Research Article

Artificial Neural Networks Investigation of Indentation Force Effects on Nano- and Microhardness of Dual Phase Steels

A. Fotovati, 1 J. Kadkhodapour, 2 and S. Schmauder 1

1 Institute for Materials Testing, Materials Science and Strength of Materials, University of Stuttgart, 70569 Stuttgart, Germany
2 Mechanical Engineering Department, Shahid Rajaee Teacher Training University, Tehran 16758-136, Iran

Correspondence should be addressed to A. Fotovati; ali-reza.fotovati@imwf.uni-stuttgart.de

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Nanoindentation test results on different grain sizes of dual phase (DP) steels are used to train artificial neural networks (ANNs). With selection of ferrite and martensite grain size, martensite volume fraction (MVF), and indentation force as input and microhardness, ferrite, and martensite nanohardness as outputs, six different ANNs are trained according to normalized datasets to predict hardness and their tolerances. A graphical user interface (GUI) is developed for a better investigation of the trained ANN prediction. The response of the ANN is analyzed in five case studies. In each case the variation of two input parameters on the output is analyzed when the other input parameters are kept constant. Reliable and reasonable results of ANN predictions are achieved in each case.

1. Introduction

During the last decades, very strong improvements in steel industries lead to produce advanced high strength steels (AHSS) which have a strong competition with low density metals in automobile industries to passenger safety improvement, vehicle performance, and fuel economy [1]. Among these alloys, DP steels are very interesting for light weight constructions because they have a high total elongation (TE) in their stress-strain curve which leads to a good formability. Another advantage of this material is its low yield strength, high hardening ratio, and the absence of discontinuous yielding. DP sheets are well suited for forming of automotive structural and crash relevant parts such as cross members, longitudinal beams, and reinforcements.

DP steels are based on a microstructure consisting of a ferritic matrix with a second phase of martensite. The size, morphology, and volume fraction of the martensite phase depend on the production process and heat treatment procedure, especially the intercritical annealing temperature and the heating and cooling rate. The variation of the martensite morphology ranges from single martensite islands which are arranged in between the ferrite grains up to a more layer-wise arrangement of the martensite with a distinct orientation of the layer. There may also exist a small amount of bainite and retained austenite in the microstructure. The most important features influencing the mechanical properties of the dual phase microstructure are shape, size, volume fraction and distribution of ferrite and martensite, carbon content of martensite, and volume fraction of retained austenite. Independently of the specific microstructure of dual phase steels, the following basic principle exists: the hard and more brittle martensite phase is distributed in a soft and more ductile ferrite phase to produce a composite mixture.

On nanoscale, extensive investigations were carried out to determine local hardening in the structure of DP steels in the past [2]. In Figures 1(a) and 1(b), local hardening in a typical ferrite grain in a DP steel is illustrated. Investigations at different locations show that the extent and rate of hardening vary in each grain, but the general trend is the same within all ferrite grains. In all cases, hardening can be observed near phase boundaries. Local hardening in this area is related to the presence of geometrically necessary dislocations (GNDs). Measurements indicate that GNDs close to the martensite boundaries are around one order of magnitude higher than GND densities inside the ferrite grains.

Among a wide range of investigations on DP steels [2–9], the effect of nanoindentation forces on nano- and microhardness
is not clearly defined. The only work that clearly shows the force effects on hardness in various grain sizes in DP steel is done by Delíné et al. [10] which is the base of creating the datasets of this paper. Figure 2 shows exactly the effect of indentation force on the hardness in the case of a Berkovich tip. In point 1 the indentation force is high enough to show the hardness of the pure ferrite phase only. In point 2 the effect of grain boundary strengthening is contained in the results of nanohardness investigation. In point 3 the effect of martensite phase is added and in point 4 the indentation force is so high and shows an average hardness of the second phase, grain boundaries, and sizes. Depending on the indentation depth (δ), the results can be categorized in nano- or microhardness.

To find out exactly the influence of these parameters on hardness, ANN is the best choice. Krajewski and Nowacki [11] used ANN to model the relationship of chemical composition and mechanical properties of DP steels. Bahrami et al. [12] developed ANN to predict mechanical properties of DP steels. Haque and Sudhakar [13] investigated corrosion-fatigue crack growth of DP steels using ANN. Other authors [14–17] also used ANN in low carbon steels for the prediction of its properties. All of them showed that a well-trained ANN is a powerful and reliable tool for predicting new situations based on datasets used in a training procedure.

Developing a procedure that could be well organized and predict the effect of indentation force on nano- and microhardness for any new situation is essentially needed for future researches. For achieving this goal, ANN is powerful tool for learning the influence of force on hardness and estimating other interested situations according to the new desired problems.

2. ANN Model Build-Up

For making a good prediction of nano- and microhardness of DP steels, a back-propagation ANN is used. This kind of network is frequently used for function approximation, where there is a relation between input parameters, here ferrite and martensite grain sizes, MVF and indentation force, and output parameters such as nano- and microhardness and their tolerances. For training such networks, there is a training algorithm, for adjusting the weights and bias of each neuron in such a way that the mean square error (MSE) of predicted and real target is minimized in each iteration. A Levenberg-Marquardt algorithm is used for this research due to its fast convergence [18]. MSE is calculated according to the following formula [12]:

$$MSE = \frac{1}{QN_0} \sum_{n=1}^{Q} \sum_{m=1}^{N_0} (d_n(m) - y_n(m))^2,$$  (1)
where $N_O$ is the number of output nodes, $Q$ is the number of training sets, $d$ is the target, and $y$ is the network prediction calculated according to the following formula [12]:

$$y_i = f \left( \sum_{j=1}^{n} w_{ij} + b \right). \quad (2)$$

Here, $w_{ij}$ is the weight of each neuron in the related layer and $b$ is the bias, while $f$ is the activation function. This function is the most important part of the learning procedure and in this research the tangent sigmoid function is used for hidden layers and a linear function is used for the output layer. As the output of the tangent sigmoid function is a number in the range of $[-1, 1]$, it is a good practice to normalize the input and target parameters to this range to help the network learn much quicker and more reliably since the importance of large numbers in comparison with decimal digits is diminished.

Figure 3 shows a typical arrangement of hidden and output layers of an ANN and connection of neurons through weights and biases. This configuration is generally called the topology of the ANN.

The training is started with a practical dataset of reference [10] with programming in the Neural Network Toolbox of MATLAB [18]. The summary of the training set for nanohardness of ferrite and martensite and their tolerances is presented in Table 1. Moreover, Table 2 shows the training set for the microhardness prediction. Although there is a possibility to train a multilayer ANN with more than one output layer, it is not really clear how the output of the trained networks is reliable. For this reason, six different ANNs are trained according to the normalized training parameters of Tables 1 and 2. During the training procedure, three groups of data are randomly selected from the whole datasets: training, validation, and test. Training sets that consist of 70% of datasets are the main series for training the networks. Validation and test sets are used to evaluate only the performance of the ANN training procedure to prevent the network from overfitting or memorizing. Each of

| Training parameters | Min  | Max  | Avr  | Std. Dev. |
|---------------------|------|------|------|-----------|
| F grain size ($\mu$m) | 0.7  | 3.9  | 1.87 | 1.48      |
| M grain size ($\mu$m) | 0.82 | 1.4  | 1.03 | 0.27      |
| MVF (%)             | 22   | 34   | 27.33| 5.11      |
| Force (mN)          | 0.25 | 12   | 3.96 | 4.23      |

Table 1: Range of 21 training parameters for nanohardness.

| Training parameters | Min  | Max  | Avr  | Std. Dev. |
|---------------------|------|------|------|-----------|
| F nanohardness (Gpa) | 2.31 | 4.2  | 2.95 | 0.49      |
| F nanohardness tolerance (Gpa) | 0.05 | 0.72 | 0.29 | 0.19      |
| M nanohardness (GPa) | 4.56 | 7.62 | 5.86 | 0.93      |
| M nanohardness tolerance (GPa) | 0.25 | 5.75 | 1.58 | 1.4       |

Table 2: Range of 18 training parameters for microhardness.
these sets is selected randomly from 15% of datasets, respectively. In this way MSE of three sets is calculated after each iteration (epoch) and then the deviation between them is measured. If this amount is in the range of the training parameters the next epoch is started; otherwise, the training is stopped. As these three sets are selected randomly at the start of training, it is important to analyze the performance of the trained network with regression coefficient that is the best linear fit between the target and the predicted values to achieve the goal of $R = 1$ for the whole datasets.

The number of hidden layers is selected according to the best regression coefficient from a large attempt of training. The summary of networks topology (number of hidden and output layers), regression coefficient ($R$), and MSE of three training sets are summarized in Table 3. When there are simple relations between input and output sets, a better $R$ is achieved with a lower number of neurons in the hidden layers and when the complexity of data increased, the need of a higher number of neurons and hidden layers is desirable.

### Table 3: Trained ANN specifications according to normalized datasets in range of $[-1, +1]$.

| Trained ANNs          | Topology | $R$   | MSE  | MSE $\nu$ | MSE $r$ |
|-----------------------|----------|-------|------|-----------|---------|
| F nanohardness (Gpa)  | 20-10-1  | 0.99  | 0.0041 | 0.0015    | 0.0173  |
| M nanohardness (Gpa)  | 40-20-1  | 0.89  | 0.0239 | 0.0925    | 0.3209  |
| Microhardness (Gpa)   | 30-30-1  | 0.93  | 0.0370 | 0.0429    | 0.0631  |
| F nanohardness tolerance (Gpa) | 20-10-1 | 0.98  | 0.0019 | 0.0338    | 0.0484  |
| M nanohardness tolerance (Gpa) | 35-20-1 | 0.93  | 0.0043 | 0.1965    | 0.0771  |
| Microhardness tolerance (Gpa) | 40-20-1 | 0.84  | 0.1014 | 0.2065    | 0.0227  |

### 3. Results and Discussion

Since there are six trained ANNs and working with them without a computer is too difficult, a GUI is developed in MATLAB. Figure 4 shows the screenshot of this package. There are three main areas designed for working: input parameters, predicted values, and plot area. As any parameter is defined in the input area, the software normalizes each input according to the rule of training and calculates automatically the nano- and microhardness and their tolerances according to the trained ANN and shows them in the related area. There is also a possibility to examine the effect of input parameters on the micro- and nanohardnesses and their tolerances in the plot area. This software is free to
According to previous works [19–21], a comparison between datasets used for training and validation of the ANN and the predicted results from ANN is illustrated in Figure 5. In Figure 5(a), the experimental data [10] for ferrite nanohardness is used. These data are presented for three DP steels: coarse grain (CG), fine grain (FG), and very fine grain (VFG). The specific detail of grain size and MVF for each category is presented in Table 4. The predicted results from the trained ANN according to fixed parameters of Table 4 are calculated and then the difference from real data drawn in this figure for three types of DP steels as error bars. As there is a smooth trend in experimental data, there is no difficulty for the ANN to learn the relations between input and output parameters and as indicated in Table 3 the regression coefficient of 0.99 is achieved. Also a close prediction to real data is watchable in this figure for the ANN output.

Figure 5(b) shows the difference between experimental data used for training the ANN and predicted data for martensite nanohardness. As it is observable, there is a fluctuation in datasets and it is a difficult situation for the ANN to learn the rule. As it is reported in Table 3 the regression coefficient for this ANN is 0.89 with a larger hidden layer than the previous ANN. According to this complexity of trained data the response of the ANN is acceptable.

In Figure 5(c) there is a shortage of experimental data especially in lower indentation forces. This will affect training of the ANN and makes it difficult to learn the rule by the ANN. According to Table 3 with a 30-30-1 ANN topology the regression coefficient of 0.93 is archived which is acceptable for this work. Although there is a good $R$ reached in this ANN, there is some super estimation or exaggerated results predicted by this network that is shown in Sections 3.3 and 3.4. Although there is no data presented to the ANN during training for VFG, the predicted data for microhardness of this steel is reasonable and it shows the power of the ANN prediction in new situations.

For a better understanding of the trained ANN prediction and its response to a variation in the input data, five case

**Table 4:** Ferrite and martensite grain size and MVF for three DP steels [1].

|          | CG     | FG     | VFG    |
|----------|--------|--------|--------|
| F grain size ($\mu m$) | 3.9    | 1.0    | 0.7    |
| M grain size ($\mu m$) | 1.4    | 0.82   | 0.87   |
| MVF (%)   | 22     | 26     | 34     |
Table 5: Input parameters range for trained ANN.

| Input parameters Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|-------------------------|--------|--------|--------|--------|
| F grain size (µm)       | ~      | 3.2    | 2.2    | ~      | 1.1    |
| M grain size (µm)       | ~      | ~      | 1.2    | 0.93   | ~      |
| MVF (%)                 | 26     | ~      | ~      | 24     | 26     |
| Nanoforce (mN)          | 3      | 3      | ~      | ~      | ~      |
| Microforce (mN)         | 18000  | 3000   | ~      | ~      | ~      |

studies on hardness prediction are defined according to Table 5.

3.1. Effects of Ferrite and Martensite Grain Sizes. In this case the effect of ferrite and martensite grain sizes on nano- and microhardness is investigated when MVF and indentation force are constant. Figure 6(a) shows these effects on the ferrite nanohardness. According to Table 5 the nanoforce is selected as 3 mN. With a look around in Figure 5(a), it is expectable that the ANN predicted the ferrite nanohardness with an error less than 0.05 GPa. There is a slight increase in the ferrite nanohardness with increasing of the ferrite grain size (although there is a first decrease in the ferrite nanohardness for larger martensite grain size and then an increase) and a reverse situation for martensite grain sizes with a higher amplitude is observed. This prediction is completely compatible with the role of carbon content in ferrite and martensite grains [10]. With this prediction the maximum ferrite nanohardness is achievable in fine martensite and coarse ferrite grains.

Figure 6(b) shows these effects on the martensite nanohardness. There exist more complex relations in the effects of grain size on martensite nanohardness. Indeed, the maximum martensite nanohardness is predictable in fine martensite and ferrite grain sizes.

The higher microhardness is achievable by the finer martensite grains according to Figure 6(c). This prediction confirms that the finer grains produce higher strength steels because of the increase of grain boundaries and an increase in the stacking faults. According to Hall-Petch effect, martensite
produces more strength than ferrite when its grain is reduced. This phenomenon is according to the type of crystalline network of martensite in blocking of dislocations and hence increasing the hardness of DP steel. Further works about this matter will be done in future publications.

3.2. Effects of Martensite Grain Size and MVF. The effects of martensite grain size and volume fraction on ferrite nanohardness are illustrated in Figure 7(a). Increasing of MVF and decreasing of martensite grain size lead to higher ferrite nanohardness. It is due to the increase of the carbon content in the ferrite matrix. A similar effect is also predictable on martensite nanohardness in Figure 7(b), but there is an apex in MVF of around 30% at the minimum martensite grain size. A similar effect is detectable in Figure 7(c) where the maximum microhardness is predicted at lower martensite grain sizes and an MVF of 28%.

Although there are some differences in these figures, all of them show that an increase in the martensite grain size will decrease the hardness while the MVF has more effect in smaller martensite grain size.

3.3. Effects of MVF and Indentation Force. Figure 8(a) shows the effects of MVF and indentation force on ferrite nanohardness. As it is obvious, the indentation force has a slight reduction effect on ferrite nanohardness due to the increase of the indentation area and more grains affecting the result. Perhaps at low forces the result is related to single grain and at high forces it is averaged over some grains and second phase and hence a slight reduction of nanohardness is predictable through the ANN. For MVF a more increasing effect on ferrite nanohardness is calculated and it is completely reasonable due to the increase of the carbon content in the ferrite matrix. Indeed, the maximum hardness is predictable at higher MVF and lower indentation force.
Figure 8: Effects of martensite volume fraction (MVF) and indentation force on (a) F (ferrite) nanohardness, (b) M (martensite) nanohardness, and (c) microhardness.

3.4. Effects of Ferrite Grain Size and Indentation Force. An increase in the ferrite grain size will increase the ferrite nanohardness at low indentation force (Figure 9(a)) while at higher forces this gradient becomes reverse. On the other hand, there is a decrease in ferrite nanohardness at higher forces as it is predictable by ANN. Meanwhile, steady changes from a positive slope to a negative one can be observed for indentation forces in such a way that the maximum point is located at 2.8 μm ferrite grain size and at 0.25 mN indentation force.

In Figure 9(b) there is a reverse prediction for martensite nanohardness in comparison with Figure 9(a). The maximum hardness is predicted at 2.4 μm ferrite grain size and for 4 mN force.

Figure 9(c) shows the effect of force and ferrite grain size on microhardness. For fine grains, there is no such force dependency in microhardness since the microstructure is a uniform mixture of ferrite and martensite. In case of increased ferrite grains, since martensite grain size is...
constant, a reverse effect in microhardness is predictable. The peak section in this figure is a super estimation by ANN and is not reasonable. Since for the lower indentation force there was no experimental data for training the ANN, prediction of the ANN is not correct for this section (according to Table 2, the maximum microhardness is 4.02).

3.5. Effects of Martensite Grain Size and Indentation Force. In the previous four cases, the effects of some parameters are investigated on hardness. Although there are more investigations, the effects of martensite grain size and indentation force on hardness are selected for the last case as illustrated in Figure 10. In Figure 10(a) increasing of martensite grain size leads to a decrease of ferrite nanohardness over all ranges of indentation forces. The maximum hardness is predictable for small martensite grains as it is expected from the experimental observation that the finer grain size has the higher hardness.

Figure 10(b) shows that the martensite grain size does not have any serious effect on martensite nanohardness and only a force increase will reduce the hardness. This phenomenon is reasonable since at lower indentation forces there is no balance between applied load and stiffness of the martensite phase and hence more reliable results are achievable for higher indentation forces. This discussion is completely extractable from Figure 10(c) where at higher indentation force there are no severe changes in microhardness. The downward trend of this curve completely approves that the finer martensite grain structure possesses a higher microhardness and this matter is more severe in comparison with the effect of ferrite grain size on microhardness as shown in Figure 9(c).
4. Conclusions

Six multilayer back-propagation ANNs are trained in this research according to a normalized data base of reference [1]. Three of them predicted the microhardness and ferrite and martensite nanohardness of DP steel and the others forecasted the tolerances of each hardness. A GUI is developed for ease of usage of ANN. Five case studies are selected to show the power and flexibility of trained ANN. The following results are predictable by trained ANN as investigated in five case studies.

(1) Fine ferrite and martensite grain sizes have higher ferrite and martensite nano- and microhardness.

(2) MVF increases ferrite nanohardness when martensite grain size is small. But, it decreases martensite nanohardness and microhardness in coarse grains.

(3) Indentation force has a decreasing effect on hardness for large MVF.

(4) Nano- and microhardness will decrease when ferrite grain size and indentation force increase.

(5) In the same way, nano- and microhardness will decrease when martensite grain size and to some extent indentation force increase.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

References

[1] R. Kuziak, R. Kawalla, and S. Waengler, “Advanced high strength steels for automotive industry: a review,” Archives of Civil and Mechanical Engineering, vol. 8, no. 2, pp. 103–117, 2008.

[2] J. Kadkhodapour, S. Schmauder, D. Raabe, S. Ziaei-Rad, U. Weber, and M. Calcagnotto, “Experimental and numerical study on geometrically necessary dislocations and non-homogeneous
mechanical properties of the ferrite phase in dual phase steels,” *Acta Materialia*, vol. 59, no. 11, pp. 4387–4394, 2011.

[3] E. Fereiduni and S. S. G. Banadkouki, “Improvement of mechanical properties in a dual-phase ferrite-martensite AISI4140 steel under tough-strong ferrite formation,” *Materials and Design*, vol. 56, pp. 232–240, 2014.

[4] E. Fereiduni and S. S. Ghasemi Banadkouki, "Reliability/unreliability of mixture rule in a low alloy ferrite-martensite dual phase steel," *Journal of Alloys and Compounds*, vol. 577, supplement 1, pp. S593–S596, 2013.

[5] K. Hayashi, K. Miyata, F. Katsuki, T. Ishimoto, and T. Nakano, "Individual mechanical properties of ferrite and martensite in Fe-0.16 mass% C-1.0 mass% Si-1.5 mass% Mn steel," *Journal of Alloys and Compounds*, vol. 577, supplement 1, pp. S593–S596, 2013.

[6] V. H. B. Hernandez, S. K. Panda, M. L. Kuntz, and Y. Zhou, “Nanoindentation and microstructure analysis of resistance spot welded dual phase steel,” *Materials Letters*, vol. 64, no. 2, pp. 207–210, 2010.

[7] M. D. Taylor, K. S. Choi, X. Sun et al., "Correlations between nanoindentation hardness and macroscopic mechanical properties in DP980 steels," *Materials Science and Engineering A*, vol. 597, pp. 431–439, 2014.

[8] G. Rosenberg, I. Sinaióva, and I. Juhar, “Effect of microstructure on mechanical properties of dual phase steels in the presence of stress concentrators,” *Materials Science and Engineering A*, vol. 582, pp. 347–358, 2013.

[9] E. Fereiduni and S. S. Ghasemi Banadkouki, “Ferrite hardening response in a low alloy ferrite-martensite dual phase steel,” *Journal of Alloys and Compounds*, vol. 589, pp. 288–294, 2014.

[10] M. Delincé, P. J. Jacques, and T. Pardoen, “Separation of size-dependent strengthening contributions in fine-grained Dual Phase steels by nanoindentation,” *Acta Materialia*, vol. 54, no. 12, pp. 3395–3404, 2006.

[11] S. Krajewski and J. Nowacki, "Dual-phase steels microstructure and properties consideration based on artificial intelligence techniques," *Archives of Civil and Mechanical Engineering*, vol. 14, no. 2, pp. 278–286, 2014.

[12] A. Bahrami, S. H. M. Anijdan, and A. Ekrami, "Prediction of mechanical properties of DP steels using neural network model," *Journal of Alloys and Compounds*, vol. 392, no. 1-2, pp. 177–182, 2005.

[13] M. E. Haque and K. V. Sudhakar, "Prediction of corrosion-fatigue behavior of DP steel through artificial neural network," *International Journal of Fatigue*, vol. 23, no. 1, pp. 1–4, 2001.

[14] H. Monajati, D. Asefi, A. Parsapour, and S. Abbasi, "Analysis of the effects of processing parameters on mechanical properties and formability of cold rolled low carbon steel sheets using neural networks," *Computational Materials Science*, vol. 49, no. 4, pp. 876–881, 2010.

[15] K. Dehghani and A. Shafiei, "Predicting the bake hardenable- ity of steels using neural network modeling," *Materials Letters*, vol. 62, no. 2, pp. 173–178, 2008.

[16] P. Saravanakumar, V. Jothimani, L. Sureshbabu, S. Ayyappan, D. Noorullah, and P. G. Venkatakrishnan, "Prediction of mechanical properties of low carbon steel in hot rolling process using artificial neural network model," *Procedia Engineering*, vol. 38, pp. 3418–3425, 2012.

[17] K. Dehghani and A. Nekahi, “Artificial neural network to predict the effect of thermomechanical treatments on bake hardenability of low carbon steels,” *Materials and Design*, vol. 31, no. 4, pp. 2224–2229, 2010.

[18] M. Hudson, M. Hagan, and H. Demuth, *Neural Network Toolbox User’s Guide*, Version 8.0.1, The MathWorks, 2013.

[19] A. Mukherjee, S. Schmauder, and M. Rühle, “Artificial neural networks for the prediction of mechanical behavior of metal matrix composites,” *Acta Metallurgica Et Materialia*, vol. 43, no. 11, pp. 4083–4091, 1995.

[20] A. Fotovati and T. Goswami, "Prediction of elevated temperature fatigue crack growth rates in Ti-6Al-4V alloy—neural network approach," *Materials and Design*, vol. 25, no. 7, pp. 547–554, 2004.

[21] A. Moayyed, V. Fallah, and A. Fotovati, "Modeling of hot deformation behavior of equiaxed Ti-6Al-4V ELI in two phase (α + β) region using neural networks," in *Proceedings of the 11th World Conference on Titanium*, pp. 319–322, Kyoto, Japan, 2007.
