Investigation of Single and Dual Step Shot Peening Effects on Mechanical and Metallurgical Properties of 18CrNiMo7-6 Steel Using Artificial Neural Network

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***Abstract*—Shot peening is a process of cold working a part that increase its resistance to metal fatigue and some forms of stress corrosion. Shot peening causes plastic deformation in the surface of the peened part and leads some changes in mechanical and metallurgical properties of it. Artificial intelligence (AI) systems such as artificial neural networks (ANNs) have found many applications to predict and optimize the engineering problems in the last few years. In present study effects of SP on mechanical and metallurgical properties of 18CrNiMo7-6 are investigated by ANN. Network has been developed based on back propagation error algorithm. In order to train the network data of experimental tests results were used. Experimental tests were concluding different SP types: single step SP and dual step SP with different SP intensities. Testing of the ANN is accomplished using experimental data not used during networks training. Distance from the surface and Almen intensity are considered as input parameters and residual stress, remnant austenite content, Cauchy breath, domain size and microhardness are regarded as output parameters of the network. The comparison of obtained results of ANN's response and experimental values indicates that the networks are tuned well and the ANN can be used to predict the SP effects on mechanical and metallurgical properties of materials.**

***Index Terms*—Step shot peening, mechanical properties, artificial neural network, back propagation algorithm.**

I. Introduction

Shot peening is a cold working process in which the surface of a part is impinged with small spherical or cylindrical meida, aimed to create the beneficial compressive residual stresses (CRS), induce both the structure change near the surface layer of the material [1]-[3]. The CRS produced in the peened layer can prevent or greatly delay the crack propagation, and thus improve the fatigue life of the material [4]-[6]. The maximum CRS achieved is typically near the yield strength of the material. The peening intensity is directly proportional to the portion of the total energy of the shot stream transferred to the component. SP process can be carried out in several steps such as single, dual and triple step SP; although all of the steps have their specific effects on related material. Dual SP may produce even better improvement in fatigue resistance than a single peening treatment. In this process a component is fully peened at the special intensity and then re-peened in a second operation at a lower intensity. Barry [7], Tekeli [8] and Lindemann [9] have proved that SP can be beneficial to the application of the steels if the appropriate SP parameters are selected. However, the shots bombardments on the surface often lead to flaws or roughness increment, which may outweigh the beneficial effect of the compressive stresses induced by SP. Therefore, the optimization of SP conditions is of great importance to maximize its beneficial effects. Previous studies [6]–[9] focus mainly on one-step SP technology, but few investigations on multistep SP technology have been reported [10].

18CrNiMo7-6. steel is widely used in many industrial components, specifically in high speed heavy-duty gear field [11]. However, mesh or angular carbide is often produced in carburizing process, and cracks are also produced in quenching or machining process, which can reduce the fatigue strength and service life of 18CrNiMo7-6 steel components. Therefore, 18CrNiMo7-6 steel components are often made surface treatment in order to increase their service life which depends mainly on the condition of the surface layer.

Artificial intelligence (AI) systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems [12]. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with nonlinear problems, and once trained can perform prediction and generalization at high speed. Artificial neural network (ANN) approach as one the AI system is well known types of evolutionary computation methods in last decades. Also ANN technique has been adapted for a large number of applications in different scientific areas.

The aim of present study proposes a new approach based on artificial neural networks (ANNs) to investigate the effects of SP process on mechanical and metallurgical properties of 18CrNiMo7-6 Steel. Residual stress, remnant austenite content, Cauchy breath, domain size and microhardness were modeled by ANN. Fifteen data of experimental tests results from the total of thirty, are used to networks training, while in the networks testing 15 different experimental data which were not used during training are used. Since the whole experimental results did not include in the training sets and performance of ANN is evaluate in a fine way.

II. Experimental Tests

Experimental data used in this study are achieved from Fu

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et al. [10] work. In their paper the effects of single and dual step shot peening on the structure and mechanical properties of low-alloy steel have been investigated using X-ray diffraction line profile analysis. The samples are manufactured from casehardened steel 18CrNiMo7-6 (EN 10084). The chemical composition of 18CrNiMo7-6 steel is shown in Table I. All specimens (15×15×7mm) were austenitized at 950°C for 50 h, subsequently heated at 860°C for 2 h and quenched in oil, followed by tempering at 180°C for 3 h and cooling in air. X-ray diffraction line profile analysis (XRDLPA) is a well-known non-destructive technique (NDT). It is often used to determine the residual stresses in the components wherein the crystalline planes are used as strain gauges [13]. When the metal components are under stresses, the resulting elastic strains can cause the spacing changes of atomic planes in the metallic crystal structure. These inter-planar atomic spacings can be directly measured via X-ray diffraction (XRD), and the total stresses on the metal can be calculated from the elastic theory accordingly [14]. Besides, the standard XRDLPA methods based on the full width at half-maximum (FWHM), the integral breadths and the Fourier coefficients of the profiles can be employed to calculate the crystallite sizes [15]. In this study, XRDLPA was used to identify the structure change and compressive stresses distribution near the peened surface of 18CrNiMo7-6 steel after single/dual step SP. All SP treatments were performed by using the air blast machines. The related information of used SP process is demonstrated in Table II and Table III. X-ray diffraction data reveals the phase transformation from austenite to martensitic phase after SP treatments. The results show that dual step shot peening can more significantly improve the mechanical properties. Table IV has been shown the obtained value of experimental results on 18CrNiMo7-6 steel for different thirty samples.

III. Artificial Neural Network

Artificial intelligence systems such as artificial neural networks (ANNs) have found applications in many optimization and prediction problems in the last decade. ANNs are computational models inspired by an animal's central nervous systems in particular the human's brain, which is capable of machine learning as well as pattern recognition [16]. The neural units in the artificial neural network are developed as a very approximate model of the natural biological neurons [17]. Fig. 1 has shown an artificial neuron that is a computational and mathematical model of the biological neuron.

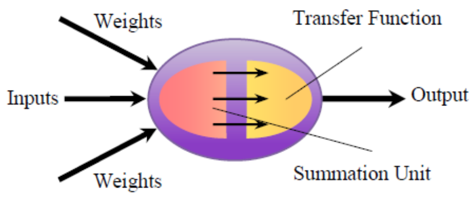


Fig. 1. An artificial neuron.

They are usually presented as systems of interconnected neurons that can compute values from inputs by feeding information through the networks. In other words, ANNs have the ability to give an interpretation of relationships among the variables of high dimensional space. ANNs have shown remarkable performance when used to model complex linear and non-linear relationships. Fig. 2 represents a neural network. In this network, each input consists of R parameters and each output comprises S parameters, while p, w, b, f and a represent the inputs, weight matrixes, bias vectors, transfer function in neurons, and outputs, respectively.

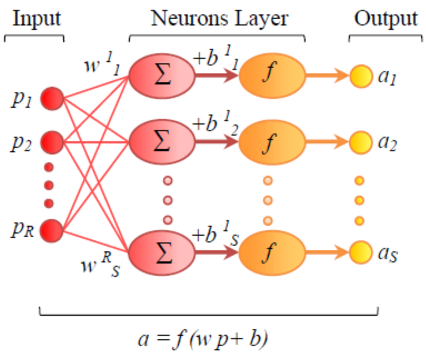


Fig. 2. One layer network, with R inputs and S neurons.

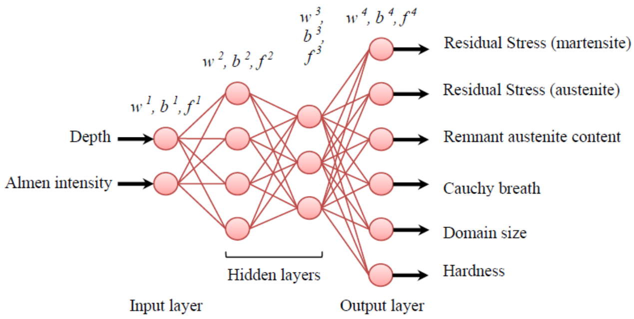


Fig. 3. A Conceptual structure of network for an example to simulate the SP process effects.

In this paper the four parameters of shot peening process effects including: residual stress, remnant austenite content, Cauchy breath, domain size and microhardness were modelled. Modelling which accomplished for residual stress is considered for two cases: martensite and austenite. Different networks with different structures were trained for determine each mentioned parameters. Distance from the surface (depth) and Almen intensity are regarded as inputs and martensite residual stress, austenite residual stress, remnant austenite content, Cauchy breath, domain size and microhardness are gathered as outputs of the network. Fig. 3 for an example represents the conceptual structure of ANN for simulating the Almen intensity: four layers with full interconnection. Two input parameters are logged into input layer to determine the six outputs.

After the neural network is trained successfully with four layers as it mentioned for an example, the values of the four parameters of the network (p, b, W and f) can be obtained. The function which correlates the inputs to the corresponding output can be calculated applying the aforementioned parameters. Finally, the model function can determined as below:

$$G(g(1), g(2),\ldots,g(6)) = a^{4}$$
$$= f^{4}(w^{4}f^{3}(w^{3}f^{2}(w^{2}f^{1}(w^{1}p+b^{1})+b^{2})+b^{3})+b^{4}). \quad (1)$$

$$PCC = \frac{\sum_{i=1}^{n}\left(f_{EXP,i} - F_{EXP}\right)\left(f_{ANN,i} - F_{ANN}\right)}{\sqrt{\sum_{i=1}^{n}\left(\left(f_{EXP,i} - F_{EXP}\right)^2\left(f_{ANN,i} - F_{ANN}\right)^2\right)}}. \qquad (2)$$

where a^1, a^2 and a^3 are outputs of the first, second and third layer, respectively; a^4 is the fourth layer output which is equal to the function $G(g(1),g(2),\ldots,g(6))$. The function G gets the values of two input parameters. Functions of $g(1),\ldots,g(6)$ represent output parameters.

There exist multifarious parameters in neural network implementation whose manipulation brings about a change in the performance, speed and accuracy of the network [18]. Number of network layers, number of neurons in each layer, network training rate, and many other factors are among those parameters. Another effective parameter of ANN is Pearson correlation coefficient (PCC) that shows the rate of accuracy in network and reveals how well a network is trained [19]. PCC determined as:

TABLE II: SP CONSTANT PARAMETERS [10]

Parameter	Type/ Value
Almen specimen	A type
Nozzle diameter	15 mm
Distance of nozzle and specimen	100 mm

TABLE I: CHEMICAL COMPOSITION OF 18CRNIMO7-6 STEEL

Material	C	Si	Mn	Ni	Cr	Mo	P	S	Al	Cu	Sn	Fe
Weight %	0.170	0.190	0.560	1.520	1.650	0.320	0.006	0.003	0.028	0.020	0.002	Bal.

TABLE III: MULTISTEP SP PARAMETERS [10]

SP treatment type	SP intensity (mmA)	Shot material	Shot diameter (mm)	Shot hardness (HV)	SP time (min)	Coverage (%)
Single step	0.15	Al_2O_3 ceramic	0.30	700	0.50	100
Single step	0.50	Cast steel	0.60	610	0.50	100
Dual step	0.50 + 0.3	Cast steel + Cast Steel	0.60 + 0.60	610 + 610	0.50 + 0.5	100

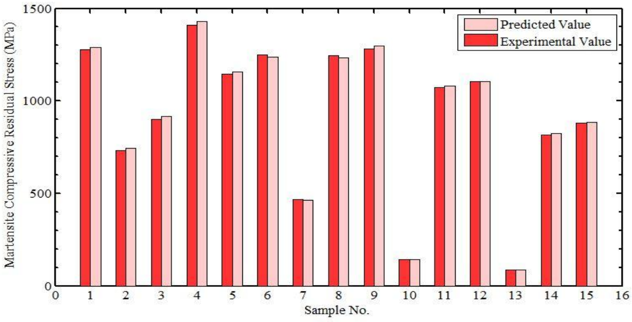
TABLE IV: THE VALUES OF SP PROCESS PARAMETERS AND EFFECTS FOR THIRTY DIFFERENT SAMPLES [10]

Sample No.	Depth (μm)	Shot Peening Intensity (mmA)	Residual stress (MPa)		remnant austenite content (%)	Cauchy breath (°)	Domain size (nm)	Microhardness (HV)
			martensite	austenite				
1	0	0.15	-1277	-597	0.20	0.11	9.8	1149
2	0	0.50	-732	-636	0.34	0.84	13.3	892
3	0	0.5+0.3	-900	-658	0.11	0.87	12.8	917
4	25	0.15	-1410	-905	8.41	0.73	13.9	735
5	25	0.50	-1146	-741	3.46	0.74	15.2	741
6	25	0.5+0.3	-1249	-785	3.00	0.77	14.5	781
7	50	0.15	-469	-541	19.93	0.62	18.5	632
8	50	0.50	-1245	-839	10.39	0.75	15.0	657
9	50	0.5+0.3	-1283	-879	9.38	0.76	14.9	683
10	75	0.15	-143	-293	21.54	0.46	25.0	606
11	75	0.50	-1072	-810	14.28	0.70	16.1	628
12	75	0.5+0.3	-1106	-833	13.47	0.74	15.1	643
13	100	0.15	-85	-85	21.90	0.44	25.8	588
14	100	0.50	-818	-721	16.72	0.61	18.5	608
15	100	0.5+0.3	-879	-746	15.35	0.64	17.7	620
16	125	0.15	-65	22	21.72	0.43	26.7	588
17	125	0.50	-537	-635	18.87	0.55	21.1	595
18	125	0.5+0.3	-564	-641	17.37	0.59	19.9	587
19	150	0.15	-57	90	21.89	0.42	27.5	595
20	150	0.50	-291	-508	21.72	0.48	23.7	586
21	150	0.5+0.3	-291	-497	18.11	0.52	22.1	584
22	200	0.15	-17	98	21.43	0.36	31.7	589
23	200	0.50	-121	-208	20.94	0.46	24.9	584
24	200	0.5+0.3	-86	-231	18.84	0.49	23.6	588
25	250	0.15	-1	103	20.87	0.36	32.0	595
26	250	0.50	-58	-68	20.85	0.45	25.4	589
27	250	0.5+0.3	-70	-92	19.76	0.46	25.0	594
28	300	0.15	3	106	20.36	0.36	32.2	585
29	300	0.50	-38	13	20.82	0.44	25.8	592
30	300	0.5+0.3	-50	8	20.40	0.45	25.9	585

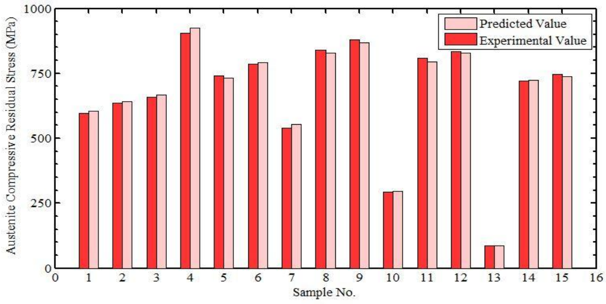
TABLE V: STRUCTURE AND RELATED PARAMETERS OF SELECTED NEURAL NETWORKS FOR EACH OUTPUT PARAMETERS

Output parameter	Rate of Training	Layers Structure	Training PCC	Training Average Error (%)
Residual stress (martensite)	0.095	4×5×5×1	0.99785	0.9011
Residual stress (austenite)	0.100	4×7×8×1	0.99821	1.0974
Remnant austenite content	0.090	6×6×6×1	0.99830	0.7845
Cauchy breath	0.095	6×7×7×1	0.99902	0.7008
Domain size	0.105	6×6×7×1	0.99698	0.9732
Hardness	0.110	4×8×8×1	0.99725	0.7944

where PCC is shown by r, $\sum x$ and $\sum y$ are summation of the values for x and y, $\sum xy$ is the summation of the products of paired values of x and y, and N is shown the number of pairs of values for x and y. If obtained PCC is close to ± 1, it means that the networks are tuned in a good way.



(a)



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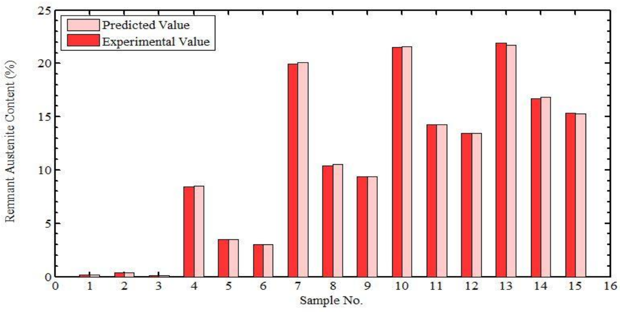

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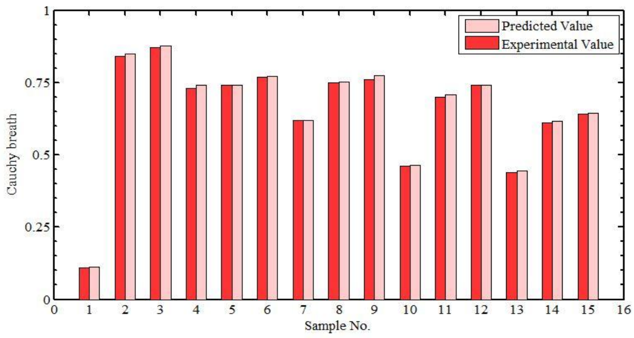

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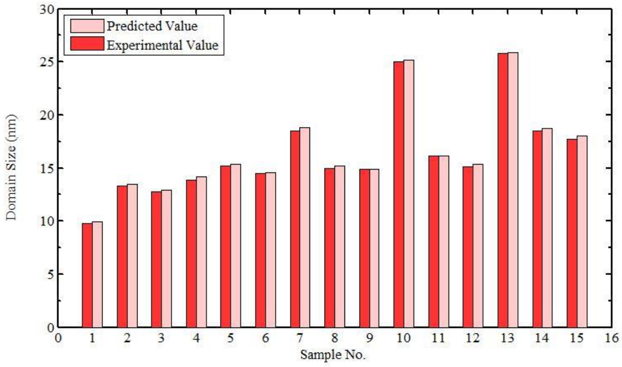

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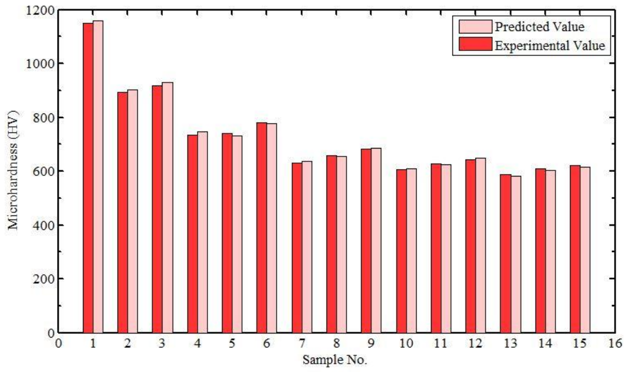

(f)

Fig. 4. Obtained values of ANN's response (predicted value) in comparison with experimental values for each fifteen testing samples for different considered output parameters, (a) martensite residual stress, (b) austenite residual stress, (c) remnant austenite content, (d) Cauchy breath, (e) domain size and (f) microhardness.

All the input and output data was normalized between 0 and 1. Back propagation (BP) error algorithm has been used for ANN training in this paper. The Back Propagation algorithm defines a systematic way to update the synaptic weights of multi-layer feed forward supervised networks composed of an input layer that receives the input values, an output layer, which calculates the neural network output, and one or more intermediary layers, so called hidden layers.

In this study, several networks have been trained with different structures to find the optimum performance of ANN, to predict the considered output parameters with the highest PCC and least errors. The ANN average error in this work is calculated as follows:

$$e_{ANN} = \frac{1}{q}\sum_{i=1}^{q}\frac{\left|f_{ANN,i} - f_{EXP,i}\right|}{f_{EXP,i}} \times 100 \qquad (3)$$

where q is the number of used sample for modeling, f_{ANN} is the network's predicted value and f_{EXP} is the experimental value.

IV. Results and Discussion

In present study the obtained experimental tests results on 18CrNiMo7-6 steel have been used to networks training. The networks were trained to achieve the optimum structure (OS) in order to generate a model function (MF). Afterward by use of achieved OS and MF, operation of the network was tested. 15 samples data (data of samples 16-30) were used from the total of 30, as data sets to train network, while in the network testing, 15 different ones (data of samples 1-15) which were not used during training are used as network testing. Since the whole experimental results did not consist in the training. For investigative purposes, 50% training data sets against 50% test data sets were considered. To decrease the average error and increase the accuracy of the predicted results, separate different networks were trained for each considered output parameters.

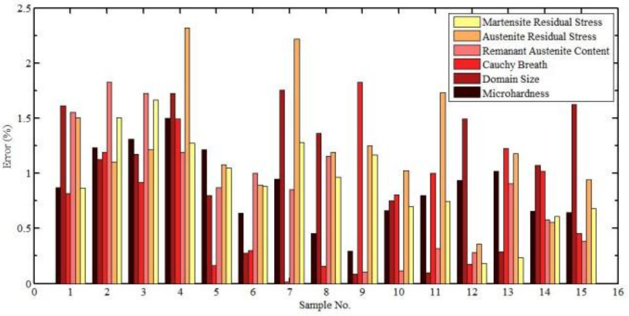

Fig. 5. Values of obtained error for each fifteen samples in accomplished different modellings.

TABLE VI: Achieved Values of PCC and the Average Error for Networks Testing

Output parameter	Testing PCC	Testing Average Error (%)
Residual stress (martensite)	0.99531	0.9202
Residual stress (austenite)	0.99144	1.2373
Remnant austenite content	0.99807	0.8566
Cauchy breath	0.99883	0.7709
Domain size	0.99216	1.0156
Hardness	0.99299	0.8783

As it is mentioned several network has been trained with different structures to find the OS of ANN, to predict the considered parameters with the least average error possible. Results of the networks were investigated and the networks with best operation are selected. The relevant information of network structure and some related results for selected networks have been shown in Table V for each output parameters. It is observed that the values of PCC which show the accuracy, are more than 99.6 % and the obtained average errors are less than 1.1 % and they both acceptable for each output parameters; so it is concluded that network s are train in well. In order to test the performance of ANN, selected networks were employed to networks testing. Fig. 4 have been illustrated the predicted values of each output parameters by use of the obtained MF and OS in comparison with the experimental values. Percentage of error values for each fifteen experiments at the whole considered output parameters are shown in Fig. 5 respectively. The achieved values of PCC and the average error for testing samples by use of the selected trained networks have been shown in Table VI. As it can be observed the obtained values of PCC from testing in comparison with training are decreased and the achieved average error values from testing in comparison with training are increased. The PCC's values are more than 99.8 % for remnant austenite content and Cauchy breath, more than 99.5 %, 99.2 % and 99.1 % for martensite residual stress, microhardness, domain size and austenite residual stress respectively. Furthermore obtained average errors are in small range (0.7709-1.2373) and the predicted values for Cauchy breath, remnant austenite content, microhardness, martensite residual stress, domain size and austenite residual stress have the least average error respectively. According to the obtained results it is observed that predicted values form the response of ANN and the experimental values are in admirable agreement. So it can be concluded that the ANNs are tuned finely to predict the FSW effective parameters and the ANNs can be used to prediction and optimization of this process parameters.

V. Conclusion

In present study the artificial neural networks were employed to predict single and dual step shot peening effects on mechanical and metallurgical properties of 18CrNiMo7-6 Steel. Six parameters of step SP process effects including: martensite residual stress, austenite residual stress, remnant austenite content, Cauchy breath, domain size and microhardness were modeled and the predicted obtained values of error are 0.9202, 1.2373, 0.8566, 0.7709, 1.0156 and 0.8783 for each mentioned parameter respectively. Also the values of PCC for all of the parameters are more than 99%. According to the achieved results it can be concluded that when the artificial neural networks are tuned finely and adjust carefully the modeling results are in admissible agreement with the experimental results. Therefore using ANNs instead of costly tests decreases costs and the need for special testing facilities and the ANNs can be employed to optimize and predict the step SP process effects.

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