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Optimization of heat treatment process parameters using neural networks and Nelder-Mead algorithm

T. CAKAR, F. KESKINKILIC[a], R. KOKER[b]
Sakarya University, Engineering Faculty, Industrial Engineering Department, 54187 Esentepe Campus Sakarya,Turkey
[a]Ahi Evran University, Mucur Technical Vocational Schools Of Higher Education Mucur Kirsehir,Turkey
[b]Sakarya University, Faculty Of Technology, Electrical And Electronics Department, 54187 Esentepe Campus, Sakarya / Turkey

Metallurgical processes consist of different and complex production operations. One of them is heat treatment. Hardness value is an important response variable for heat treatment process. Heat treatment parameters and interactions between each other are not known clearly. Hence it is hard to define convenient parameters for requested hardness value. In this study, effects of heat treatment parameters on hardness are modelled using back propagation artificial neural network (BPANN) model. BPANN is used to formulate a fitness function for predicting the value of the response based on the parameter settings and then Nelder-Mead algorithm takes the fitness function from the trained network to search for the optimal heat treatment parameters (furnace heat and heat treatment time) combination.

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1. Introduction

High quality and cheap parts are always preferred by costumer. This situation is result of the increasing competition. There are some uncontrollable parameters in heat treatment process because of using different raw material in casting process. Trial-and-error technic has been used for investigate to optimization of materials processing for a long time [1]. Thus increases cost and makes products less qualified. According to Lahoucine-Abaih et al. [2] the most important control factors for the mechanical properties are the chemical composition and the tempering treatment after the quenching.

In this study, Back Propagation Artificial Neural Network (BPANN) model is used for determining the effects of heat treatment parameters on hardness. Modelling and also prediction specialty of BPANN is used for increasing casting parts quality and decreasing manufacturing costs. BPANN trained with heat treatment parameters that determined as input and hardness value that determined output. BPANN is used to formulate a fitness function for predicting the value of the response based on the parameter settings and then Nelder-Mead algorithm takes the fitness function from the trained network to search for the optimal heat treatment parameters (furnace heat and heat treatment time) combination. This study is applied in a casting factory that produces casting grinding media for the cement and mining industries.

The flexibility and simplicity of neural networks have made them a popular modelling and forecasting tool across different research areas in recent years. A variety of neural network models have been developed, among which the back-propagation (BP) network is the most widely adopted in the present study. According to Song and Zhang [1] an artificial neural network can be applied very well to model the effects of the heat treatment technique on mechanical properties.

2. Building the neural network model and optimization

The use of artificial neural networks has become popular. Material properties such as hardness, tensile strength, fatigue, and yield strength are a complex function of many parameters such as alloying elements and heat treatment conditions and developing theoretical models that can quantitatively predict these parameters is not a straightforward task [3]. The artificial neural networks are one of the most powerful modelling techniques with very quick return for the practice [4].

In this study the reasons of using neural network are;

- Complex problems can be easily modelled
- Does not need any prior knowledge. Appropriate samples are enough for the model
- Neural networks can be applied to problems that do not have algorithmic solutions or algorithmic solutions that are too complex to be found [5].
- Applications of artificial neural networks are the cheapest in terms of costs and they are the most efficient in terms of time [6].

Complicated and non-linear complex relationships between outputs and inputs can be modelled and provided sufficient reliable data is available for training by BPANN.

2.1. Dataset and Input/output Parameters

The neural relationships would be very useful to industries for designing their experiments, an eventually their alloy [7]. To develop a neural network with good performance, there needs to be an adequate quantity of experimental data available [8]. In this study 130 parameters used for BPANN model. In order to modelling heat treatment process 110 operation parameters have taken for learning 20 parameters picked randomly for testing. Experts opinion literal review were choosing heat treatment process parameters [5][9]. All data sets were normalized to a -1:1 range for computation.

Table 1. Analyse of training and test sets.

	C%	Si%	Mn%	P%	S%	Cr%	T	C^o	HRC
Min	2,20	0,50	0,70	0,01	0,01	16,00	338,00	956,00	55,00
Max	2,60	1,00	1,00	0,05	0,05	17,99	358,00	990,00	65,00
Mean	2,42	0,68	0,88	0,03	0,03	16,75	348,33	973,57	59,14
Std. D.	0,12	0,15	0,09	0,01	0,01	0,65	5,24	11,16	3,47

Chemical properties of balls percentages of Carbon (C %), percentages of Silisium (Si %), percentages of Manganese (Mn %), percentages of Phosphors (P %), percentages of Sulphur (S %), percentages of Chrome (Cr %) are determined as input parameter for BPANN. Heat treatment process time (T) and furnace heat (C^o) are determined as input parameter for BPANN as well. Measured hardness value in Rockwell (HRC), after heat treatment determined as output for the model[10].

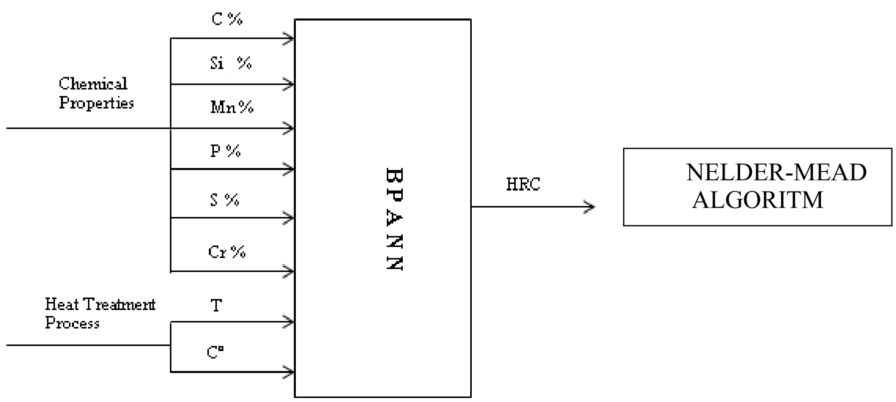

Fig. 1. Schematic model of Back Propagation Artificial Neural Network and Solution System

2.2. Neural Network Training

Before the determination of this architecture of BPANN model many different of experiments has performed. Fig. 2 shows the determined back propagation neural network model architecture. BPANN has 8 neurons on input layer and two hidden layers one of them has 6 neurons and the other has 4 neurons. There is one neuron on output layer. The architecture was chosen as a result of these experiments gives the closest results.

Artificial neural network model generated with Matlab R2010a. Neural network has reached desired performance value (Mean Square Error) in 525th iteration as shown Fig. 3. Artificial neural network training data is given below. Momentum rate (γ) and learning rate (α) obtained by simulation.

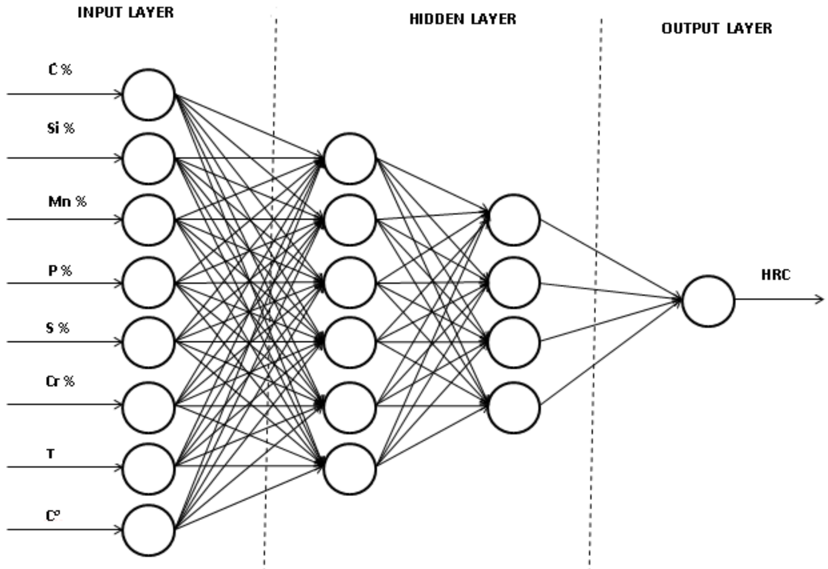

Fig. 2. The architecture of Back Propagation Artificial Neural Network.

MSE	10^{-4}		
α	0,05		
γ	0,8		
Transfer Functions	First Layer	Second Layer	Third Layer
	Hyperbolic Tangent Sigmoid	Hyperbolic Tangent Sigmoid	Hyperbolic Tangent Sigmoid

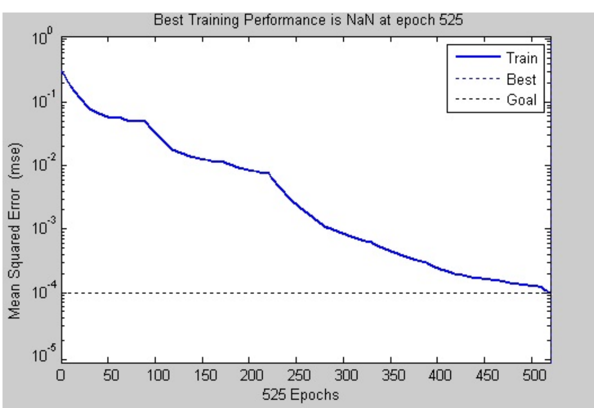

Fig. 3. Learning Curve

2.3. Nelder –Mead Algorithm

In this study Nelder–Mead Algorithm is used for optimization. This method first was introduced by Spendley et. al. in 1962 [11] and later in year 1965 Nelder and Mead expanded their method (Malek and Shekari Beidokhti ,2006)[12]. Nelder–Mead Algorithm is a direct search method that does not use numerical or analytic gradients. The MATLAB r2010 program built-in routine ‘‘fminsearch()” uses the Nelder–Mead algorithm to minimize a multivariable objective function. .

Nelder-Mead algorithm takes the fitness function from the trained network to search for the optimal heat treatment parameters (furnace heat and heat treatment time) combination.

According to factory experiments and customer's request 90 mm. diameters grinding ball hardness value determined as 64 HRC and Nelder-Mead Algorithm used for searching optimum parameters. Table 2 shows the parameters were used for Nelder –Mead Algorithm.

	C%	**Si%**	**Mn%**	**P%**	**S%**	**Cr%**	**T**	**C^o**	**HRC (required)**
	0.8002	-0.3243	0.4876	0.4543	-0.9123	0.3042	?	?	0.8
formulation	x1	x2	x3	x4	x5	x6	x7	x8	y_ysa

C%, Si%, Mn%, P%, S%, Cr% values comes from casting. For this parameter furnace heat (C^o) and heat treatment time (T) optimized by Nelder-Mead Algorithm and figure 4 shows the result.

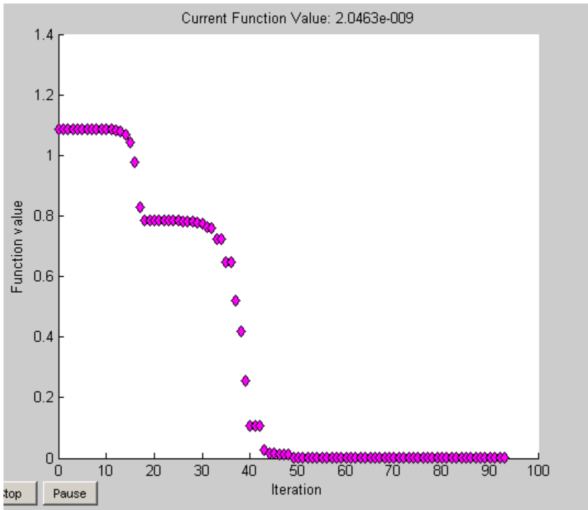

Fig. 4. Optimization Function Value Plot

Fitness function of trained BPANN model is designed as M File For Matlab R2010 is below.

```
function fitness1= neldermead1(v)

x1= 0.8002;
x2= -0.3243;
x3= 0.4876;
x4= 0.4543;
x5= -0.9123;
x6= 0.3042;
y_ysa = 0.8;
x7 = v(1)< 1 > -1 ;
x8 = v(2)< 1 > -1 ;

a1=-0.58485*x1+0.035466*x2+0.20587*x3-0.89896*x4+0.59904*x5+0.41987*x6+1.088*x7 0.21724*x8+1.878;
 B1 = 2 / (1 + 2.71828182846 ^ (-2 * a1)) - 1;
a2=0.31238*x1+0.83279*x2-0.73064*x3+0.30797*x4-0.59127*x5+0.26436*x6-0.74227*x7-0.63316*x8-1.1742;
 B2 = 2 / (1 + 2.71828182846 ^ (-2 * a2)) - 1;
a3=-0.070326*x1-0.49116*x2-1.0824*x3-0.12381*x4+0.12421*x5+0.63875*x6-0.68887*x7+0.84183*x8+0.53773;
B3 = 2 / (1 + 2.71828182846 ^ (-2 * a3)) - 1;
a4=-0.26509*x1+0.79434*x2-0.090284*x3-0.86625*x4-0.60704*x5-0.030157*x6-0.041022*x7-1.2133*x8-0.21271;
B4 = 2 / (1 + 2.71828182846 ^ (-2 * a4)) - 1;
a5=0.66158*x1+0.43736*x2+0.59978*x3-0.33718*x4+0.14022*x5-0.8339*x6-0.96417*x7+0.59696*x8+1.0625;
 B5 = 2 / (1 + 2.71828182846 ^ (-2 * a5)) - 1;
a6=0.010804*x1-0.33588*x2+0.93053*x3-0.64992*x4-0.60707*x5-0.75099*x6-0.89232*x7+0.73777*x8+1.6353;
B6 = 2 / (1 + 2.71828182846 ^ (-2 * a6)) - 1;
c1 = 0.93723*B1+0.7665*B2-0.61156*B3+0.21256*B4+0.33913*B5-1.0644*B6-1.7561;
D1 = 2 / (1 + 2.71828182846 ^ (-2 * c1)) - 1;
c2 = -1.3156*B1-0.021737*B2-0.94637*B3+0.1057*B4-0.49716*B5-0.84176*B6+0.4679;
D2 = 2 / (1 + 2.71828182846 ^ (-2 * c2)) - 1;
c3 = -0.17678*B1+0.85063*B2-0.76109*B3-0.8328*B4+0.066926*B5-0.90953*B6-0.68646;
D3 = 2 / (1 + 2.71828182846 ^ (-2 * c3)) - 1;
c4 = -0.38197*B1-0.72463*B2+1.0987*B3+0.9584*B4-0.1934*B5-1.0225*B6-1.5855;
D4 = 2 / (1 + 2.71828182846 ^ (-2 * c4)) - 1;
e1 = (-0.26368*D1+0.49131*D2-0.38967*D3+1.1713*D4+0.69527);
 Y1 = 2 / (1 + 2.71828182846 ^ (-2 * e1)) - 1;
 fitness1 =  abs(Y1 - (y_ysa));
```

3. Conclusions

Back propagation artificial neural network model has shown good agreement with tested heat treatment model. Nelder-Mead Algorithm is used for optimization the parameters. The algorithm proposed here finds the approximate solution in a closed analytical form. Results are very useful for optimizing heat treatment parameters to fulfill a highly efficient output state. In this study BPANN use for just 90 mm diameters grinding ball heat treatment process. Results can be extended for other heat treatment parts.

References

[1] R.G. Song, Q.Z. Zhang, Journal of Material Processing Technology **117**, 84 (2001).

[2] L. Lahoucine-Abaih, A. Van Bennekom, M. Fathi, IEEE International Symposium on Industrial Electronics. 1-4244-0755 IEEE2007

[3] G. Sidhu, S. D. Bhole, D. L., Chen E. Essadiqi, Materials and Design **41**, 99 (2012).

[4] S. Malinov, W. Sha, Materials Science and Engineering **A365**, 202 (2004)

[5] G. Khalaj, H. Yoozbashizadeh, A. Khodabandeh, A. Nazari, Journal of Neural Comput & Applic. DOI 10.1007/s00521-011-0779-z, 2001.
[6] F. Keskinkilic, Analysis of parameters which effect casting product hardness with artificial neural networks and a case Study, M.Sc. Thesis. Kırıkkale University Graduate School of Natural and Applied Sciences Department of Industrial Engineering 2010.
[7] N. S. Reddy, J. Krishnaiah, Y. Kiran Kuma, N. N. Acharya, Proceedings of the 9th International Conference on Neural Information Processing (ICONIP'O2), Vol.. 2. 2002
[8] W. Sha, K.L. Edwards, Materials and Design **28**, 1747 (2007)
[9] L. Chang, L. Liu, J. H. Liu, Journal Of Iron And Steel Research, International., **14**(5): 47 (2007).
[10] F. Keskinkilic, T. Cakar,. The Modellıng Of Heat Treatment Process Parameters Usıng Neural Networks. Proceedings of 8th International Symposium on Intelligent and Manufacturing Systems. **27-28**, 714 (2012).
[11] W. Spendly, G. R. Hext, F. R. Himsworth, Sequential Application of Simplex Designs in Optimization and Evolutionary Operation, Technometrics, **4**., 441 (1962).
[12] A. Malek, R. Shekari Beidokhti, Applied Mathematics and Computation **183,** 260 (2006).

*Corresponding author: tcakar@sakarya.edu.tr