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Prediction of 4340 Steel Hardness Profile Heat-treated by Laser Using Artificial Neural Networks and Multi Regression approaches

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Abstract— Laser hardening is one of the promising manufacturing processes to enhance the materials mechanical properties. Due to its capacity to heat locally and rapidly the mechanical components, the process is able to produce reliable parts able to challenge to wear and fatigue failures. However, it is still difficult to predict the hardness profile using simulation or experimental data since the process parameters and material properties have a great effect on the process behavior. An accurate prediction of the hardness profile heat-treated by laser is a necessity to overcome the time consumption issue and achieve best cost effective solution. The purpose of the present study is to develop some approaches and compare them to determine the hardness profile shape in relation with the laser hardening parameters values range. The experimental data used for modeling and validation were obtained based on systematic tests according to Taguchi experimental design. Finally, artificial neural network and mathematical based regression models are built and confronted one to the other to converge towards the best prediction model. The artificial neural network model is distinguished by its high capability and good precision by comparing the modeling and validation experimental data.

Keywords: **Laser hardening; Hardness Profile; Experimental data; Taguchi method; artificial neural network; nonlinear regression.**

I. INTRODUCTION

Surface hardening is very promising process applied to low and medium-carbon steels to enhance wear resistance and improve fatigue life. The surface hardening can be performed using several techniques such as thermo chemical, induction and laser processes. In fact, the laser hardening process is more and more integrated in industries since it permits to develop ultimate features mentioning selective and local heating capacities, negligible distortion and short cycle times. Secondly, it can be characterized by its ability to improve the mechanical properties of the materials by changing the superficial microstructure without affecting greatly the core due to high temperature gradient and high rate of its change. This combination of hard surface and tough core is greatly desirable because it provides favorable compressive stress distribution which reduces the crack initiation and propagation processes [1]. Laser surface hardening is considered by industrial to increase the hardness and strength by quenching the material from the austenite region to form hard marten site. Once the material surface is heated by laser beam, the initial microstructure is transformed to austenite in the regions heated above Ac3. Thanks to the good harden ability of used steel (4340), the austenitized layers are transformed to hard and fine martensite forming the hardened region upon self-quenching effect. An over-tempered region is noticed between the hardened region and the material bulk which consist of tempered martensite containing a small amount of retained austenite. Emphasizing that high source of heat energy can lead to melted region near the surface as shown in Figure 1 [2–3].

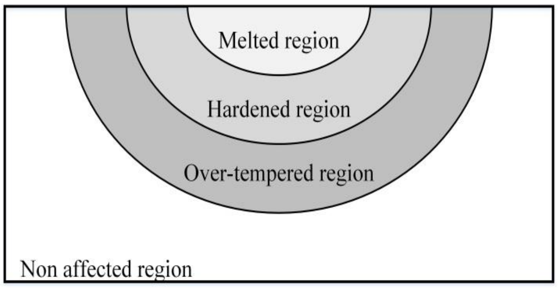

Fig 1. Schematic representation of regions produced by laser hardening

The case depth that represents the hardened region depth depends on the process parameters and material properties. Therefore the process parameter value range should be selected to ensure the complete austenitization of the steel layer during the heat treatment. Over the past two decades, laser hardening has experienced strong growth and because of the growing number of applications, several studies are performed with the aim to determine the optimal parameters that affect the process outcome. As a result, the most influential factors undisputed in laser hardening process are the laser beam power and the scanning speed which can be incorporated within the machine parameters category, that affect strongly the interaction time of the laser radiation with the hardened part of the component [4]. While other parameters such the beam spot diameter, the focal length of the laser, material absorption rate , the initial hardness and the surface state of material can be considered minor comparing to the two parameters mentioned above which their influences varies from one to another [5]. The hardness profile sensitivity can be defined as the behavior of outcome variables in relation to process parameters levels. The case depth (mm), the max and min hardness (HRC), the depth and the hardness of the melted region are the usual outcome variables with which the hardness profile regions can be determined (Figure 2). Shiue and al [6] studied the effect of

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the initial microstructure of AISI 4340 on hardness profile behavior treated by CO2 laser; they mentioned that the hardness curve can be generally divided into four regions, such as the hardened zone, the over-tempered zone in which the partial transformation occurred and the heat-unaffected base metal. On the other hand, Purushothaman and al [7] performed the laser hardening process using steel EN25 Nd: YAG laser system, he denoted that the hardness profile consist of three regions such as the hardened zone, the over-tempered zone, and the heat-unaffected material core. He denoted also that using the higher power densities, the surface of the steel gets melted for all the travel speeds which forming the melting zone.

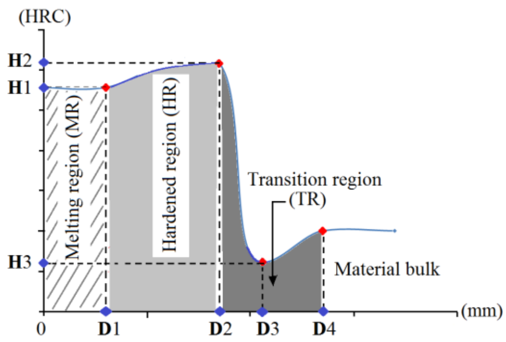

Fig 2. Typical hardness curve

From literature survey, the few studies which have been conducted with regard to the prediction of the laser hardening process interest responses in relation with process parameters levels were generally focused on the prediction of the hardened layer dimension. As an experimental work, Woo [8] estimated the hardened layer dimensions of SM45C steel treated by 4 kW CO2 laser using special techniques for prediction, such as the multi-regression model and the artificial neural network model. He focused mainly on the effect of the coating thickness on the hardened layer. Shercliff and all [9] conducted a theoretical study that aims the exploration of case depth prediction by developing an approximate heat flow model. This model uses the laser sources distribution such as Gaussian, rectangular and uniform to exploit dimensional relationships between process variables to provide ideal diagrams for the hardened depth [9]. The literature reveals clearly the lack of works that highlight the prediction of other hardness profile outcomes. Based on the information related to the number of the regions mentioned in references [6-7], and the lack of the relevant work, it is highly possible and very interesting to predict the overall hardness profile by estimating its outcomes mentioned above. The originality of this research lies in the development of robust models capable to predict and characterize the hardness curve produced by the laser heat treatment. This research makes it possible to predict the three regions produced with high accuracy and provides the useful ingredients to prepare an optimization of the laser process. The objective of this study is to predict the hardness profile of AISI 4340 steel treated by Nd: YAG laser source, by using two prediction approaches. First, a multi-regression mathematical model was developed for the purpose of assessing the prediction accuracy of the ANN model. Data used to train and validate the models are obtained from experimental and validation tests which conducted based on Taguchi orthogonal array method. The process parameters in the present study were the laser power, the scanning speed, the initial hardness and the surface nature. Finally, a comparative study was performed to determine the accuracy of each model for prediction the hardness profile.

II. EXPERIMENTATION

A. Experimental setup

AISI 4340 is a low alloy steel mainly used in power transmission gears and shafts, aircraft landing gear, and other structural parts with high performances. It's known for its good toughness, high harden ability, wear resistance and excellent fatigue resistance. After initial drawing, heat treatment is carried out to render the AISI 4340 steel suitable for machining, and to meet the mechanical properties limits specified for the steel's particular applications. Both CO2 and Nd: YAG systems have often been used as an energy source for heat treatment in several case studies. As a best utility to harden the superficial layer of material, the Nd: YAG system provides a laser beam with a short wavelength which allows the beam to penetrate more heat energy than classical laser technology [10-11]. Because of the AISI 4340 high consideration in the laser hardening process [12-13], a sample material was used under the form of parallelepiped plates (50 mm x 30 mm x 5 mm) to carry out the experiment. The experience took place in a laboratory equipped with Nd: YAG system with laser head mounted on Fanuc 6 joints robot emphasizing the accuracy of 50 µm (Figure 3) and a micro-hardness Clemex machine used to characterize the hardness profiles. The tested plates were mounted on the robot table using clamps in a position which allows the laser beam to travel longitudinally through the plates with 310 mm focal length (ϕ 2.226 mm focal diameter).

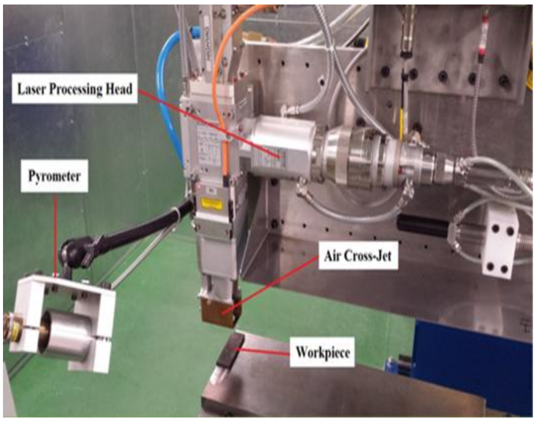

Fig 3. Experimental setup - Laser cell

B. Experimental design (Taguchi method)

Once the experimental setup is effective, it is important to select the useful tests with some rigor and minimum errors.

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In fact, a structured approach developed by Taguchi [14] was used to determine best combinations of process parameters to perform the study. In fact, it is an experimental design used in order to achieve a high quality level process and reduce the number of tests to what is strictly necessary to make a decision and targeting a best cost and time effectiveness. In the current study, two classes of parameters were considered in which are the machine parameters such as laser power (P) and scanning speed (V) pointing that their values range has to be selected to ensure a complete austenitisation [15]. The other factors are related to the initial hardness (H) and the surface nature (S).

Table 1. Experiment tests factors levels

Factors	Level
Initial hardness (HRC)	40, 50
Surface nature	As treated (1) - finished (2)
Power (kW)	0.4, 0.7, 1.0 and 1.3
Speed (mm/s)	10, 20, 30 and 40

The experimental tests of this study are summarized in Table 2. These tests were performed according to Taguchi L16 orthogonal array based on the number of parameters and their levels (Table 1). The hardness profile is characterized by using Clemex micro-hardness measurement machine which provide the hardness curve of each test in the experiment. Table 3shows the output variables extracted from hardness curve. Their values are key elements for the hardness profile because their variations in relation to the process parameters are what define the sensitivity of the hardened profile. As noted in Figure 2, the hardness curve is simulated with highlighted dots which are nothing but coordinates that presents the output variables, and therefore the best way to predict the hardness profile is by predicting theses coordinates that represent a good characterization of the hardness curve.

Table 2. Experimental tests (L16 orthogonal array)

Test	P (kW)	V (mm/s)	H (HRC)	S
1	0.4	10	40	1
2	0.4	20	40	1
3	0.4	30	50	2
4	0.4	40	50	2
5	0.7	10	40	2
6	0.7	20	40	2
7	0.7	30	50	1
8	0.7	40	50	1
9	1.0	10	50	1
10	1.0	20	50	1
11	1.0	30	40	2
12	1.0	40	40	2
13	1.3	10	50	2
14	1.3	20	50	2
15	1.3	30	40	1
16	1.3	40	40	1

C. ANOVA results for optimal parameter setting (D2)

The analysis of variance (ANOVA) is a computational technique used to investigate which design parameter significantly affects the various variables characterizing the hardness curve such as case depth. Generally ANOVA table contains the degrees of freedom, sum of squares, mean square, and P-value and F-value with which the process parameters are ranked in terms of importance in the experiment and also to find out which parameter have significant effects in controlling the overall response. The interest of choosing D2 among the other outputs variable to study the effect of the process parameters and determine the most controllable parameter. This output is related to the case depth that represents the main objective of the application of laser heat treatment in steels. The F-values, indicated in Table 4, shows that both laser power and initial hardness are the controllable factors with higher importance which considered the two main parameters for obtaining an optimum regime work. As is evident in the graphic below (Figure 4), changing in levels values of all of laser power (from 0.7 kW to 1.0 kW), and initial hardness result a large variation in the case depth. Whereas, the change of scanning speed and surface nature levels causes small variations in this output, which is confirmed by the F-value mentioned below. Finally, both of laser power and initial hardness are positively correlated with case depth unlike the other parameters. Based on statistical techniques, the analysis of variance is useful for the modeling problems and obtains the linear regression equations [17].

Table 3. Hardness curve values used for predicting the hardness profile

Depth (mm)	D1: Melted region	D2: Case depth	D3: Over-tempered region	D4: No affected region
Hardness (HRC)	H1: Hardness at D1	H2: Hardness at D2	H3: Hardness at D3	Core hardness

Table 4. Case depth ANOVA results

Source	DF	Sum of Squares	Mean Square	F-Value	P-Value	Contributions (%)
Power	3	0.94092	0.31364	55.94	0	58.66
Scan Speed	3	0.25717	0.085723	15.29	0.002	16.03
Initial Hardness	1	0.30526	0.305256	54.45	0	19.03
Surface Nature	1	0.06126	0.061256	10.93	0.013	3.81
Error	7	0.03924	0.005606	--	--	2.47
Total	15	1.60384	--	--	--	100

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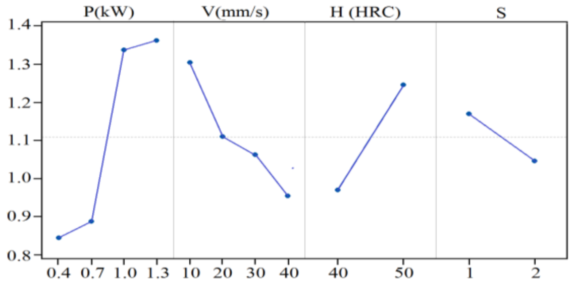

Fig 4. Effect of parameters on the case depth (D2)

III. HARDNESS PROFILE PREDICTION

As previously mentioned, this study aims to predict the hardness profile of the AISI 4340 heat-treated by Nd: YAG laser which four parameters were varied. The sequences of prediction are made by dividing the hardness curve according to of the four characterizing zones (Figure 2). As result, these zones can be determined by four points with their coordinates in terms of depth (mm) and hardness (HRC) as given in Table 3. The fact that the hardness profile can be drawn by using these coordinates, good prediction of the hardness profile can be achieved by predicting those coordinates. To achieve this goal, two approaches have been used for prediction; the first was based on artificial neural networks (ANN), which is a useful prediction tool that can be implemented successfully in the research and development of laser surface hardening [16]. The second approach was based on analytical nonlinear regression.

A. Artificial Neural Network

Neural network is the ideal way of trying to simulate the brain electronically, as oppose to the generic definition. Artificial Neural Network (ANN) is term which narrows the broad definition to the artificial intelligence (AI) research field. ANN is widely used to challenge an overcome issues provided by traditional analytical approaches. Several types of ANN used for modeling such as; feed forward neural network (FNN), radial basis function network(RBF), Kohonen self-organizing network (KSON), learning vector quantization (LVQ) and multilayer perceptron (MLP). Because of its simplicity and great forecast ability for modeling, multilayer perceptron (MLP) was used in this study to learn the mapping characteristics and then to predict the hardness profile from the experimental conditions (power (P), scanning speed (S), initial hardness (H) and surface nature (S)).As defined in numerical computing software (Matlab), the architecture of the back propagation neural network consists of three layers depending to the number of the hidden layers; an input layer where its neurons number is identical to input parameters number, an output layer where also its neurons number is identical to output variables number. Generally, one hidden layer is sufficient to converge towards the desired model [18]. The hidden layer consists in 12 neurons that met the requirement for best prediction of hardness profile. The ANN modeling architecture is presented in Figure 5.

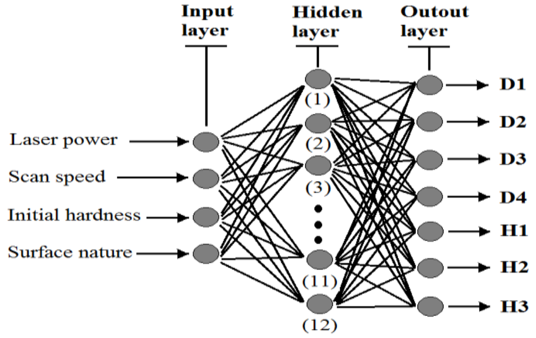

Fig 5. ANN model architecture

B. Regression model

Among the most known techniques that can model and analyze problems where some response variables are influenced by several factors is the response surface methodology [19]. It can be defined as collection of mathematical and statistical techniques useful to generate empirical models that present the relationship between the input parameters and output responses of the problem. As a second part of prediction, the present study is based on response surface methodology to develop mathematical models with best fits which can represent the relationship between the interest responses and the process parameters. A statistical tool was used to develop the approximating model based on the same observed data that were used to train Artificial Neural Networks where the purpose is to compare the suitability of each model for predicting the outcome variables. Usually, the mathematical formulation of the approximation model is presented by the following second order polynomial (equation 1):

$$y = a_0 + \sum_{i=1}^{k} a_i X_i + \sum_{i=1}^{k} a_{ii} X_i^2 + \sum_{j=1}^{k-1} \sum_{i=j+1}^{k} a_{ji} X_j X_i \qquad (1)$$

Where: y can be applied to the different output D1, D2, D3, D4, H1, H2 and H3. The variables X_1, X_2, X_3, X_4 represent Power (W), Scanning speed (mm/s), Initial hardness (HRC) and nature of surface respectively. When a_0 presents the regression equation constant, coefficients a_i are linear terms, coefficients a_{ij} are interaction termsand the coefficients a_{ii} are the quadratic terms and k is the number the process parameters. In order to obtain mathematical models with best fits, it is critical to select the number of regressors which they represent the indeterminate of the model polynomial. The best way to achieve the appropriate number of regressors for each outcome regression model was done by an effective technique. The technique is consists to select a minimum number possible of regressors and verification of the matched multiple coefficient of determination (R^2).The process is defined by a continuous increment in the number of regressors until reaching of the best multiple coefficient of determination (R^2) based on confidence level less than 5%. Table 5 shows the adequate regression coefficients values and corresponding regressors in the regression

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models developed during this study. It is obviously that the best-fit models are represented by the quadratic form and the models terms are statistically significant at p-value of less than 5%. Table 6 presents the result of the analysis of variance (ANOVA) that used to test the adequacy of the regression model. The accuracy of the regression model varies from an output to another according to F-value. Based on the F-value, the regression model has an excellent ability to predict D1 and D2, while its prediction accuracy decreases for the other outputs.

IV. RESULT AND DISCUSSION

Figures 6, 7, 8, 9, 10, 11 and 12 show the results of the responses prediction using ANN and nonlinear regression (NLR). All figures present the measured data in X axe and predicted data in Y axe of 16 tests exposed in Table 2. The comparisons between measured and predicted values for each interest response is in order to test the coherence, efficiency and accuracy of prediction of two models by calculating the multiple coefficient of determination (R^2) value. Table 7 presents the summary of the statistical estimator's accuracy of ANN and NLR. The statistical estimators are mean absolute error (MAE), mean relative percentage error (MRE%), maximum relative error (XRE), mean square error (MSE) and total square error (TSE).MAE is a generic term used to define a statistical quantity to demonstrate the convergence relationship between the predicted and the eventual data. The MRE is usually expresses accuracy as a percentage of this relationship. The MSE measures the average of the squares of the difference between the estimator and what is estimated (error).Finally; The TSE represents the sum of all squares errors. In the studied range related to the process parameters, the prediction of the outcome variables by the two models such as the NLR and ANN models are summarized in Table 7.

These results confirm the possibility of the prediction all those outcome variables with good accuracy. Starting with D1 and D3, according to the mean absolute percentage error (MRE) result, the mathematical model and the ANN model were not in the highest level of prediction although they have excellent values of the multiple coefficient of determination (R^2), which is about 0.9938, 0.96 for the mathematical and 0.9923, 0.9922 for the ANN model respectively to D1 and D2.In D2, A significant difference in the mean absolute percentage error (MRE%) for both models, so the ANN model presents better accuracy than the nonlinear regression model and it is confirmed by the MSE, in which the regression model present more than three times of MSE than the ANN model. It is also confirmed by coefficient of determination (R^2) value (99.37% and 97.37%, ANN and regression model respectively. Finally, and regarding to H1, H2 and H3 prediction, it is noted that both models have good accuracy with very small mean absolute percentage error (MRE) values comparing to the other outcomes (D1, D2, D3 and D4). Unlike the MSE which shows inverse value relationship. From the scatter plot figures, it is clear notice that for each measured value of all of D1, D2, D3 and D4, the predicted value is close to the diagonal line, unlike the case of H1, H2 and H3 where the dots are somewhat scattered around the diagonal line. The dispersion around the diagonal line can be estimated by the mean absolute error value expressed by the residual errors.

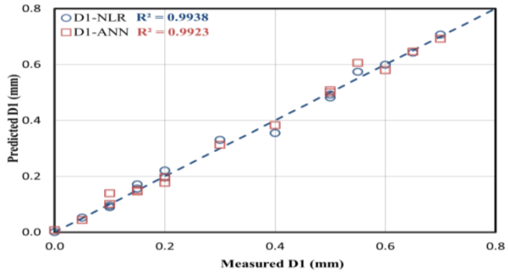

Fig 6. Scatter plot - Measured and predicted D1

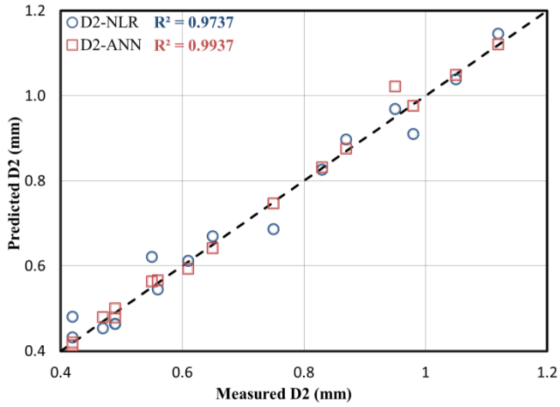

Fig 7. Scatter plot - Measured and predicted D2

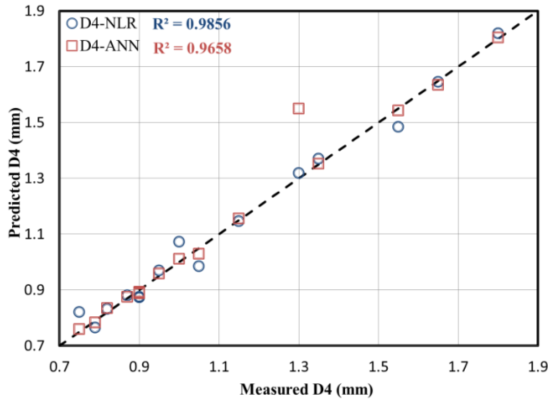

Fig 8.Scatter plot - Measured and predicted D4

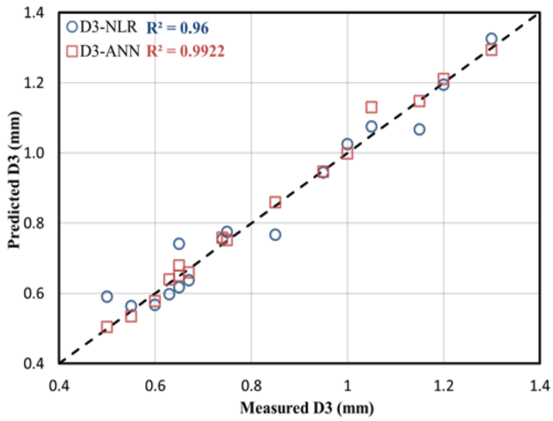

Fig 9. Scatter plot - Measured and predicted D3

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Table 5. Regression coefficients values and corresponding regressors in the regression models

Outcome Variables	D1	D2	D3	D4	H1	H2	H3
a_0	-0.44244	-0.17386	0.04256	-0.54781	52.57226	68.8544	33.54686
a_1	0.000942	0.001851	0.001009	0.002168	0.024773	-0.02134	0.006167
a_2	0.012004	-0.01095	0.012663	0.026769	-0.67722	-0.08168	-0.02581
a_{12}	-4.2E-06	-5.2E-06	-8.3E-06	-1.6E-05	0.000147	4.33E-05	-1.7E-06
a_{13}	-1.8E-05	-4.4E-05	-2.6E-05	-2.9E-05	-0.00067	0.000539	0.000319
a_{14}	6.94E-05	8.06E-05	-5.6E-06	-0.00011	0.001278	-0.00194	-0.00397
a_{23}	-0.00059	-0.00047	-0.00092	-0.00123	0.01242	0.00574	0.00219
a_{24}	0.00545	0.01105	0.01144	0.01087	0.0566	-0.0198	-0.0063
a_{34}	-0.00559	-0.0102	-0.00953	-0.00782	-0.03858	0.035617	0.087031
a_{11}	2.59E-07	4.01E-07	5.01E-07	1.69E-07	1.35E-06	-1.7E-08	-8.6E-06
a_{22}	3.12E-05	0.000156	0.00015	0.000219	-0.00213	-0.00212	0.000188
a_{33}	0.000461	0.000778	0.000728	0.000947	0.004436	-0.00679	-0.0041
No. of regressors	11	11	11	11	11	11	11

Table 6. ANOVA of the mathematical model

Variables	Sum of the squares		Degrees of freedom		*F*-ratio	R^2
	Regression	Residual	Regression	Residual		
D1	0.809	0.005	14	4	57.735	0.9938
D2	0.816	0.022	14	4	13.448	0.9737
D3	0.899	0.0374	14	4	8.731	0.96
D4	1.580	0.023	14	4	24.866	0.9856
H1	15.215	1.625	14	4	3.405	0.9052
H2	7.116	1.281	14	4	2.019	0.8474
H3	17.621	1.102	14	4	5.811	0.9411

Table 7. Summary of statistical estimators performances - ANN and NLR

Variables	MAE		MRE%		XRE		MSE		TSE	
	R-M	ANN-M	R-M	ANN-M	R-M	ANN-M	R-M	ANN-M	R-M	ANN-M
D1	0.0131	0.0132	5.1309	5.9179	0.0752	0.0796	0.000315	0.000397	0.0050544	0.006363
D2	0.0295	0.0107	4.7073	1.5731	0.1415	0.0889	0.00138	0.0003838	0.02208	0.006132
D3	0.0386	0.0139	5.3244	5.3244	0.1737	0.1021	0.002342	0.000541	0.03747	0.00867
D4	0.0303	0.0245	3.0091	2.0909	0.1376	0.2694	0.001444	0.003982	0.02311	0.06371
H1	0.2656	0.1360	0.4553	0.2196	1.1	1.3379	0.099818	0.101223	1.5971	1.61957
H2	0.219	0.0568	0.3626	0.0940	1.149	0.6103	0.0801	0.018161	1.2816	0.29058
H3	0.2219	0.0404	0.5829	0.1061	0.8935	0.1680	0.0689	0.00257	1.1026	0.041263

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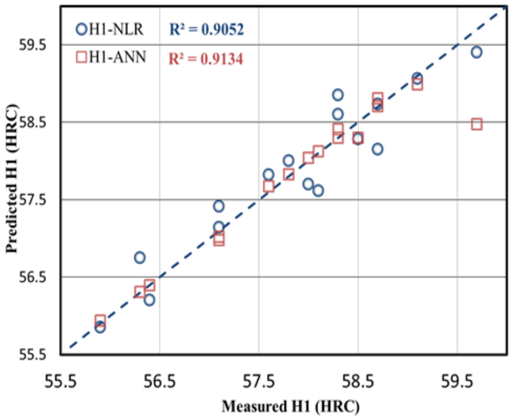

Fig 10. Scatter plot - Measured and predicted H1

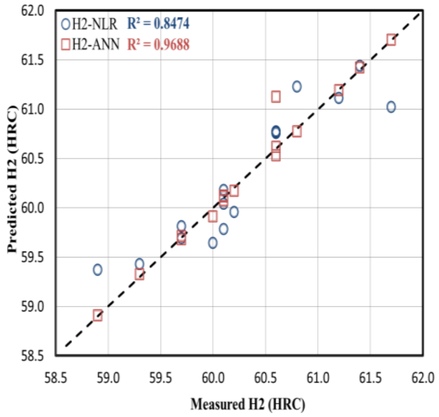

Fig 11. Scatter plot - Measured and predicted H2

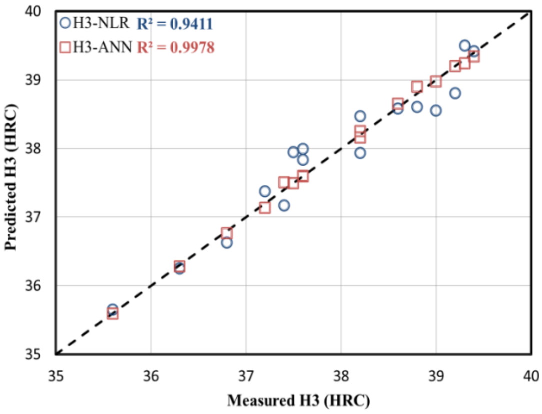

Fig 12. Scatter plot - Measured and predicted H3

V. VALIDATION

Other tests are performed in this study according to an experience design shown in Table 9 whose goal is to have a new set of data to validate the neural network and the mathematical models. The new parameters levels that were conducted in the validation tests are presented in Table 8.

Table 8. Validation test factors levels

Factors	Level
Initial hardness (HRC)	40, 50
Surface nature	As treated (1) - finished (2)
Power (W)	550, 1100
Speed (mm/s)	15, 35

Table 9. Experimental tests (L9 orthogonal array)

Test	P (kW)	V(mm/s)	H (HRC)	S
1	0.55	15	40	1
2	0.55	15	50	2
3	0.55	35	50	1
4	1.15	15	50	2
5	1.15	15	50	1
6	1.15	15	40	2
7	1.15	35	50	1
8	1.15	35	40	2
9	1.15	35	40	1

The results of the validations tests are presented in the following figures (13-19). Models validation process was carried out with the same ANN architecture and the same number of regressors of the mathematical model used for data prediction of the study case (NLR).According to the validation tests results, ANN model still gives excellent prediction accuracy for all of the interest results. Its accuracy ranged from 92.3% to 99.79%. Contrary to the mathematical model, who knew drops of the prediction accuracy in all of D1, D3 and H2 of up to about 87.79%, 86.6% and 85.86% respectively? Even though, the mathematical model provided best fit to the experimental results, the validation results tests emphasized that the mathematical model cannot overcome the ANN model in terms of high prediction accuracy and good performances of the study outcome variables.

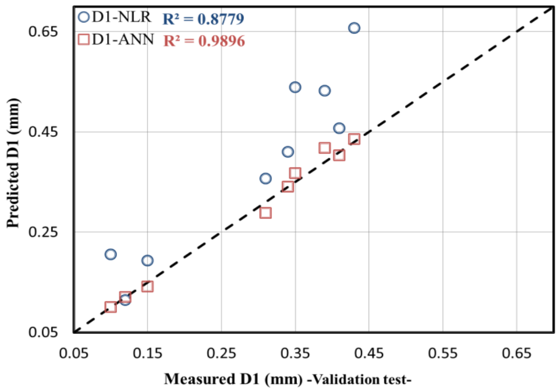

Fig 13.Scatter plot - Measured and predicted D1

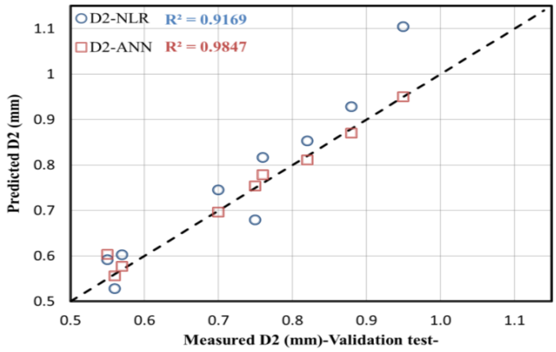

Fig 14. Scatter plot - Measured and predicted D2

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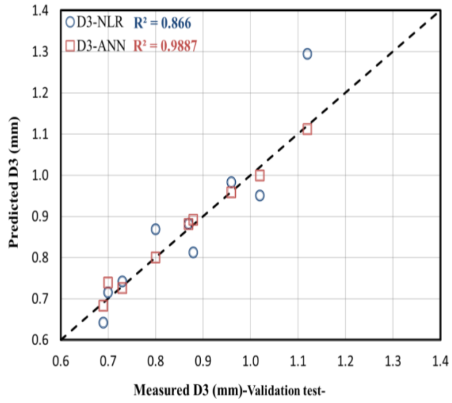

Fig 15. Scatter plot - Measured and predicted D3

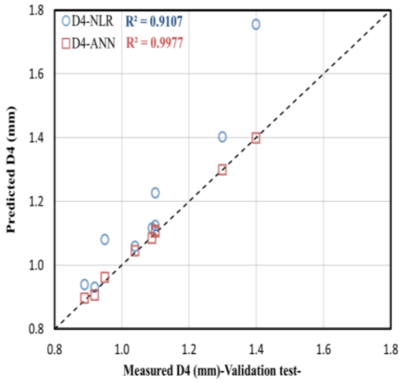

Fig 16. Scatter plot - Measured and predicted D4

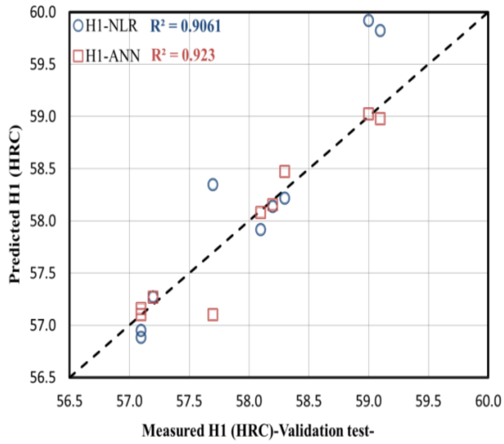

Fig 17. Scatter plot - Measured and predicted H1

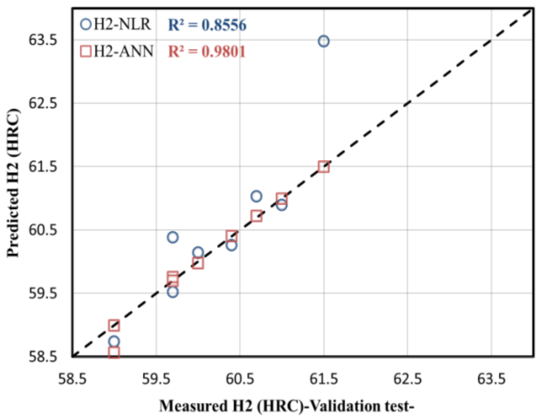

Fig 18. Scatter plot - Measured and predicted H2

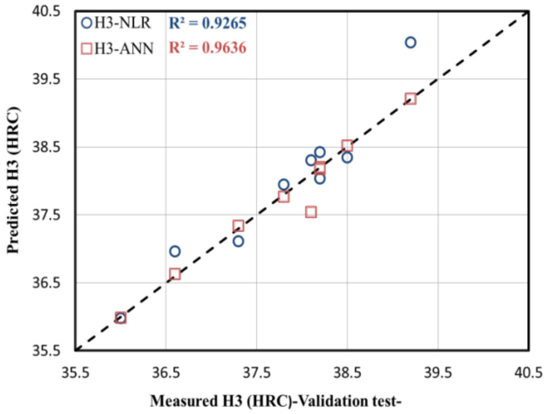

Fig 19.Scatter plot - Measured and predicted H3

Figure 20 shows comparison between modeling and validation. It is clear to notice that the figure contains three curves which the black one represent the hardness profile resulting from the validation (Test 7); while the other curves are the predicted hardness profiles obtained by the mathematical model (Blue dashed line) and the ANN model (Red dashed line).It is clear to note through the form the Figure 6 that the hardness curve provided by the ANN model is almost identical to the measured hardness profile, while there is no similarity between the measured hardness profile and hardness curve provided by the mathematical model (NLR). This means that the ANN model has a better fit of the experimental results and provides a better prediction of the hardness profile than the traditional nonlinear regression model. Table 10 confirms that the performances demonstrated by ANN model are superior comparing to those produced by nonlinear regression. In fact, the precision of ANN model of overall hardness curves characterized by the variables D*i* and H*i* is less than 4%.

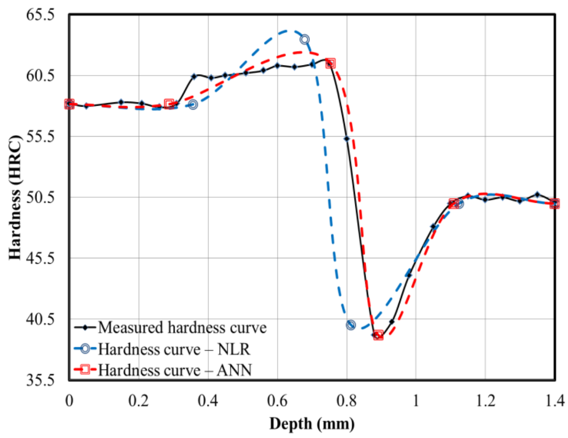

Fig 20. Predicted and measured hardness curves (Validation - Test 7)

VI. CONCLUSION

The paper presented a comparison study between two prediction models used to evaluate the hardness profile of plates made of 4340 and heat-treated by laser. Experimental data used for the prediction are obtained by performing tests through orthogonal arrays using Taguchi design in order to

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Select the optimal parameter setting necessary to obtain higher performances. In first step, ANOVA leads to determine the most important parameters that can affect the hardness profile of the hardened part. Then, the regression model was choosing based on the best regression coefficients values and adequate regressors while the artificial neural network consist of three layers in which in the hidden layer, the best prediction accuracy was correspondent to twelve neurons. The experiment predicted data values by both models were equal to a large extent the eventual values, which proves the excellent predictive capability of both models with a slight difference in accuracy for the benefit of the artificial neural network. As an accurate confirmation, the validation tests were the decisive statement and the ultimate proof that the neural network is most useful technique for data prediction.

Table 10. Predicted absolute mean error (Validation tests)

Mean absolute percentage error (MRE %)	D1	D2	D3	D4	H1	H2	H3
Regression model (%)	36.5	7.555	5.899	7.935	0.581	0.796	0.669
ANN Model (%)	3.137	1.908	1.445	0.652	0.213	0.108	0.215

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