 10 mm, Ball ratio: 350, Material: 17 - 4 pH gas atomized), E (Enviromental: Ar, Speed: 500 rpm, Ball diameter: 12 mm, Ball ratio: 250, Material: 17- 4 pH gas atomized),

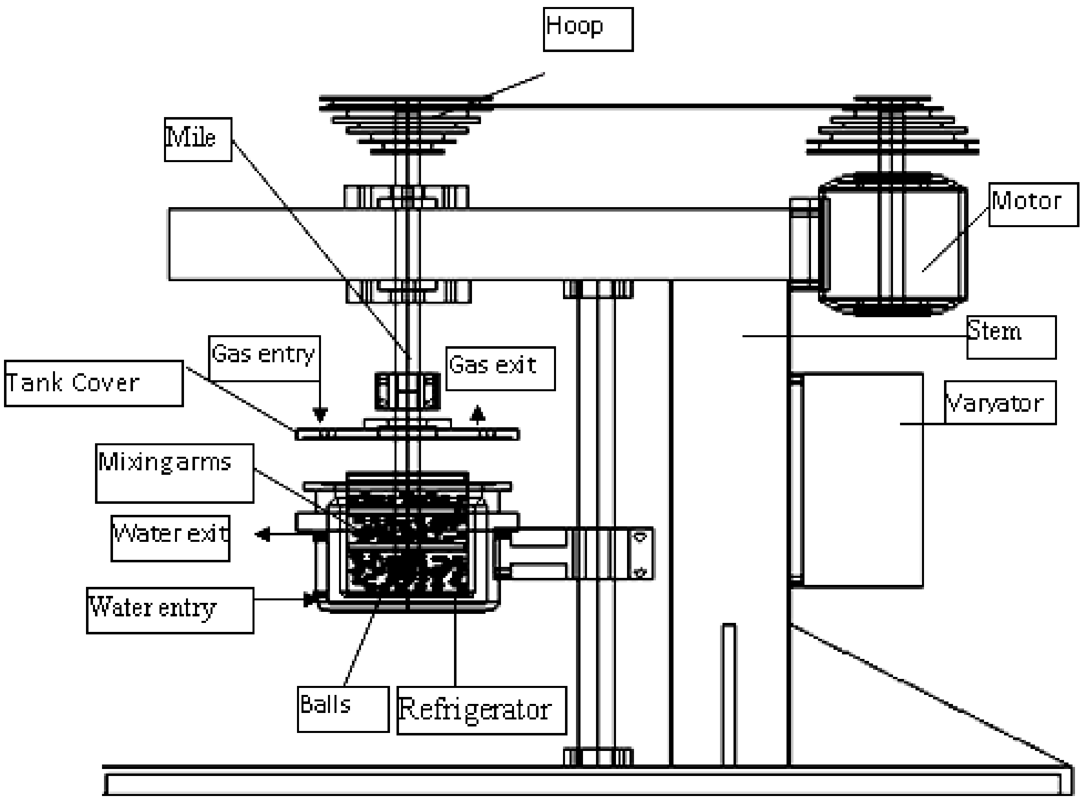

Figure 1. Two-dimensional schematic view of mechanical alloying/milling mill (Çetinkaya et al., 2006).

F (Enviromental: Ar, Speed: 500 rpm, Ball diameter: 10 mm, Ball ratio: 250, Material: 17-4 pH water atomized) and G (Enviromental: Ar, Speed: 750 rpm, Ball diameter: 10 mm, Ball ratio: 250, Material: 17 - 4 pH gas atomized) olarak kodlanmıştır. The time in all the parameters was changed to 5, 10, 15, 30, 45, 60 and 90 min. In this study, the data was (Çetinkaya et al., 2006) obtained from Experimental work.

THE APPLICATION OF ARTIFICIAL NEURAL NETWORK

ANN has been developed as a generalization of mathematical models of human cognition and neural biology. The available data set is partitioned into two parts, one corresponding to training, and the other corresponding to test of the model. The purpose of training is to determine the set of connection weights and nodal thresholds that cause the ANN to estimate outputs that are sufficiently close to target values. This fraction of the complete data to be employed for training should contain sufficient patterns so that the network can mimic the underlying relationship between input and output variables adequately (Satish and Pydi, 2005; Kalogirou, 2003; Menlik et al., 2009, Oguz et al., 2007).

There are many types of ANN architectures in the literature; however, a back-propagation multi-layer feed-forward network (MLN) is the most widely used for prediction and in engineering applications. A MLN typically has an input layer, an output layer, and one or more hidden layers. There are many ways to define the activation function, such as threshold function, step activation function, sigmoid function, and hyperbolic tangent function. The type of activation function depends on the type of neural network to be designed. A sigmoid function is widely used for the transfer function (Sozen et al., 2004; Dincer et al., 2008; Sencan, 2006; Scalabrin et al., 2006).

The training process continues until the network output matches the target, that is, the desired output. The calculated difference between these outputs and target outputs is called “error”. The error between the network output and the desired output is minimized by modifying the weights. When the error falls below a determined value, or the maximum number of epochs is exceeded, the training process is terminated. Then, this trained network can be used for simulating the system outputs for the inputs that have not been introduced before (Dincer et al., 2008; Taşdemir et al., 2008; Sencan, 2006).

The proposed ANN model was resolved by software developed using a Matlab. In this study, the data (Çetinkaya et al., 2006) is used obtained from Experimental work.

Each variable is min-max normalized within the range of 0 - 1 for ANN modeling. Since, the transfer functions generally modulate (Equation 1) the output to values between 0 and 1.

$$S_N = \frac{S - S_{\min}}{S_{\max} - S_{\min}} \tag{1}$$

Where, S_N is the normalized value of a variable S (real value in a parameter), S_{max} and S_{min} are the maximum and minimum values of S, respectively.

In this study, the ANN structure is three layers namely, inputs, outputs, and hidden layer.The input layer consists of six neurons; the output layer consists of one neuron, and the one hidden layer. Environment (Ar and air), time (min.), speed (rpm), ball diameter (mm), ball ratio (gr.) and material (stainless steel powder) were taken as the input parameters and the output parameter was taken

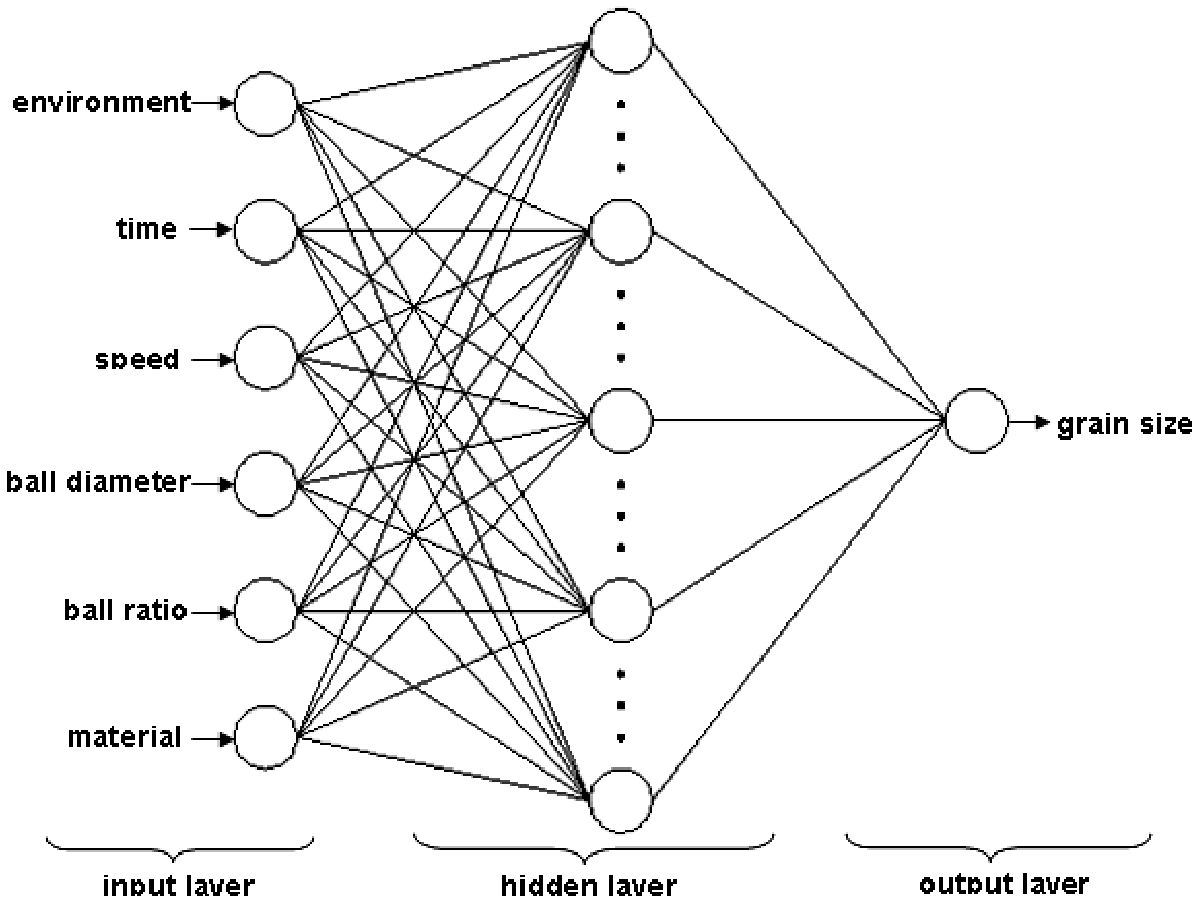

Figure 2. Developed ANN for prediction of GS.

as grain size (μm) in which an experiments were conducted in this study (Figure 2).

The ANN designed according to these parameters are shown in Figure 3. The back-propagation learning algorithm has been used in feed forward single hidden layers. The back-propagation algorithm has been implemented to calculate errors and adjust weights of the hidden layer neurons. Hyperbolic Tangent-Sigmoid transfer function was chosen in this study. (Equation 2 - 3).

$$NET_j = (W_1)_{i,1} * X_1 + (W_1)_{i,2} * X_2 + (W_1)_{i,3} * X_3 + (W_1)_{i,4} * X_4 + (W_1)_{i,5} * X_5 + (W_1)_{i,6} * X_6 + (W_b)_{i,7} * b \quad (2)$$

$$F_j = \frac{2}{1+\exp^{(-2 * NETj)}} - 1 \quad (3)$$

In the Equation 2, NETj is the sum of the multiplication products of the input parameters and their weights. The sub-scripts i and j are input and hidden neuron numbers, respectively.

Traingd is a network training function that updates weight and bias values according to gradient descent back-propagation. 78 data were obtained from experiments and 65 (83.33% of total data) of them were chosen for training, whereas, 13 (16.67% of total data) of them were chosen for the test data. They all are chosen randomly. Inputs and outputs are min-max normalized in the (0 - 1) range for ANN modeling by the operation given in Equation 1 in Matlab. Here, environment (X1), time (X2), speed (X3), ball diameter (X4), ball ratio (X5) and material (X6) are six input parameters. In ANN, 50 hidden neurons were used. Therefore, 50 equation parts ranging from NET1-NET50 and F1-F50 were used as sum and activation functions, respectively.

Neuron numbers in the hidden layer (from 10 - 80 neurons step by step) and epoch numbers (from 1000 - 5000 epochs step by step) were tested for different values. The most suitable neuron number for the hidden layer can be obtained by trying various networks. The training of the network is stopped when the tested values of MSE stop decreasing and begin to increase. The most suitable epoch number with mean square error (MSE-Equation 4) (Kalogirou, 2003, Oguz et al., 2007) of the ANN performance was determined. After these trials, a network of 6 - 50 - 1 neurons and 3000 epochs were chosen as it yielded the most appropriate result. Variation of the MSE with training and test epoch is 0.0074491.

$$MSE(\%) = \frac{1}{n}\sum_{i=1}^{n}(d_i - O_i)^2 \quad (4)$$

Here, di is targeted or real value, Oi is network output or predicted value and n is the output data number.

RESULTS AND DISCUSSIONS

When the results which are obtained from the experiment have been determined, there was no significant

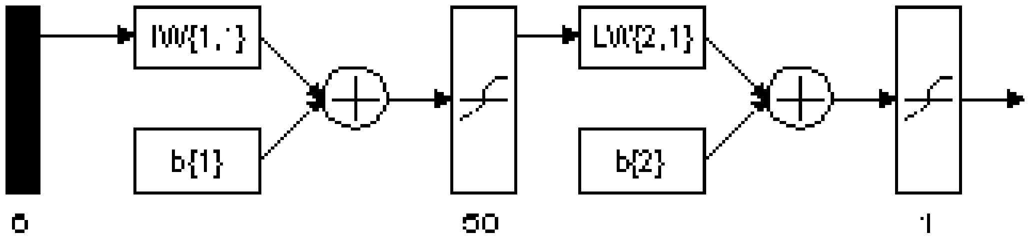

Figure 3. Designed model of ANN for present study.

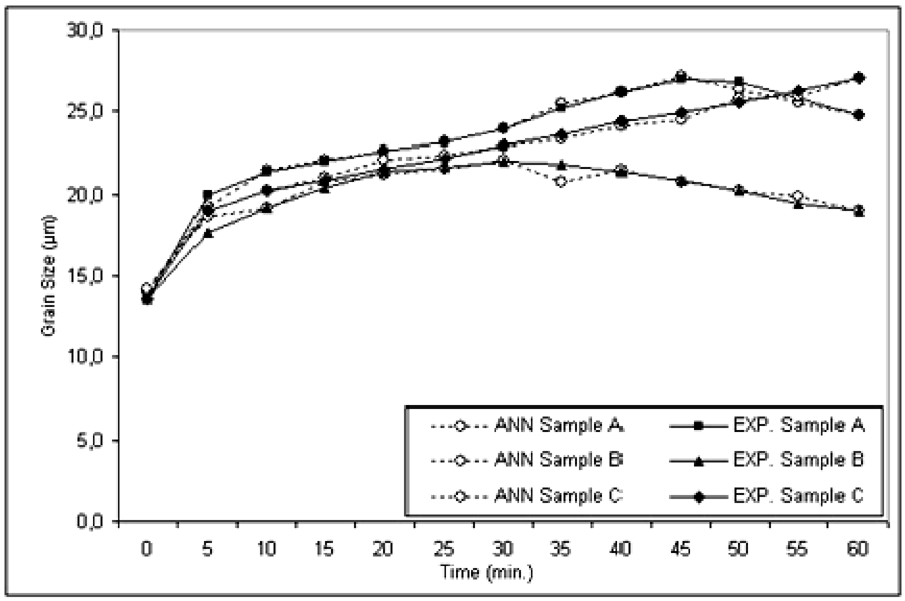

Figure 4. Comparison of experiment and ANN GS data change graphics.

difference between them. The comparison of ANN and Experimental (EXP.) results for GS are shown in Figure 4 - 5. The results of graphics comparisons showed the similarities between experimental study and ANN model and supported reliability of the model. The regression curve of the output variable (GS) for the experiment and ANN data set is in Figure 6-7 (training R =0.99747, testing R =0.97761). As the correlation coefficients get closer to 1, estimation accuracy increases. The estimation results and Exp. results are in a good agreement. The deviation between Exp. and ANN prediction value is very small and negligible for GS. Performed independent t-test for ANN training and test data analyzed one by one with experimental data. The same results were obtained by ANN model. Since $p > 0.05$ (Table 2) as the result of the statistical analysis done in the 95% confidence interval between data obtained from experiments and ANN model, the reliability of the ANN model was proven. According to results of performed t-tests, there is no difference between experimental data and the one obtained from ANN.

Moreover, the GS values which are not carried out in the experiment are applied to ANN to obtain intermediate values. First, environment, time, speed, ball diameter, and material are fixed and ball ratio is changed (300 gr.) and GS results are obtained (Figure 8). Then, Environment, time, speed, ball ratio and material are fixed and ball diameter is changed (8 mm - 11 mm) and GS results are obtained (Figure 9). Finally, environment, time, ball ratio, ball diameter, and material are fixed and speed is changed (600 rpm) and GS results are obtained (Figure 10). As seen from the graphics, intermediate values which are not performed on the experiment set, but obtained from the designed system are fitting with the experimental results, the results of GS estimated by ANN were compared with experimental data. And their accuracy was tested as a percentage by using mean relative percentage error (MRE-Equation 5), (Sayın et al., 2007). Mean percentage accuracy is 98.97% for ANN. It was observed that the estimated GS values were close to real

Table 2. SPSS statistical analysis result (t-test for equality of means of ANN training and testing output).

	Training			Testing		
	t	df	Sig.(p)	t	df	Sig. (p)
Grain Size	0.66	76	0.985	-0.19	76	0.947

* P>0.05.

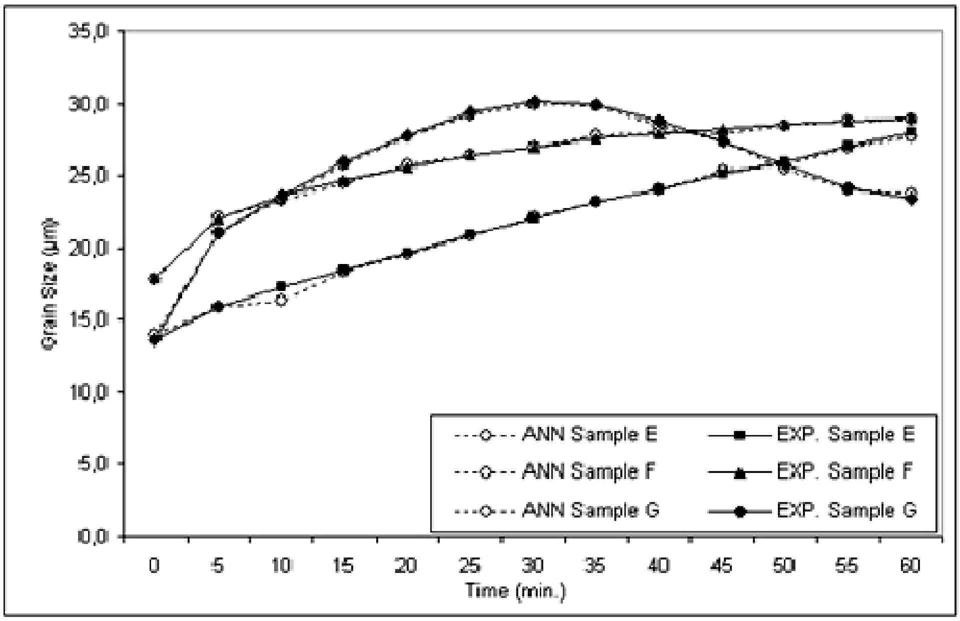

Figure 5. Comparison of experiment and ANN GS data change graphics.

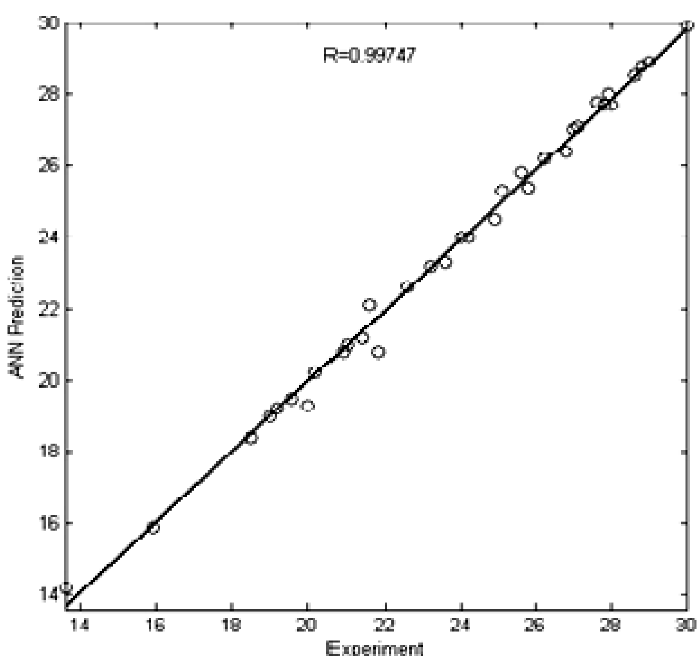

Figure 6. The relationship between experimental results and ANN training predicted values.

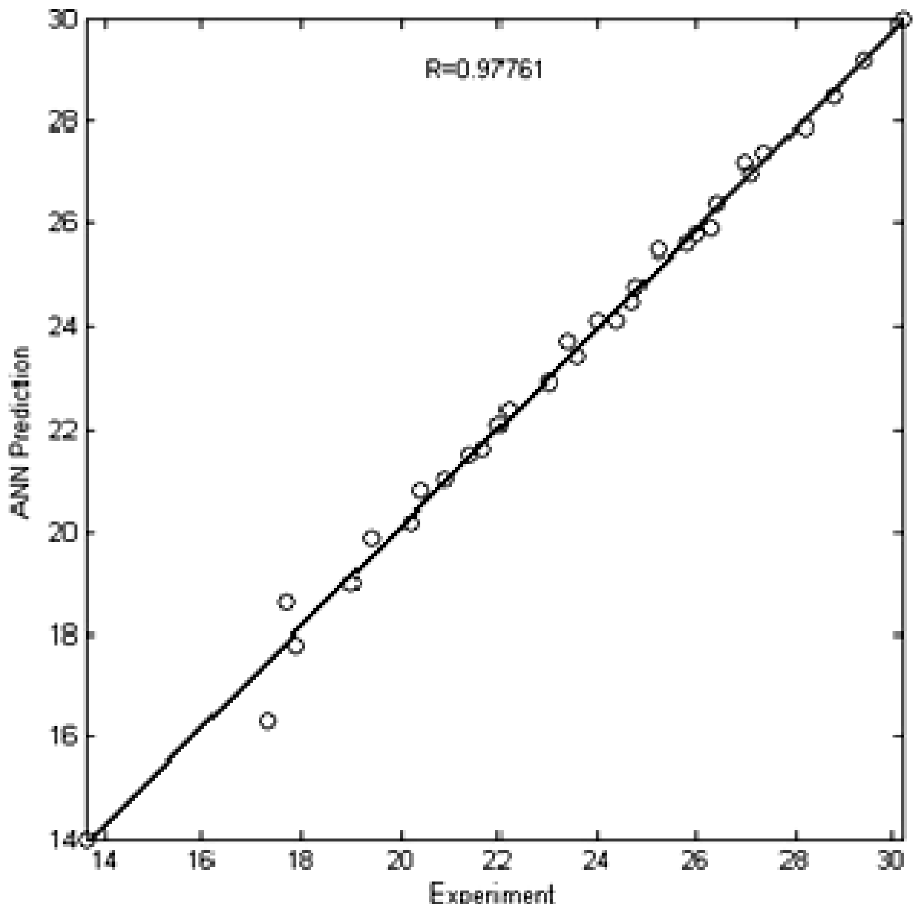

Figure 7. The Relationship between experimental results and ANN test predicted values.

value.

$$MRE(\%) = \frac{1}{n}\sum_{i=1}^{n}\left[100 * \frac{|d_i - O_i|}{d_i}\right] \quad (5)$$

Here, di is targeted or real value, Oi is network output or predicted value, and n is the output data number.

Conclusions

This paper presents an ANN application used for GS estimation of 17 - 4 pH Stainless Steel Powders in metallurgy industrial area. Finally, the ANN modeling has been applied to atritor for prediction GS. The results of this investigation show that ANNs can effectively model. It is understood that, ANN can be used for modeling of GS. The biggest advantages of the ANN compared to classical methods are speed of calculations and capacity to learn from examples. Also, in order to calculate different parameters, mathematical formulations were derived from this model.

Experimental data were compared with result obtained from ANN and all data were analyzed statistically. When analysis's was assessed, value of results obtained from ANN was very close to the experimental results value and therefore, it was seen that the ANN's might be used safely. ANN as an alternative method can be used to estimate the grain size. The values of experimental work that did not use was performed this developed system and interval values had been obtained. Experiments that have not been done in model input parameter values between applied values were obtained. In this way, predictive results were obtained without the experiment mechanism set up. Therefore, time, material, and money can be saved. With this approach that was seen, gives results about to try. As seen from the results, the ANN approach has sufficient accuracy rate for the estimation of GS.

Moreover, quite close results to GS results can been obtained by either increasing number of input, output parameters or including other artificial intelligence techniques such as genetics algorithms, fuzzy logic. The experimental data and the developed system analyses showed that ANN reduces disadvantages such as time, material, and economical losses to a minimum.

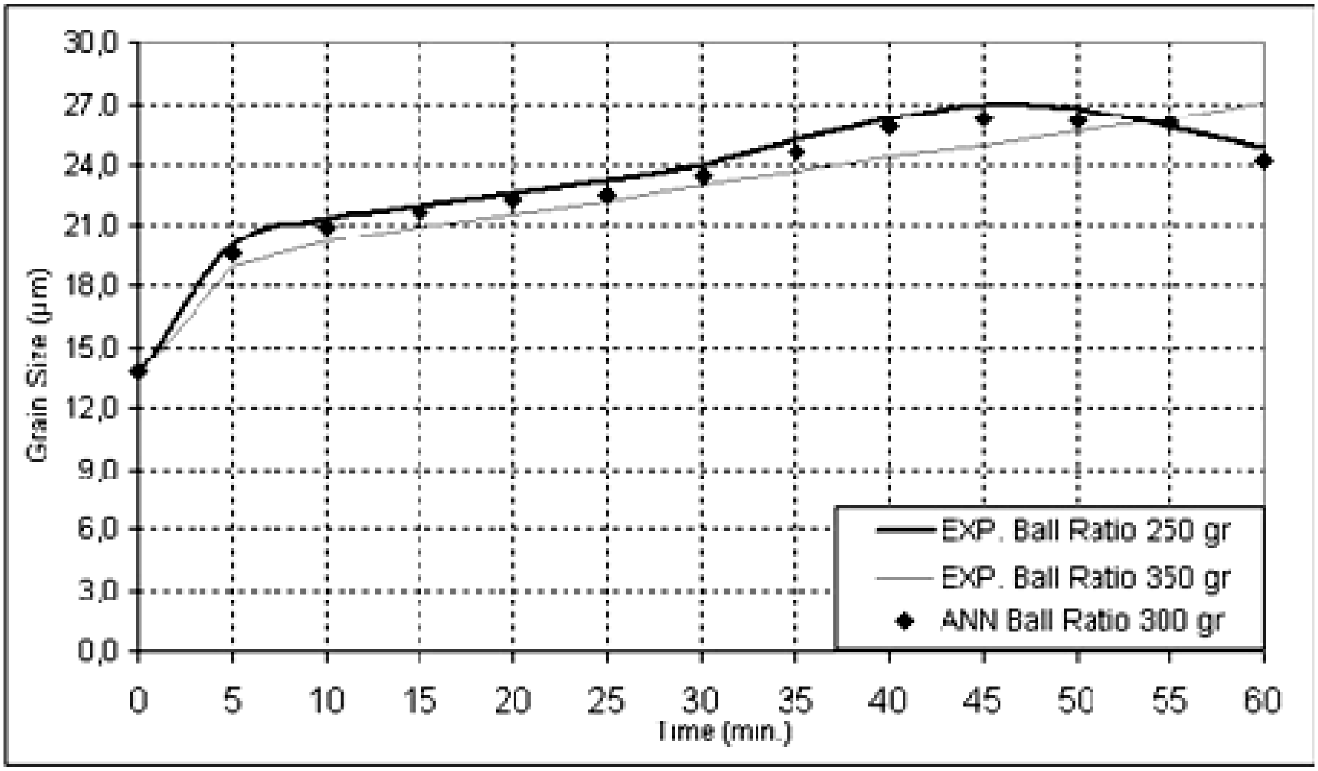

Figure 8. Predicted results of ANN that unperformed experiment work which is ball ratio.

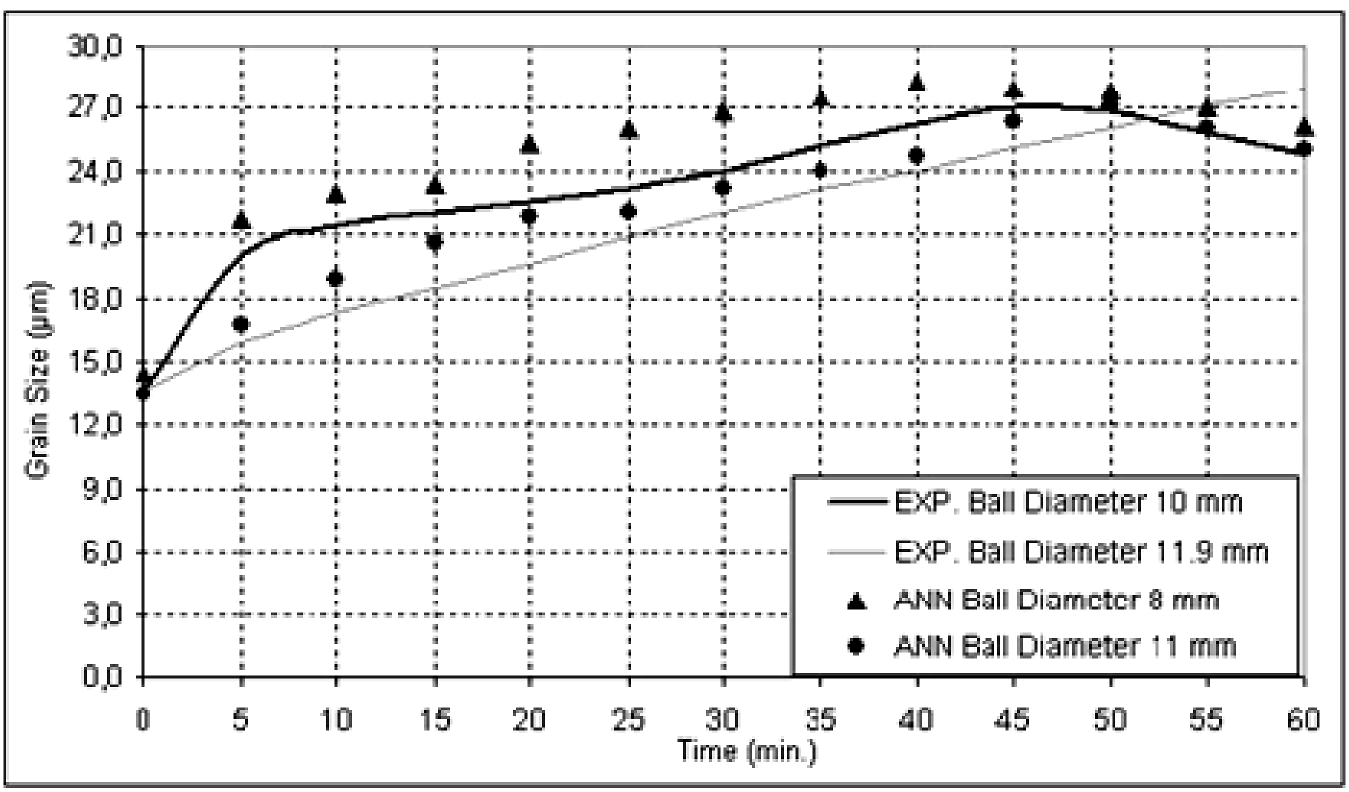

Figure 9. Predicted results of ANN that unperformed experimental work which is ball diameter.

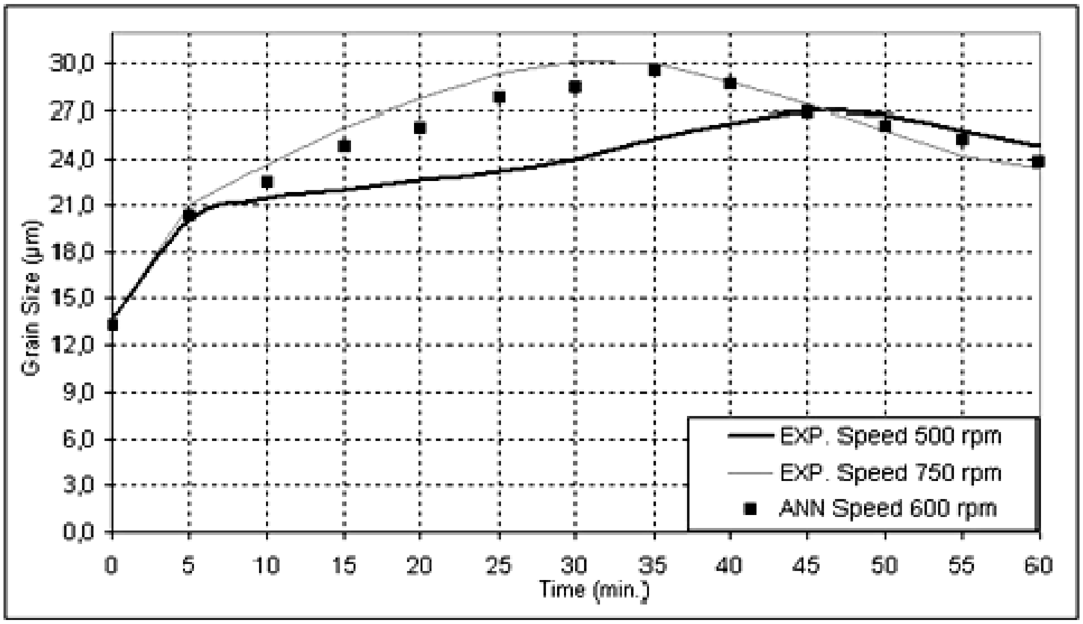

Figure 10. Predicted results of ANN that unperformed experimental work which is speed.

REFERENCES

Benjamin JS (1976). Mechanical alloying. Sci. Am. 234(5): 40-48.

Benjamin JS (1988). In: Mechanical alloying. A perspective, Proceedings conference of new materials by MA Technigues E D. By E. Arzt and L. Shultz, alw-Hirasu. pp. 3-7.

Benjamin JS (1989). In: Arzt E, Schultz L, editors. New materials by mechanical alloying techniques. Oberursel, Germany: DGM Informationgesellschaft. pp. 3-18.

Benjamin JS (1990). Mechanical Alloying-A Perspective. Metal Powder Report., 45(2): 122-127.

Çetinkaya C, Fındık T, Özbilen S (2006). An Investigation Into The Effect of Experimental Parameters on Powder GS of The Mechanically Milled 17-4 Ph Stainless Steel Powders. Materials & Design., 28: 773-782.

Cherian RP, Smith LN, Midha PS (2000). A neural network approach for selection of powder metallurgy materials and process parameters. Artificial Intelligence Eng., 14: 39-44.

Çöl M, Ertunc HM, Yılmaz M (2007). An artificial neural network model for toughness properties in microalloyed steel in consideration of industrial production conditions. Mater. Design., 28: 488-495.

Datta S, Banerjee MK (2006). Mapping the input–output relationship in HSLA steels through expert neural network. Mater. Sci. Eng., 20: 254-264

Dincer K, Tasdemir S, Baskaya S, Uysal BZ (2008). Modeling of the effects of length to diameter ratio and nozzle number on the performance of counterflow Ranque–Hilsch vortex tubes using artificial neural Networks, Appl. Therm. Eng., 28: 2380-2390.

Dincer K, Taşdemir Ş, Başkaya Ş, Uysal BZ (2008). Modeling of the Effects of Plug Tip Angle on the Performance of Counter-Flow Ranque-Hilsch Vortex Tubes Using Artificial Neural Networks. J. Therm. Sci. Technol., 29: 1-7.

Ermakov AE (1981). Yurchikov E. E, Barinov V. A. Phys. Met. Metallogr. 52(6): 50-58.

Iacoviello F, Iacoviello D, Cavallini M (2004). Analysis of stress ratio effects on fatigue propagation in a sintered duplex steel by experimentation and artificial neural network approaches. Int. J. Fatigue, 26: 819-828.

Kafkas F, Karataş Ç, Sozen A, Arcaklioglu E, Saritas S (2006). Determination of residual stresses based on heat treatment conditions and densities on a hybrid (FLN2-4405) powder metallurgy steel using artificial neural network. Mater. Design. 28: 2431-2442.

Kalogirou SA (2003). Artificial intelligence for the modeling and control of combustion processes: A review. Progress in Energy and Combustion Sci., 29 (6): 515-566.

Koch CC, Cavin OB, McKamey CG, Scarbrough JO (1983). Preparation of ``amorphous'' $Ni_{60}Nb_{40}$ by mechanical alloying. Appl. Phys. Lett., 43: 1017-1019.

Lee CS, Hwang W, Park HC, Han KS (1999). Failure of carbon/epoxy composite tubes under combined axial and torsional loading 1. Experimental results and prediction of biaxial strength by the use of neural Networks. Composites Sci. Technol., 59: 1779-1788.

Malinov S, Sha W (2004). Application of artificial neural networks for modeling correlations in titanium alloys. Mater. Sci. Eng., 365: 202-211.

Menlik T, Kırmacı V, Usta H (2009). Modeling of Freeze Drying Behaviors of Strawberries by Using Artificial Neural Network. J. Therm. Sci. Technol., 29: 11-21.

Oguz H, Sarıtas I, Baydan HE, Prediction of Diesel Engine Performance Using Biofuels with Artificial Neural Network, Expert System with Application, Article in Press.

Ohdar RK, Pahsa S (2003). Prediction of the process parameters of metal powder preform forging using artificial neural network (ANN). J. Mater. Processing Technol., 132: 227-234.

Satish S., Pydi SY (2005). Modeling of a continuous fluidized bed dryer using artificial neural Networks, Int. Commun. Heat Mass Transf., 32: 539-547.

Sayin C, Ertunc HM, Hosoz M, Kilicaslan İ, Canakci M (2007). Performance and exhaust emissions of a gasoline engine using artificial neural network. Appl. Therm. Eng., 27(1): 46-54.

Scalabrin G., Condosta M, Marchi P (2006). Mixtures flow boiling: modeling heat transfer through artificial neural Networks. Int. J. Therm. Sci., 45(7): 664-680.

Sencan A (2006). Artificial intelligent methods for thermodynamic evaluation of ammonia–water refrigeration systems. Energy Conversion and Manage., 47: 3319-3332.

Smith LN, German RM, Smith ML (2002). A neural network approach for solution of the inverse problem for selection of powder metallurgy materials. J. Mater. Processing Technol., 20: 419-425.

Sozen A, Arcaklioğlu E, Erisen A, Akçayol MA (2004). Performance prediction of a vapour-compression heat-pump. Appl. Energy, 79(3): 327-344.

Suryanarayana C (2001). Mechanical alloying and milling. Progress in Mater. Sci., 46: 1-184.
Taşdemir Ş, Neşeli S. Sarıtaş, İ., Yaldız S (2008). Prediction of surface roughness using artificial neural network in Lathe. CompSysTech'08: International Conference on Computer Systems, Bulgaria, IIIB.6-1-IIIB.6-8.
Zhang YF, Lu L, Yap SM (1999). Prediction of the amount of PCA for mechanical milling. J. Mater. Processing Technol., 89-90: 260-265.