

Investigation by means of Artificial Neural Networks on the influence of the shot peening parameters on the hardness of seamless tubes manufactured in TX304HB stainless steel

Diego Ferreño^a, Ruth González^b, Isidro A. Carrascal^a, Diego García^a, Rubén Erañab, Federico Gutiérrez-Solana^a.

^aLADICIM (Laboratory of Materials Science and Engineering), University of Cantabria. E.T.S. de Ingenieros de Caminos, Canales y Puertos, Av/Los Castros 44, 39005, Santander, Spain.

^bTUBACEX SERVICES, Avda de Orejo, nº3, 39719, Spain.

Keywords: Shot peening (SP), Artificial Neural Network (ANN), TX304HB stainless steel.

Introduction

Shot peening (SP) is a widely used cold working process. A number of analytical solutions were developed in the past to understand the relation between the input parameters and the final outcome; unfortunately, these models were necessarily oversimplifications of the complex reality behind a real SP providing only an approximate description of the process, since they were severely restricted by the underlying hypotheses. In contrast, the evolution of the Finite Element (FE) method in the last 20 years, linked to the development in computational capabilities, has provided accurate and more general solutions. Nevertheless, in many instances FE is still too rigid for the needs of the industry during an actual industrial SP process.

Artificial intelligence (AI) methods have been used as an alternative way to deal efficiently with complex and ill-defined problems in very diverse fields of engineering as in (Maleki and Sherafatnia, 2016) and (Kalogirou, 2003). Among their advantages it is worth mentioning that AI methods are able to deal with noisy and incomplete data, with nonlinear problems, and that, once they have been trained, they can perform predictions and generalizations at high speed. An artificial Neural Network (NN) represents a computational approach to solve problems imitating the human brain. In this sense, a NN consist of a number of simple processing units called neurons (or neural units) arranged in layers connecting the inputs to the outputs. An important necessary (but not sufficient) condition for the reliability of a NN as a predictive tool is that the data should be representative of the complete input-output space. This method has been successfully employed in many engineering applications. For the reader interested, (Iliadis and Jayne, 2013) gathers the contributions to the Engineering Applications of Neural Networks conference, showing a large number of examples proving how NN provide practical solutions in a wide range of applications.

Objectives

To the best of these authors' knowledge, no previous research has been focused on correlating the machine parameters of the SP process to the final material properties. In this work, an ANN that takes the process parameters (rather than the physical parameters) of the SP treatment and obtains the final hardness of the material has been developed and experimentally validated. Hardness was chosen as the most important mechanical property of the material after SP. The SP was applied on seamless TX304HB stainless steel tubes. The output of the ANN is the hardness at a depth of 40 μm as well as its uncertainty, measured through the standard deviation.

Methodology

Material

TX304HB (18Cr-9Ni-3Cu-Nb-N; UNS S30432; ASTM A213 S30432; ASME SA213 Code Case 2328) is an austenitic steel with high strength and high steam oxidation resistance. Its superior steam oxidation resistance is achieved by means of a fine-grained microstructure thermo-mechanically obtained. The minimum 0.2% proof stress for this material is 590 MPa. A total of 228 tubes fabricated in TX304HB steel were available for the present research. The length of the tubes was 6 m and the internal diameter (ID) ranged from 25 to 35 mm. These tubes were subjected to shot-peening under different conditions, varying the processing parameters; the total number of combinations was 76. After peening, samples with a length of 20-25 mm were machined and polished to be subjected to the microhardness Vickers test.

The shot peening process

The SP machine employed in this industrial research, which is schematically depicted in Fig.1, allows four different processing parameters to be modified: air pressure (P), material flow (MF), line speed (LS) and rotation speed (RS). The machine consists of two different parts, a fixed one and a mobile one, respectively. The fixed part is constituted by the elements necessary to expel the shot to the appropriate values of P and MF whereas the mobile part controls the RS of the tube as well as the LS. As can be seen in Fig.1, the motion of the moving part with speed LS to the right, allows the lance to be inserted into the tube, which is rotating with rotational speed RS. The following three nozzle sizes, L, were employed: 3/8", 1/2" and 3/4". A stainless steel shot was used in the process, in conformance with the SAE AMS 2431/4C standard (SAE International, 2007). The typical ranges of the machine parameters are the following. P (75–120 psig), MF (3.6–17 kg/min), LS (0.1–0.9 m/min), RS (30–140 rpm). The final quality of the tubes rests on obtaining an increase in hardness (relative to the initial value of the raw material) to a certain depth (usually 40 μ m) provided that the coverage uniformity is achieved. Once the shot blasting media is chosen, the final outcome of the process depends exclusively on the adequate combination of the above mentioned parameters.

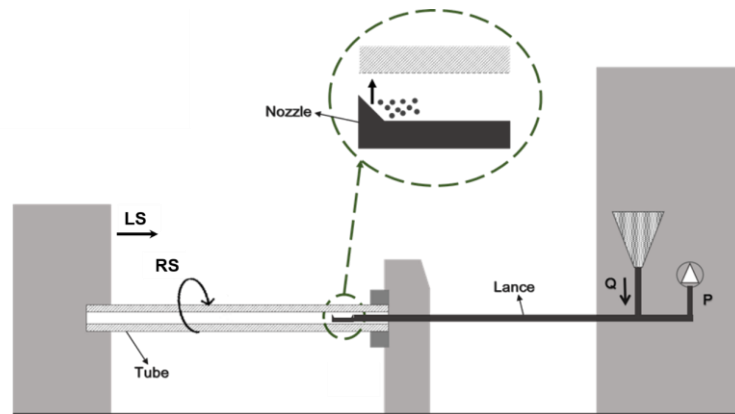


Figure 1. Sketch of the SP machine used in this research.

Microhardness Vickers test

Vickers tests with a load of 50 gf (HV0.05) and a holding time of 10 seconds were performed in the cross sections of the samples, in a plane perpendicular to the axis of the tubes. The tests were carried

out with a Qness Q10-Q30 device. The total number of tests involved in this study at a depth of 40 μm was 3127 and 2316 for bulk material, respectively.

Artificial Neural Networks

In a preliminary stage of this study various transfer functions, architectures and training algorithms were compared, using the Neural Network Toolbox of MATLAB 14 software. The linear transfer function was used in the final layer of the networks whereas a sigmoid transfer function was employed in the hidden layers. Single-layered NNs were early discarded because of their bad performance, due to the complexity of the problem. Regarding the training method, two approaches are available in MATLAB for “small” problems (as in this case), namely, the Levenberg-Marquardt (LM) and the Bayesian Regularization (BR) algorithms. As a rule of thumb, the LM algorithm is recommended for most problems, but for some noisy and small problems, BR can provide a better solution. The initial tests allowed the superiority of the LM approach to be verified in this case. Therefore, several multilayer NNs trained by means of the LM algorithm were employed in this research. Finally, after a trial and error process, it was found that a network with three hidden layers consisting of 25, 20 and 15 neurons each one, best represented the experimental data. In principle, six processing parameters must be considered as inputs for the NN: the four machine parameters - LS, RS, MF, P- and the size of the nozzle, L, together with the ID of the tube. Moreover, the experimental data collected during the study demonstrated the advisability of including the material bulk hardness, HV_{bulk} , as an additional input parameter. Therefore, the input vector consists of 7 data. The output vector is comprised of two results, the mean and the standard deviation of the hardness at a depth of 40 μm from the interior circumference of the tube. The distribution of hardness was considered to follow a Gaussian model; this hypothesis was validated experimentally. For the training of the NN, 30% of the dataset was randomly removed, using the remaining 70% data for training; the removed 30% of the data was subsequently used for testing the network.

Experimental scope

In this research, 228 tubes manufactured in TX304HB steel were subjected to SP. Seven variables were considered as input parameters for the NN analysis. These include the four machine processing parameters (RS, LS, MF and P) as well as the size of the nozzle ($L=3/8''$, $1/2''$ and $3/4''$). The internal diameter of the tubes, ID, was also a variable, as it ranged from 25 to 35 mm. The final input parameter is the hardness of the bulk material. A total of 76 combinations of these parameters was applied and characterized. Thus, after peening, samples with a length of 20-25 mm were machined and polished to be subjected to the microhardness Vickers test. The total number of Vickers tests on treated and bulk material was 3127 and 2316, respectively.

Results and analysis

Gaussianity of the Vickers hardness

The present research assumes that the hardness distributions of HV_{bulk} and $HV_{40\mu\text{m}}$ are of a Gaussian type; to validate the reliability of this hypothesis, all the data sets (the 76 groups of data with the same processing parameters) were subjected to the KS test of normality at a significance level $\alpha=0.05$. The results showed the validity of the Gaussian assumption since $p>0.05$ for 71 and 75 out of the 76 cases, for HV_{bulk} and $HV_{40\mu\text{m}}$, respectively. Therefore, except for these very few occasions, it can be concluded that there is no evidence to reject the null hypothesis.

Validation of the NN

The tests carried out indicate that the hardness distribution of shot-peened tubes can be reproduced in a reliable way by means of artificial NNs. Networks were employed to predict the mean and standard deviation of the distributions of hardness. In Fig. 2(a) the experimental mean values, $HV_{40\mu m}(exp)$, and the results obtained by means of NNs, $HV_{40\mu m}(NN)$, are compared for the total dataset. These data were linearly fitted obtaining a fairly accurate 1:1 correlation (the slope of the fitting line is 0.9982) between experimental and numerical data. The coefficient of determination R^2 is 0.859 (which means that 85.2% of the variability in $HV_{40\mu m}(NN)$, is explained by its relationship with $HV_{40\mu m}(exp)$). Moreover, the 95% prediction bounds are represented in the figure; the difference between the prediction bounds and the fitting amounts to ~ 15 Vickers units (VU). With respect to the standard deviation, in Fig. 2(b) the NN predicted values, $SD(NN)$ are represented against the experimental ones, $SD(exp)$. Again, the linear fitting shows a slope close to 1:1 but the scattering of points is more pronounced. The 95% prediction bounds were represented too; the difference in this case between them and the linear fitting is ~ 15 VU. Fig. 2(c) and (d) are equivalent representations including only the 30% of the dataset that was used for testing (as explained above, 70% of the dataset was used for training the NN). As can be seen, the patterns mentioned above are reproduced again, although with a greater dispersion which results in a reduction of the coefficient of determination, more pronounced in the case of the mean.

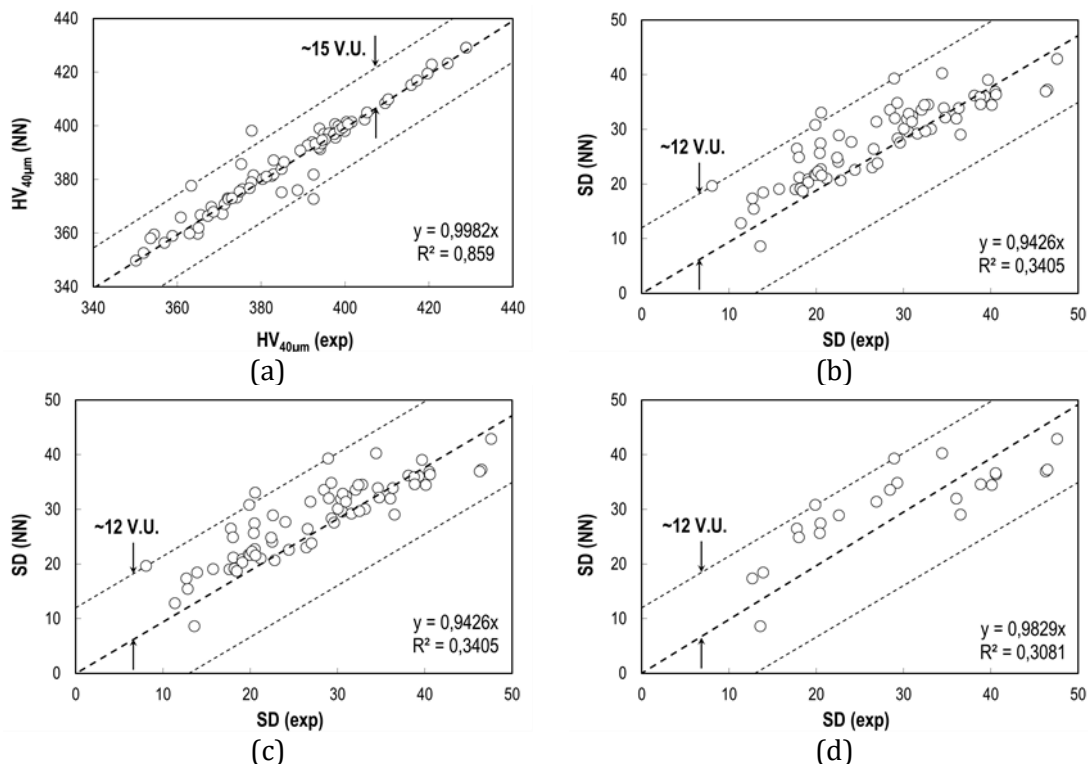


Figure 2. Comparison between experimental and NN predicted data. (a) mean values, total dataset; (b) standard deviation, total dataset; (c) mean values, testing dataset; (d) standard deviation, testing dataset.

As an additional example, in Fig. 3 a comparison between the empirical CDF and the prediction obtained by means of NN (for one arbitrary combination of processing parameters) is shown.

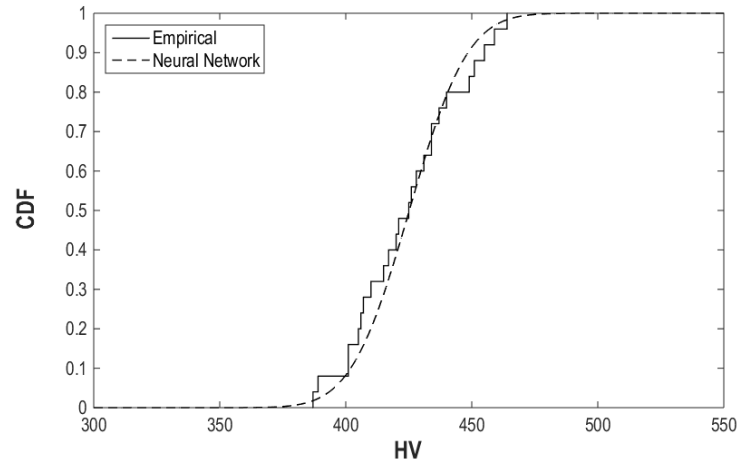


Figure 3. Comparison between the empirical and the NN predicted CDFs (arbitrary combination of processing parameters).

Conclusions

The following conclusions can be drawn from this experimental and analytical research:

- The distribution of hardness for each of the combinations of processing parameters was modelled as a Gaussian one. This hypothesis was experimentally validated by means of the Kolmogorov-Smirnov test. On this basis, the output vector of the neural network is comprised of two results, the mean and the standard deviation of the hardness (at a depth of 40 μm from the interior circumference of the tube). For the training of the network, 30% of the dataset was randomly removed, using the remaining 70% data for training; the removed dataset was subsequently used for testing.
- The Neural Networks were designed and validated using the corresponding toolbox provided by MATLAB 14. Feed-forward networks with back-propagation were employed in all cases, using the Levenberg-Marquardt algorithm for training. After a trial and error process, it was found that a network with three hidden layers consisting of 25, 20 and 15 neurons each best represented the experimental data. The linear transfer function was used in the final layer of the networks whereas a sigmoid transfer function was employed in the hidden layers.
- The neural networks defined this way were able to faithfully reproduce the experimental results. Thus, the correlation between experimental and numerical values of hardness show a slope of 0.9982) and a coefficient of determination of 0.859. The corresponding values for the standard deviation are 0.994 and 0.4934, respectively. The ability of the networks to predict the experimental results was demonstrated by comparing the experimental cumulative distribution function against the distribution obtained from the neural network.

Acknowledgements

This paper describes the work performed together by TUBACEX SERVICES S.A technical staff and the Laboratory of Science and Engineering of Materials (LADICIM) of the University of Cantabria within the research project "OPTIMIZACIÓN DEL PROCESO DE APLICACIÓN DEL TRATAMIENTO DE SHOT PEENING Y ESTUDIO DE SU INFLUENCIA SOBRE LAS PROPIEDADES DEL MATERIAL". This Project was partly carried out with the financial grant of the program FEDER of the European Union (EU), through the Government of Cantabria, in collaboration with the company TUBACEX SERVICES S.A..

The technical contributions from the members of the project and the financial contribution from the EU-Government of Cantabria are gratefully acknowledged. The authors would also like to express their particular gratitude to all the shot-peening staff of TUBACEX SERVICES S.A., without whom it would have not been possible to conduct the experimental part of the present research.

References

- Iliadis L, Jayne C. Engineering Applications of Neural Networks. : Springer; 2013.
- Kalogirou SA. Artificial intelligence for the modeling and control of combustion processes: a review. Progress in energy and combustion science 2003;29:515-66.
- Maleki E, Sherafatnia K. Investigation of single and dual step shot peening effects on mechanical and metallurgical properties of 18CrNiMo7-6 steel using artificial neural network. Int.J.Mater.Mech.Manuf 2016;4:100-5.
- SAE International. SAE AMS 2431/4C, Peening Media (AWS), Conditioned Stainless Steel Cut Wire Shot. 2007.