COMPARATIVE STUDIES OF SIMULATION, ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC FOR LASER SHOCK PEENING

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The paper focuses on a development of various modeling techniques to obtain the value stress and deformation for the process of Laser peening on Titanium alloy (Ti6Al4V). The prediction techniques like simulation, artificial neural network (ANN) and fuzzy logic are discussed in this paper. All the three prediction techniques consider overlap of laser spot, power density and pulse duration of laser as input parameters. A design of experiment (DOE) was created according to the Taguchi's experimental design with L18 orthogonal array. Statistical values of the coefficient of determination and absolute percentage error were employed to compare the three developed models by considering initial experiments as well as additional experimental (validation) data. Analysis and results indicate that all three modeling approaches can be equally effectively used for the prediction of compressive stresses with laser peening. However, fuzzy logic model showed the best overall prediction results, while developed ANN model best generalization capability.

Keywords: Laser Shock peening, artificial neural network, fuzzy logic, modeling, simulation

1. Introduction

Titanium and its alloys are being used extensively in many fields like biomedical and aerospace industries because of its high strength, low density, ability to withstand high temperatures and excellent corrosion resistance property. However irrespective of such superior properties, Titanium and its alloys suffers degradation during the course of service because of the varying loads and stress levels over a number of loading cycles. The degradations like crack formation results to failure of material which is highly unfavorable. In general, the surface of material is exposed to the working conditions, so the material failure is more likely to start at the surface. So instead of treating the whole material, a more economical way is to provide a surface treatment to the material.

There are several methods of surface enhancement like shot peening, water jet peening, low plasticity burnishing, laser shock peening etc. out of which laser shock peening is found to be best for titanium and its alloys. Laser Shock

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Peening (LSP) is a surface hardening method in which a high energy pulse laser beam generates shock waves which propagate throughout the material inducing cold work in the microstructure of the material and thus ultimately resulting in the improved performance. But the experimentation of laser shock peening is very commercial, complicated and time consuming. So, in order to analyze the process and produce an accurate output values for various input parameters various prediction techniques is employed. The various prediction techniques discussed in this paper are simulation using ANSYS software, artificial neural network (ANN) and Fuzzy logic.

Singh et al. [1] develop and investigation on simulation-based design approach for an efficient Laser Shock Peening process with a three-dimensional simulation. Further investigated is carried on the effect of LSP parameters such as pressure pulse shape and magnitude, spot size and shape, number of shots, layout of shots, and multiple shot sequences towards residual stress. Application of ANN is markedly growing its use in laser peening modeling. Sibalija et al. [2] used artificial neural networks to build the process model, and by using simulated annealing a set of optimal process parameters are found in a global continual space of solutions. Chaki et al. [3] was targeted to predict and optimize LASOX cutting process quality of mild steel plates. Where simulated annealing-ANN model is developed an optimized to yield best results, indicate that simulated annealing-ANN model can predict the optimized output. Yang et al. [4] projected a progressive Taguchi-ANN technique, which combines the ANN with Taguchi method to build a prediction model for a CO_2 laser cutting trial. The results and analysis deep rooted that hybrid Taguchi-ANN prediction model enhanced the conventional ANN, which has the inborn disadvantage of large trailing of samples. Kramar et al. [5] investigated on surface roughness prediction model with help of fuzzy expert system for machining Inconel 718, by using two bio inspired algorithms: particle swarm optimization and genetic algorithm the fuzzy system is optimised. The results of both the approaches are compared with the real experimental data. It is reveals that the hybrid bio inspired algorithms and fuzzy systems provide a better optimized result. Karatas et al. [6] proposed an ANN model to predict the residual stresses of shot peening based on various strengths using experimental results. ANN is designed with two transfer function namely back-propagation learning algorithm with two different variants and logistic sigmoid for predicting residual stress. And the results of calculated residual stresses and ANN modelling are clearly acceptable. Maleki et al. [7] investigated the predicting capability of shot peening output parameters on titanium matrix composites with help of ANN model. An algorithm named back-propagation (BP) error is developed for training the ANN model. Back-propagation error algorithm based ANN model prediction results are close enough with experimental ones. Billaud et al. [8] proposed a comprehensive and structured approach developed to design an efficient ANN based model for quality estimation and prediction in laser surface transformation hardening process with a commercial 3 kW Nd: Yag laser. The results reveal that the proposed ANN based evaluation and prediction approach effectively leaded to prediction of hardened surface characteristics under variable hardening parameters and conditions. Madic et al. [9] developed predictive models with ANN and real coded genetic algorithm (RCGA) approach for the development of CO_2 laser cutting of mild steel. Taking into account the disadvantages of the back propagation done by Erfan, the RCGA was used for training of the ANNs. Results have shown a good correlation between the applied ANN predictions and experimental results confirming the reliability of the applied approach. Milos et al. [10] made a comparison of various models for the prediction of kerf width achieved in CO_2 laser cutting of stainless steel using ANN, regression analysis and fuzzy logic. Analysis o results specify that applied three modelling approaches shown uniformly effectiveness in prediction of kerf width in laser cutting. However, developed ANN showed model good generalization capability and fuzzy logic model showed the excellent overall prediction capability. Pandey et al. [11] proposed a hybrid approach, by combining Fuzzy logic theory and robust parameter design methodology has been applied to calculate the fuzzy multi-response performance index which is further used for multi-objective optimization. The validated predicted optimum results have shown significant reduction in kerf deviations at sides.

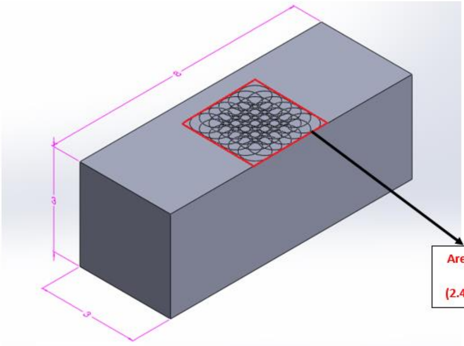
2. Modeling

2.1 ANSYS Modeling

Application of advanced materials is increased due to their unique strength, corrosion resistance and surface properties. Surface degradation of advanced materials at elevated temperatures and pressures, demands the need to explore new method to improve surface properties. The trialing of various surface enhancement processes is difficult as in some cases it may be time consuming due to the complexity of the geometry. Thus, computational exploration method needs to be introduced for easier study of various processes and there comes the role of finite elemental simulation [12].

But before proceed to simulation the Modeling of the geometry needs to be done. The Modeling of the geometry is achieved using software called SolidWorks as shown in Fig 1. The important modeling parameters to be considered are the laser spot shape and overlap percentage. These parameters are determined based on published experimental and simulation results. Once the model is obtained the material is defined with the properties as shown in Table 1 and the various boundary conditions like fixed support and pressure load are applied. The pressure pulse shape is shown in Fig 2.

Fig. 1 Laser spot overlap arrangement & laser pulse and resulting pressure pulse [12]



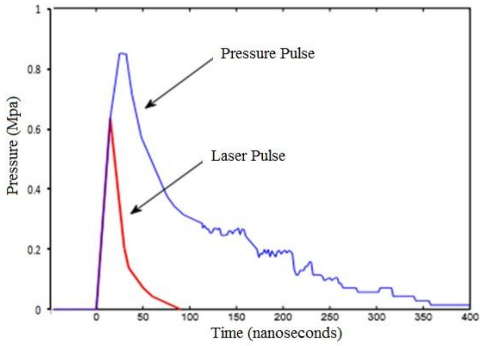


Table 1

Mechanical properties of Ti 6Al 4V

S.No.	Name of the property	Value of the property
1.	Young's Modulus	1.15×10^{11} MPa
2.	Poisson's Ratio	0.35
3.	Bulk Modulus	1.20×10^{11} MPa
4.	Shear Modulus	4.3×10^{11} MPa

A Design of Experiment (D.O.E) table is tabulated in Table 2 using Taguchi Design which considers various laser parameters like overlap, power density and pulse duration. There are three laser peening parameters of which one of the parameters has two levels and the rest two parameters has three levels each. The resultant table will have L36 runs which mean a total 36 set of experiments. Since 12 sets of parameters are repeating in the 36 arrays, however repeated sets give the same results. So, repeated sets are omitted and as a table of 12 arrays are considered as shown below.

The pressure is calculated corresponding to each set of parameters using the formulas mentioned below

$$P = 0.01\sqrt{\frac{\sigma}{(2\sigma+3)}}\sqrt{I(GW/cm^2}\sqrt{Zgcms^{-1}} \quad (1)$$

$$\frac{2}{Z} = \frac{1}{Z_1} + \frac{1}{Z_2} \quad (2)$$

Where P is the pressure generated by shock waves, I is the power density, Z is the resultant acoustic impedance of the medium which is equal to product of density of that medium (ρ) and velocity of sound (u) in that medium, Z1 is the acoustic impedance of Ti6Al4V= $2.75*10^6$ g/cm^{2}s and Z2 is the acoustic impedance of water = $1.65*10^5$ g/cm^{2}s and σ is the efficiency of interaction =0.1 for water.

Table 2

Parameter sets for Simulation Modeling

S.No.	Wavelength (nm)	Overlap (%)	Power Density (GW/cm^2)	Pressure (GPa)
1.	532	60	3	1.708
2.	532	60	6	2.416
3.	532	60	9	2.959
4.	532	70	3	1.708
5.	532	70	6	2.416
6.	532	70	9	2.959
7.	1064	60	3	1.708
8.	1064	60	6	2.416
9.	1064	60	9	2.959
10.	1064	70	3	1.708
11.	1064	70	6	2.416
12.	1064	70	9	2.959

The pressure obtained for each set of parameters is applied on the array of laser spots considering the temporal profile of laser pulse and pressure pulse. The simulation is solved, and the maximum Von-Misses stress and maximum deformation obtained over the entire peened region is recorded.

2.2 Artificial Neural Network modeling

ANN is an extremely powerful modeling tool at present widely employed in various fields of engineering. ANN, with their extraordinary ability to develop meaning from complex data, can be used to identify trends that are excessively complex and extract patterns to be observed by either computer techniques or humans. The main advantage of this technique is that it has the ability provide data that fits better as compared to other regression techniques. The process of modeling using ANN requires the loading of input data, sample data and target data.

Furthermore, modeling with ANNs is much more complex since numerous decisions related to the selection of ANN architecture, training parameters, transfer functions, parameters of the training algorithm, etc. had to be made. Above all, there is limited theoretical and practical background to assist in systematical selection of these parameters.

Developing mathematical ANN model for the prediction of compressive stress and deformation, considers 36 randomly selected input data from literature review and the corresponding output data is obtained. This data was used for training of the neural network. The input parameters laser wavelength, power density and pulse duration were loaded with one output parameter i.e. maximum equivalent stress. Once the neural network is trained, testing is performed and the results are recorded. The same procedure is followed to obtain best results.

Once the ANN has been trained, the knowledge acquired by the ANN can be represented in the form of mathematical equation. Levenberg–Marquardt algorithm [13] was used for training purpose and the training process was monitored by calculating the mean squared error.

$$\hat{Y}(X) = g(\sum jW_{ij} \cdot f(\sum jW_{ij}.x_i + b_j) + b_k) \quad (3)$$

where ŷ (*X*) is the calculated ANN output (estimated) for the input vector b_j , b_k and *X* are biases of the output and hidden neurons, respectively w_{ji} and w_{kj} are the input to hidden and hidden to output neuron weights respectively, g and f are the transfer functions used in the output and hidden layers, respectively.

2.3 Fuzzy Logic

Fuzzy logic is technique which employs two different stage determinations of structure and adjustment of parameter to predict output values for different values of input parameters [14], [15]. The first step is to identify the structure which comprises defining of input/output parameter and creating membership function. The four component of a fuzzy system are fuzzifier, interface engine, rules and defuzzifier. The fuzzifier is used to convert all the input parameters into fuzzy variables. The input values relating to a single parameter is mapped into between 0 and 1. This mapping is obtained by the help of membership function.

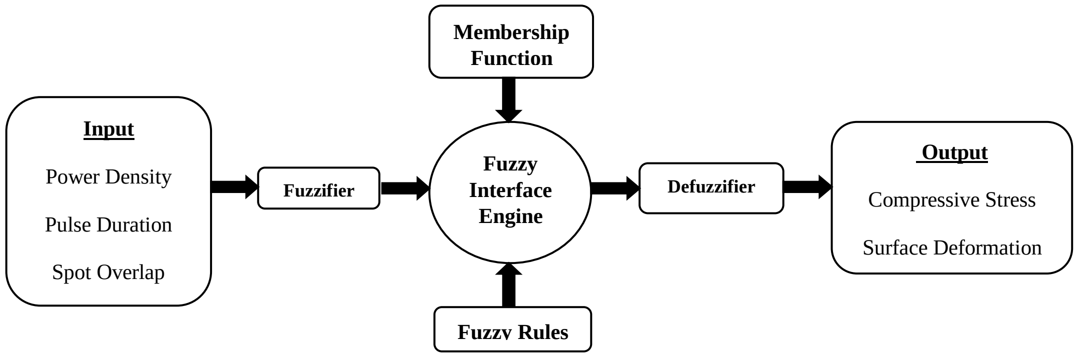


Fig. 2 Fuzzy logic structure with input and output parameters.

Membership function was defined corresponding to each input parameters and the value of each input parameters were defined in terms of linguistic variables [16]. Various literatures are reviewed and ranges of input and output parameter is defined in table 3 and triangular shape is fixed.

Table 3

Laser Peening Parameters Range and Linguistic Variables

INPUTS		
Laser Peening Parameters	Range	Linguistic Variables
Overlap (%)	60-70	low, high
Power Density (GW/cm^2)	3-9	low, medium, high
Pulse Duration (ns)	8-12	low, medium, high
OUTPUT		
Stress(MPa)	1200-3500	Extremely low, Very less, Less, Medium, High, Very High, Extremely high

The fuzzy system uses IF-THEN rule to predict the output [17]. Every rule plays a role in predicting the appropriate result for proposed input values [18]. Some of the rules that are loaded into fuzzy system are mentioned below

1) If (O is Low) and (I is Low) and (t is Low) Then (Maximum Eq. stress is Extremely Low).

2) If (O is Low) and (I is Low) and (t is Medium) Then (Maximum Eq. stress is Very Low).
3) If (O is Low) and (I is Low) and (t is Low) Then (Maximum Eq. stress is Low).

18) If (O is high) and (I is high) and (t is high) Then (Maximum Eq. stress is Very High).
Where O, I and t denotes overlap, power density and pulse duration respectively.

The rule base is used by the fuzzy inference engine to provide the fuzzy output. Finally, the defuzzifier [19] converts the fuzzy output into the actual value. The defuzzification method selection plays a vital role as it deeply influences the accuracy and speed of the model. In this study, centroid defuzzification method is used to carry out defuzzification [20].

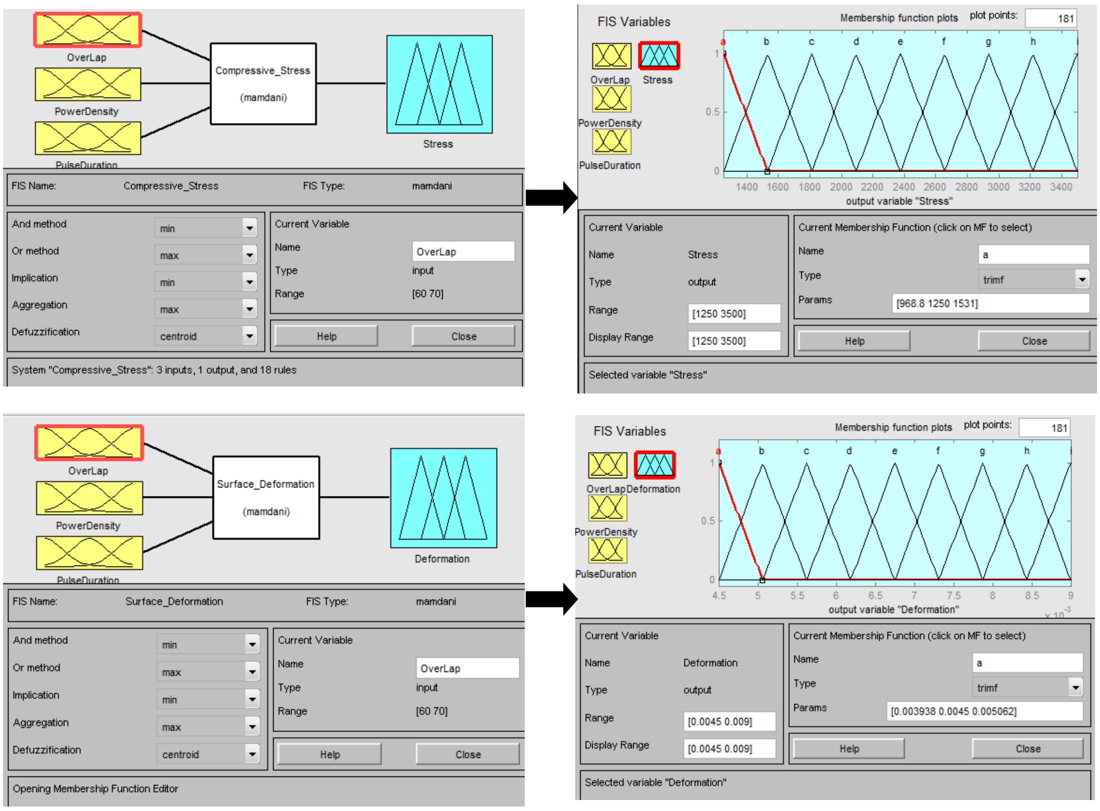


Fig. 3. Block diagram used for fuzzy modeling

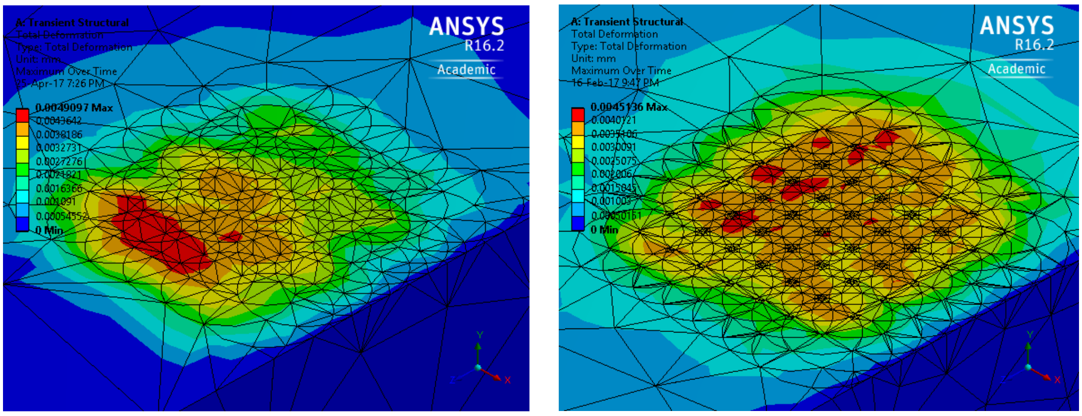
3. Results and Discussion

Explanation about the effect of various parameters like power density, wavelength of laser, pulse duration etc. on the material discussed below. Simulation is optimized with Taguchi technique to obtain the best set of parameters of LP which will result in the best lifespan of Titanium alloy (grade 5). Finite element simulation of Laser shock peening has been performed on the Titanium alloy (grade 5- Ti6Al4V) and various results such as total deformation, Von-Misses stress and plot of residual stress vs. depth from surface have been found out. The area which is simulated for peening deforms under the action of pressure. This large pressure is applied for a time in nanoseconds. This results in the deformation of the test surface. The effect of various parameters on the amount of deformation is discussed below.

3.1 Effect of Overlap of Laser Shots on Residual stresses and Deformation

It has been found that when the overlap percentage of laser spot is increased keeping all other LP parameters constant, the surface is deformed more for the case with higher overlap percentage. The magnitude of residual stress is more for the case with higher overlap percentage. The effect of overlap of laser spot on residual stresses and deformation have shown in figure 4,5 and 6 where the power density is kept is kept constant as 3 GW/cm2, pulse duration as 10 ns and the overlap is varied as 60% and 70%.

Fig. 4. Total deformation for 60% and 70% overlap, 10ns pulse duration and 3 GW/cm2 power



density

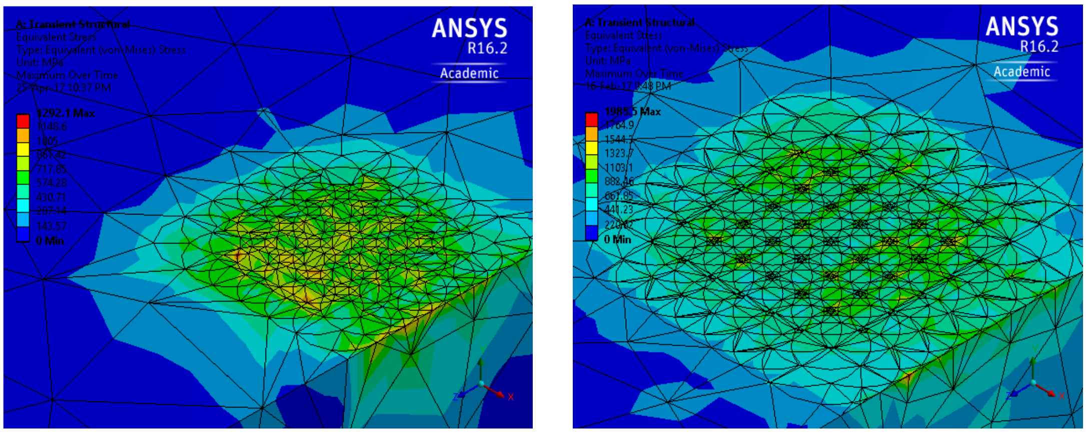


Fig. 5. Total deformation for 60% and 70% overlap, 10ns pulse duration and 3 GW/cm^2 power density

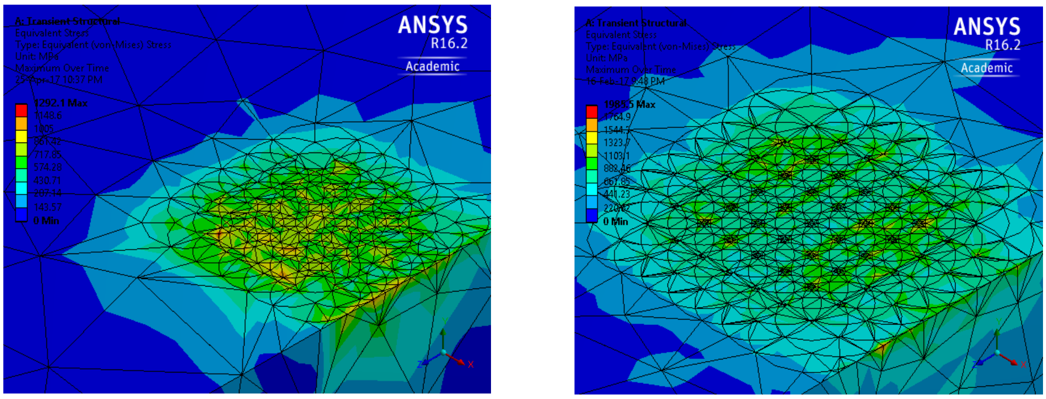


Fig. 6. Residual stress for 60% and 70% overlap, 10ns pulse duration and 3 GW/cm2 power density

3.2 Effect of Power Density of Laser Shots on Residual stresses and Deformation

Power density of laser spot is increased keeping all other LP parameters constant, the surface is deformed more for the case with higher power density. And, the magnitude of residual stress is more for the case with higher power density. The effect of power density of laser spot can be seen in the below figure 7 and 8 where the overlap is kept constant as 70%, pulse duration as 10 ns and the power density is varied as 3, 6, 9 GW/cm2.

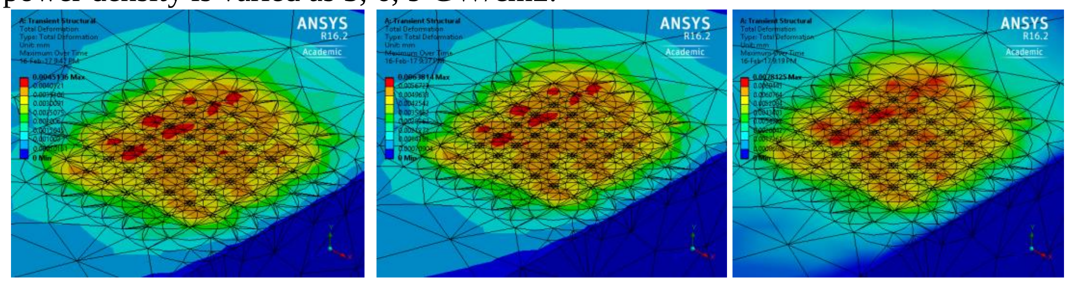


Fig. 7. Total deformation for 70% overlap, 10ns pulse duration and 3, 6 and 9 GW/cm^2 power density

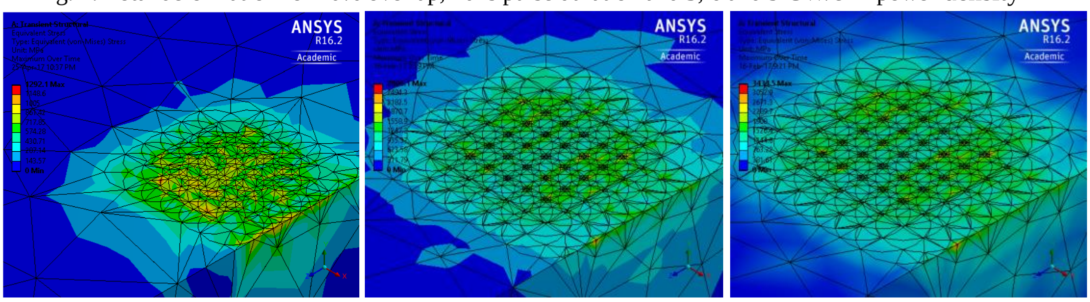


Fig. 8. Residual stresses for 70% overlap, 10ns pulse duration and 3, 6 and 9 GW/cm2 power density

3.3 Comparison of ANN and Fuzzy model predictions with Ansys Simulation values.

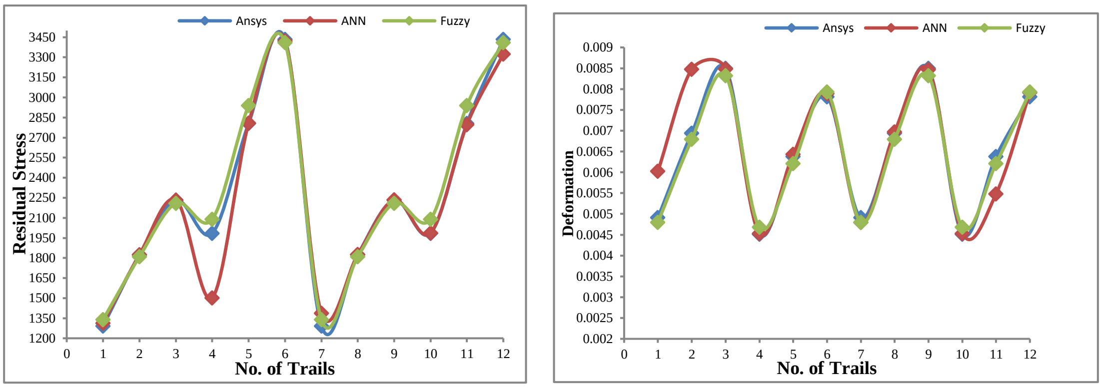


Fig. 9. Comparison of ANN and Fuzzy models with corresponding Ansys model values

The comparison is made among predicted value of three modeling software’s i.e. fuzzy logic, ANN and Ansys Simulations are given in Figure 9. As could be seen from Figure 9, the fuzzy logic model yielded the maximum coefficient of determination in perdition of both stresses and deformation, followed by ANN model, respectively. In sum, both the models gave reasonable predictions.

From these predictions comparison, it is clearly identifiable that three models display good prediction act, however it is noticed that the exactness of the ANN model was much enhanced when new data was used. In other words, generalization capability was best shown by ANN model. In this case, by using the fuzzy logic model, the main effects of the laser peening parameters on the residual stress and deformation was observed: an increase in spot overlap increases the deformation, an increase in power density increase the compressive stress, and simulation is still carrying to find the saturation point of compressive stresses.

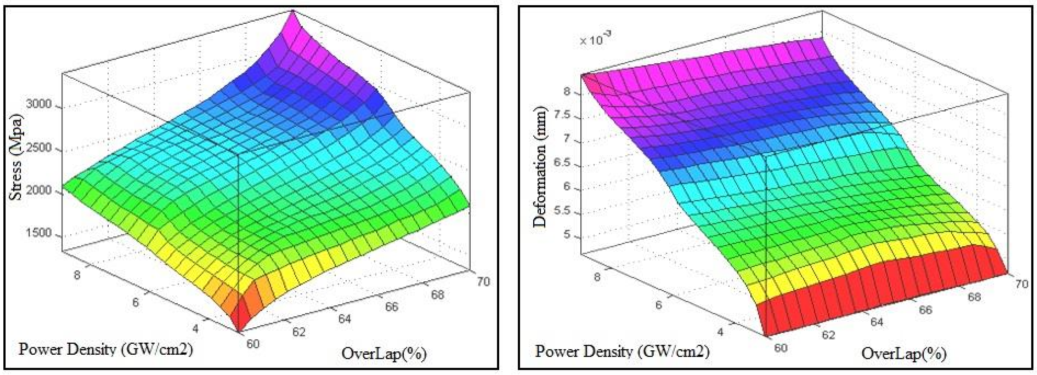


Fig. 10. Interaction effect of the Power Density, Spot Overlap on the Compressive stress and deformation.

Figure 10 represents the fuzzy logic modeling 3D surface plots of deformation and compressive stress obtained in laser peening of titanium grade 5. Among six possible combinations of interaction effects, this plot has simultaneous change of power density and spot overlap, produces the most significant change in deformation and compressive stress.

4. Conclusions

In this paper, an attempt was made to develop and compare mathematical models for compressive stress and deformation prediction in laser peening of Titanium Grade5 using Ansys simulation, Fuzzy logic and ANN. This paper contributes the development and comparison of three competitive models. The drawn conclusions are summarized by the following points:

- Three modelling approaches provide reasonably accurate models for the Compressive stresses and deformation prediction. Ansys modelling is user responsive in creating/altering boundary and loading conditions for predicting the results in 3D graphics. The development of fuzzy logic model requires considerable experience and knowledge, but it provides the accurate predictions of all modelling approaches. ANN model development in quite time taking for architectural and training parameters and can able to provide reasonable perditions.
- Three modelling methods can be used professionally for complete analysis of the process parameters effect and their interactions on the compressive stress and deformation. Ansys modelling show the optimised compressive stress and deformation at wavelength 532nm, 70% overlap and 3 GW/cm^2. And, fuzzy logic model results an optimum deformation region at power density 4-6 GW/cm^2 and spot overlap 62-68%. Even though ANN model showed the best generalization capability, an enhanced prediction performance is required for make use of the complete potential of the ANNs through very well tuning of its training and architectural parameters.
- Three modelling techniques are uniformly suitable for laser peening modelling. By the author’s opinion the first choice should be Ansys simulation model, because of its simplicity and user responsive, and if Ansys model is not possible or providing unacceptable results then ANN and fuzzy modelling are to be practised. Finally, one needs to sense that a new hybrid model is to be developed when an individual model is not providing sufficient acceptable predictions.

REFERENCES

[1]. *G. Singh, R. V. Grandhi, D.S. Stargel*, Modeling and Parameter Design of a Laser Shock Peening Process, nternational Journal for Computational Methods in Engineering Science and Mechanics, **vol. 12,** no. 5, 2011, pp. 233–253.

[2]. *T. V. Sibalija, S.Z. Petronic, V.D. Majstorovic, A. Milosavljevic*, Modeling and optimization of laser shock peening using an integrated simulated annealing-based method, International Journal of Advanced Manufacturing Technology, **vol. 73**, 2014, pp. 1141–1158.

[3]. *S. Chaki, S. Ghosal*, Application of an Optimized SA-ANN Hybrid Model for Parametric Modeling and Optimization of LASOX Cutting of Mild Steel, Production Engineering, **vol. 5**, no. 3, 2011, pp. 251–262.

[4]. *C.B. Yang, C.S. Deng, H.L. Chiang*, Combining the Taguchi method with artificial neural network to construct a prediction model of a CO2 laser cutting experiment, The International Journal of Advanced Manufacturing Technology, **vol. 59**, 2012, pp. 1103–1111.

[5]. *D. Kramar, D. Cica*, Design of fuzzy expert system for predicting of surface roughness in high-pressure jet assisted turning using bioinspired algorithms, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, **vol. 30,** no. 1, 2014, pp. 96–106.

[6]. *C. Karataş, A. Sozen, E. Dulek*, Modelling of residual stresses in the shot peened material C-1020 by artificial neural network, Expert Systems with Applications, **vol. 36**, no. 2, 2009, pp. 3514–3521.

[7]. *E. Maleki, A. Zabihollah*, Modeling of shot-peening effects on the surface properties of a (TiB + TiC)/Ti–6Al–4V composite employing artificial neural networks, Materials and technology, **vol. 50**, no. 6, 2016, pp. 851–860.

[8]. *G. Billaud, A. El Ouafi, N. Barka*, ANN Based Model for Estimation of Transformation Hardening of AISI 4340 Steel Plate Heat-Treated by Laser, Materials Sciences and Applications, **vol. 6**, no.11, 2015, pp.978–994.

[9]. *M. Madic, M. Radovanovic*, Application of RCGA-ANN approach for modeling kerf width and surface roughness in CO2 laser cutting of mild steel, Journal of the Brazilian Society of Mechanical Sciences and Engineering, **vol. 35**, no. 2, 2013, pp. 103–110.

[10]. *M. Milos, C. Zarko*, Comparison Of Fuzzy Logic , Regression and Ann Laser Kerf Width Models, UPB Scientific Bulletin Series D, **vol. 78**, no. 1, 2016. pp. 197–212.

[11]. *A.K. Pandey, A.K. Dubey*, Taguchi based fuzzy logic optimization of multiple quality characteristics in laser cutting of Duralumin sheet, Optics and Lasers in Engineering, **vol. 50**, no. 3, 2012, pp. 328–335.

[12]. *N. Hfaiedh, P. Peyre, H. Song, I. Popa, V. Ji, V. Vignal*, Finite element analysis of laser shock peening of 2050-T8 aluminum alloy, International Journal of Fatigue, **vol.70**, no.4, 2015, pp. 480–489.

[13]. *J. Nocedal, S. Wright*, Numerical Optimization, 2nd Edition, Springer, 2006.

[14]. *E. Zalnezhad, A. A. D. M. Sarhan, and M. Hamdi*, Prediction of TiN coating adhesion strength on aerospace AL7075-T6 alloy using fuzzy rule based system, International Journal of Precision Engineering and Manufacturing, **vol. 13**, no. 8, 2012, pp. 1453–1459.

[15]. *E. Zalnezhad, A. A. D. Sarhan, and M. Hamdi*, A fuzzy logic based model to predict surface hardness of thin film TiN coating on aerospace AL7075-T6 alloy, International Journal of Advanced Manufacturing Technology, **vol. 68**, no.4, 2013, pp. 415–423.

[16]. S. Pratik Kumar , S. K. Chandrakar, A. Jain, Optimized Design of Machine Elements Subjected to Fatigue Loading Using Fuzzy Logic, Journal of Basic and Applied Engineering Research, **vol. 1**, no. 5, 2014, pp. 91-94.

[17]. *H.R. Karbalaian, A. Yousefi-koma, M. Karimpour, S.S. Mohtasebi*, Investigation on the Effect of Overlapping Laser Pulses in Laser Shock Peening with Finite Element Method, Procedia Materials Science, **vol.11**, no.5, 2015, pp. 454–458.

[18]. *S. Sivarao, W.J.G. Castillo, T. Taufik*, Machining Quality Predictions: Comparative Analysis of Neural Network and Fuzzy Logic, International Journal of Electrical and Computer Sciences, **vol. 9**, no. 9, 2009, pp. 60–64.

[19]. *S. Sumathi*, *S. Paneerselvam*, Computational Intelligence Paradigms: Theory & Applications using MATLAB, CRC Press, 2010.

[20]. *E. Zalnezhad*, *A.A.D. Sarhan*, *M. Hamdi*, A Fuzzy Logic Based Model to Predict Surface Hardness of Thin Film TiN Coating On Aerospace AL7075-T6 Alloy, International Journal of Advanced Manufacturing Technology, **vol. 68**, no. 1-4, 2013, pp. 415–423.