World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:8, No:8, 2014

Artificial Neural Network Application on Ti/Al Joint Using Laser Beam Welding – A Review

K. Kalaiselvan, A. Elango, N. M. Nagarajan

***Abstract*—**Today automobile and aerospace industries realise Laser Beam Welding for a clean and non contact source of heating and fusion for joining of sheets. The welding performance is mainly based on by the laser welding parameters. Some concepts related to Artificial Neural Networks and how can be applied to model weld bead geometry and mechanical properties in terms of equipment parameters are reported in order to evaluate the accuracy and compare it with traditional modeling schemes. This review reveals the output features of Titanium and Aluminium weld bead geometry and mechanical properties such as ultimate tensile strength, yield strength, elongation and reduction of the area of the weld using Artificial Neural Network.

***Keywords*—**Laser Beam Welding (LBW), Artificial Neural Networks (ANN), Optimization, Titanium and Aluminium sheets.

I. Introduction

ARTIFICIAL NEURAL NETWORK (ANN) is widely established in Artificial Intelligence (AI) research where a nonlinear mapping between input and output parameters is required for a function approximation [1]. Various types of ANN like multilayer perception (MLP), radial basis function (RBF) and self-organizing map (SOM) is used for modeling. The MLP with back propagation algorithm is widely used because of its simplicity and great forecast ability in weld modeling [2]. Fig. 1 shows the flow chart of ANN modeling procedure which indicates the two phases involved, the first phase is to train the network model and the second phase is to validate the network model with data, which is not used for training.

A. Neural Network Architecture

Artificial neural network (ANN) is a non linear statistical technique that can explore non linear relationships between the input and the output variables [3]. It can be applied for alloys for predicting their properties at different temperatures and at different compositions whose relationships are non linear in nature. Choosing the optimum network architecture is one of the challenging steps in neural network modeling. Fig. 2 shows the neural network architecture for predicting weld bead geometry.

K.Kalaiselvan is with the Department of Mechanical Engineering, Anna University, Tamilnadu – 630004 (Cell: 8891491686; e-mail: kalaiesanai@gmail.com).

Dr. A. Elango is a Vice Principal, Anna University Engineering College, Tamilnadu – 630004 (e-mail: elango.arum69@gmail.com).

Dr. N. M. Nagarajan is a Professor (Retd), National Institute of Technology, Kerala-673601 (e-mail: dr.nmnagarajan@gmail.com).

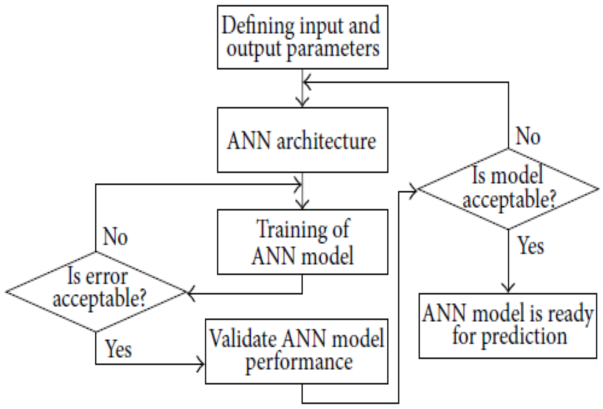


Fig. 1 Flow chart of ANN modeling procedure

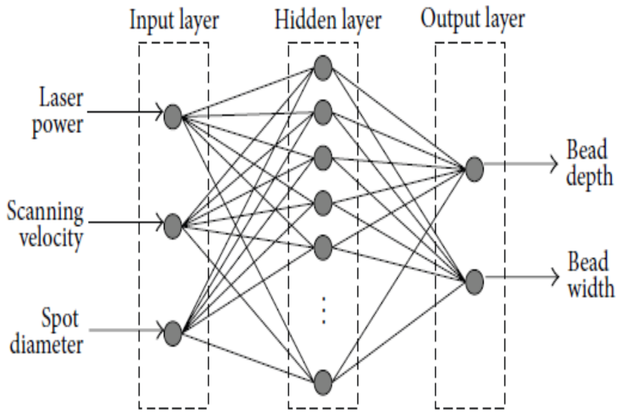


Fig. 2 Neural network architecture for predicting weld bead geometry

The back propagation neural network (BPNN) has three layers like input layer, hidden layer and output layer. As there are three inputs and two outputs, the numbers of variables in the input and output layer had to be set to 3 and 2 respectively. In the many applications back propagation architecture with one hidden layer is enough [4]. In order to find an optimal architecture different numbers of variables in the hidden layer are considered and prediction error for each network is calculated.

II. ANN Applied By Different Researchers

A. Weld Bead and Pool Geometry

Mohd Idris Shah Ismail et al. [5] developed a neural network model in order to predict accurately the weld bead geometry in the laser welding process by changing parameters such as laser power, scanning velocity and spot diameter. The experimental work was carried out on a thin stainless steel sheet using a single mode fiber laser with high speed scanning system for data collection to train and validate the effectiveness of the neural network model. The prediction capability of neural network model is also compared with the performance of statistical regression model which has been developed from the same experimental data sets used for the neural network model.

After laser welding the specimens were cut perpendicular to the scanning direction for the measurement of weld bead geometry by optical microscope. Fig. 3 shows the weld bead profile of laser welded bead on sheet joint [5].

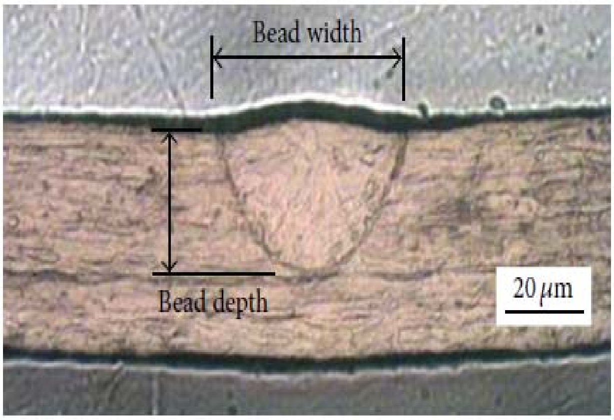


Fig. 3 Weld bead profile of bead on sheet joint

Young Whan Park et al. [6] applied Genetic algorithms and Neural Network for process modeling and parameter optimization of aluminum laser welding automation. Vasudevan et al. [7] used a Genetic algorithm (GA) to achieve the target bead geometry in Tungsten inert gas welding by optimizing the process parameters. It can be understood from the review that many research works have been carried out on the welding process in particular with the laser welding process; but few of them concentrated on the volume deposition and its controlling parameters, their behavior and influence on the weld bead quality when used with materials such as Ti/Al, Ni / Fe or Ti / Ni and Inconel. In this work emphasis is given mainly for Ti/Al alloy.

Vitek et al. [8] have developed a model to predict the weld pool shape parameters like penetration, width, width at half penetration and cross section area in pulsed Nd-YAG laser welds on Al alloy 5754 using neural network. The top surface of the weld is often highly irregular as shown in Fig. 4. They have considered the process parameters such as travel speed, average power, pulse energy, and pulse duration.

Figs. 5 (a) and (b) show five weld pool cross sections from a typical weld. These are superimposed top line on the top surface of the sheet. The weld pool shape is not exactly constant along the length of the weld. This kind of superposition provides some guidance on various pool shapes that can be expected within the same weld. The range in weld pool cross sections also provides a basis for assessing the accuracy of the predicted pool profiles.

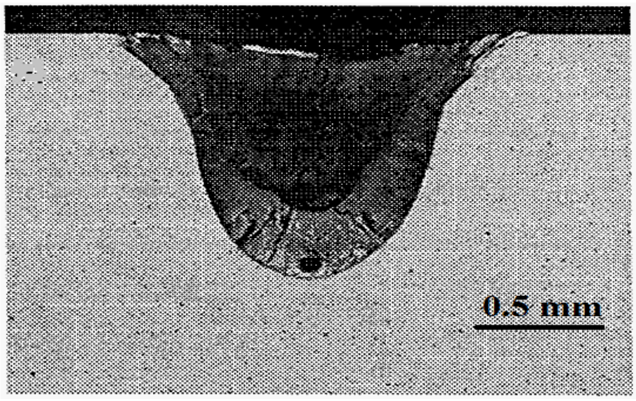


Fig. 4 Cross-section micrograph of weld pool shape

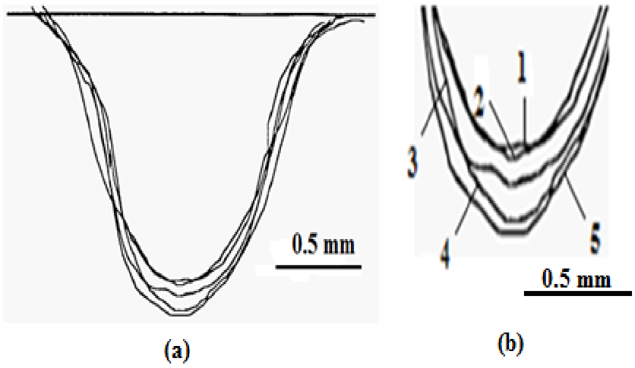


Fig. 5 (a) Typical variations in weld pool cross-section along the length of a single weld (b) Five weld pool cross sections

ANN model is developed to convert the shape parameters into a predicted weld profile which is based on the actual experimental weld profile data [8]. The heavy line is the predicted profile while the lighter lines are the experimental profiles taken along the length of the weld as shown in Fig. 6. The accuracy of the model is excellent. It is concluded that ANN approach allows for instantaneous results and therefore, offers advantages in applications where real time predictions are needed whereas computationally intensive predictions are too slow.

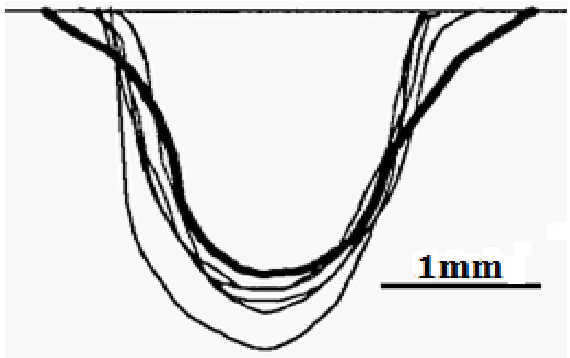


Fig. 6 Predicted weld pool shapes compared to experimental pool profiles

Park et al. [9] have analyzed the signal of the plasma or spatter and bead size to develop a bead size estimation system using the regression method and a neural networks method. It is found that the relationship is a nonlinear function caused by the penetration state. In contrast the authors concluded that the regression models were appropriate for estimation when classifying the penetration state as partial penetration and full penetration, whereas the neural network gives very accurate estimation approach for bead size.

Dhavalkumar et al. [10] have explored various approaches for predicting the behavior of the laser welding process and they also suggested using ANN or by neuro fuzzy approach. It is also observed the main important parameters which affect the weld bead geometry. Balasubramanian et al. [11] applied neural networks to modeling and Buvanasekaran et al. [12] studied the Analysis of laser welding parameters using artificial neural networks.

Banakar Nagaraj et al. [13] identified the important bead parameters like total volume and geometry which control most of the other bead parameters and it minimizes most of the other bead quality parameters such as bead width and penetration. But for a sound and strong weld bead penetration should be maximized. So in optimizing the total volume of the weld bead the penetration is advised to be included as a constraint. Minimizing the size of the weld bead reduces the welding cost through reduced heat input and energy consumption also increases welding productivity through a high welding speed. Because of these advantages the total volume of the weld bead should be optimized and other bead parameters as constraints rather than optimizing all the bead parameters individually.

The effect of energy input per unit length of weld from the travelling heat source on the laser efficiency and weld quality have been investigated by Casalino et al. [14]. A number of austenitic stainless steel butt joints are produced by CO_2 laser welding irradiation. The welding efficiency is calculated as the melted area to energy input per unit length ratio. Moreover weld crown and depth are measured in order to evaluate the quality of the joint. ANN is used to correlate the collected data to the process parameters like laser power, speed, and material thickness after these parameters are clustered using a fuzzy C-means algorithm. In order to select the optimum network parameters a 24-factorial design is used. Finally a model is built to choose the most suitable laser welding process for producing high efficiency and superior quality. It is recommended to consider more input factors such as laser focus, different materials and different weld beads.

B. Mechanical Properties

Wei et al. [15] studied different welded joints with significant variation in their mechanical properties. Accordingly, welding is usually done with the aim of getting a welded joint with excellent mechanical properties. The schematic model of the neural network for modeling [15] mechanical properties of welds are shown in Fig. 7. The input of the model includes chemical compositions, heat treatment, tested temperature and the output model includes five most important mechanical properties namely ultimate tensile strength, tensile yield strength, elongation, reduction of area, hardness and toughness.

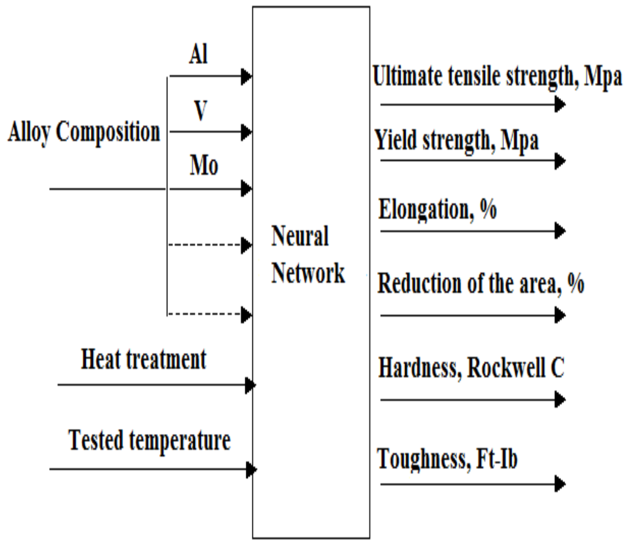
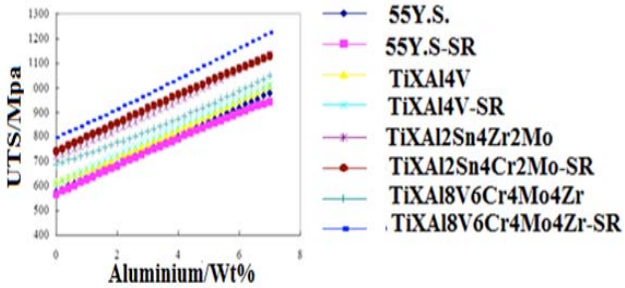


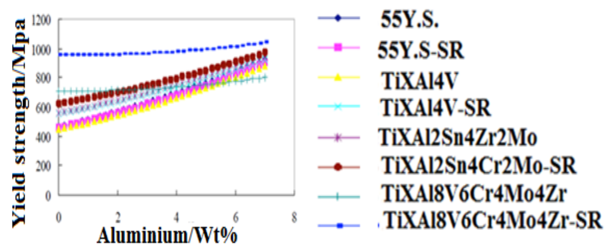
Fig. 7 Schematic model of the neural network for modeling mechanical properties in weldments

To determine these welding combinations that would lead to excellent mechanical properties, ANN technique is adopted and also for the purpose of optimizing the welding process in order to achieve the desired mechanical properties of the welded joint.

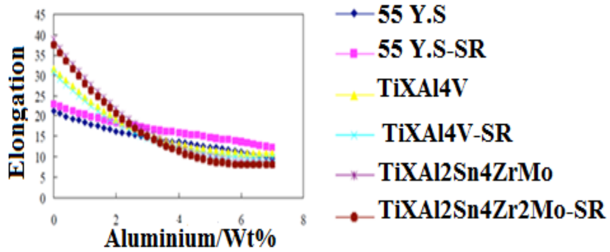
The influence of aluminum on the mechanical properties of welded metal of titanium is shown in Figs. 8 (a)-(d) according to the neural network model predictions.



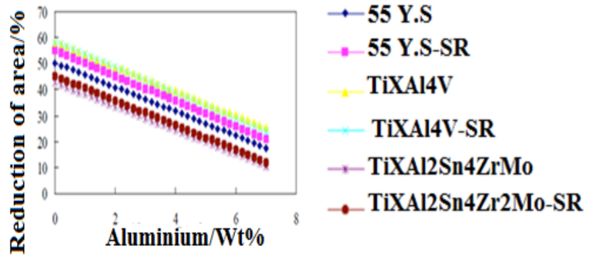
(a) Ultimate Tensile strength



(b) Yield strength model



(c) Elongation model



(d) Reduction of area

Fig. 8 Neural network predictions for the influence of aluminium content the mechanical properties for different titanium alloy system

From the simulated results in Fig. 8, increasing aluminium content the ultimate tensile strength and yield strength increases. When aluminium content is less than 3.0 and drops after that the elongation and reduction of the area drop dramatically. These results accord very well with the neural network predictions for influence of the aluminium on the mechanical properties for the titanium [16].

Sterjovski et al. [17] introduced ANN modelling as an alternative technique to those currently to predict the hardness of HAZ (Heat Affected Zone) and trying to control it to minimize the risk of hydrogen assisted cold cracking in welding pipelines by the hot tapping technique. The model developed included materials characteristics like chemical composition and hardness as inputs, the peak temperature, holding time and cooling rate of the HAZ thermal cycle simulation also used as key inputs in the model to predict the HAZ hardness. It is reported that the hardness of HAZ increases with increasing the following like carbon content, original hardness of pipe or fitting material and more rapid cooling. They compared the predictive capabilities of the models developed with other published works to the neural network model they developed. It is clear that the neural networks model produced a much lower error across a broader range of HAZ hardness values.

Sterjovski et al. [18] have applied the ANN models to predict the mechanical properties of steels in various applications like impact strength of quenched and tempered pressure vessel steel exposed to multiple postweld heat treatment cycles, the hardness of the simulated HAZ in pipeline, lap fitting steel after welding, the hot ductility and hot strength of various microalloyed steel over the temperature range for stand or slab straightening in continuous casting process. It is found that the three ANN models successfully predicted the mechanical properties. ANNs could successfully predict multiple mechanical properties and the result of the sensitivity analysis were in agreement with both findings of the experimental investigation and reported results. Furthermore it is mentioned that the use of ANNs resulted in large economic benefits for organizations through minimizing the need for expensive experimental investigation and inspection of steels used in various applications.

Murugananth et al. [19] have coupled ANN model with optimization software which utilize linear and nonlinear techniques to explore possible combination of carbon, manganese and nickel concentrations for a given set of welding parameters to predict the weld metal composition that would maximize the toughness at – 60°C.

Factors that affect weld mechanical properties with the addition of oxygen, nitrogen, carbon, hydrogen and iron contents in the weld joint as well as the cooling rate of commercially pure titanium have been investigated by Wei et al [20]. ANN techniques used to predict the ultimate tensile strength, yield strength, elongation, reduction of area, Vickers hardness, and Rockwell B hardness. The input data is obtained from mechanical testing of single pass autogenous welds. The ANN models are developed. An oxygen equivalent equation (OEE) used to predict the mechanical properties of titanium welds. A good agreement is found between both ANN and OEE. The obtained results indicate that both oxygen and nitrogen have the most significant effect on the strength while hydrogen has the least effect. Also it is reported that cooling rate is more important than the carbon addition or iron content in ultimate tensile strength model and the iron content is equally important as the carbon content in the yield strength model.

III. Comparison Between The Optimization Techniques

From the foregoing discussions it is observed that ANN perform better than other techniques like Response Surface Methodology (RSM) and Taguchi method when highly nonlinear behavior is the case. This technique can build an efficient model using a small number of experiments and accuracy would be better when a larger number of experiments are used to develop a model. The most popular ANN are vector quantization neural networks, back propagation and counter propagation networks.

IV. Conclusion

From the above studies the following are the conclusions:

1. ANN technique is used to find out the optimal welding combinations namely Ti/Al using LBW and it is considered safe, environment friendly and economical.
2. The input parameters impose significant effect on responses such as bead penetration, bead width and bead volume.
3. The output of the neural network are mechanical properties of the weld metal of titanium and aluminium alloy sheet, namely ultimate tensile strength (UTS), yield

strength, elongation and reduction of the area. These have been modeled with neural network and the models were analyzed.

4. The neural network predicts the mechanical properties of Ti/Al weld joints with least error across a broader range of HAZ. Also it minimizes the need for expensive experimental investigation and inspection.
5. ANN technique result in low cost weld joints and the welding process can be automated based on optimal settings.

References

[1] I. Kim., J. Son., S. Lee. and P.K.D.V. Yarlagadda, “Optimal design of neural networks for control in robotic arc welding”, Robotics and Computer-Integrated Manufacturing, (2004), Vol.20, no.1, pp.57– 63.

[2] S. Pal., S.K. Pal. and A.K. Samantaray, “Artificial neural network modeling of weld joint strength prediction of a pulsed metal inert gas welding process using arc signals”, Journal of Materials Processing Technology, (2008), Vol. 202, no. 1–3, pp. 464–474.

[3] Malinov S, Sha W, "Application of artificial neural networks for modelling correlations in titanium alloys". Materials Science and Engineering: A, vol.365 no.1–2, pp.202–211, 2004.

[4] S. K. Dhara., A. S. Kuar. and S. Mitra, “An artificial neural network approach on parametric optimization of laser micromachining of die-steel”, International Journal of Advanced Manufacturing Technology, (2008) Vol. 39, no. 1-2, pp. 39–46.

[5] Mohd Idris Shah Ismail., Yasuhiro Okamoto. and Akira Okada, “Neural Network Modeling for Prediction of Weld Bead Geometry in Laser Microwelding”, Advances in Optical Technologies, (2013), Article ID 415837, 7 pages.

[6] Young whan park, “Genetic algorithms and Neural network for process modeling and parameter optimization of aluminium laser welding Automation”, International Journal of Advanced Manufacturing Technology, (2008).

[7] Vasudevan M., Bhaduri A.K., Baldev R., Rao P.K., “Genetic algorithm based computational methods for optimizing the process parameters of a TIG welding to achieve target bead geometry in type 304 L(N) and 316 L (N) stainless steels”, Materials and Manufacturing processes, 22, 641-649, 2007.

[8] J.M. Vitek., Y.S. Iskander, E.M. Oblow et al, “Neural network modeling of pulsed-laser weld pool shapes in aluminum alloy welds”, proceedings of 5th Inter. Conf. on Trends in Welding Research, Pine Mountain, GA, (1998), June 1-5, ASM Inter, pp.442-448.

[9] H. Park. and S.Rhee, “Estimation of weld bead size in Co_2 laser welding by using multiple regression and neural network”, J. of Laser Application, (1999), Vol. 11. n. 3, pp.143-150.

[10] Dhavalkumar. and K. Soni, “A Review of Laser Welding Process for Thin Steel Sheets”, (IJRMEET), (2013), ISSN: 2320-6586, Vol. 1, Issue: 3.

[11] Balasubramanian K.R., Bhuvanasekaran G. and Sankaranarayanaswamy K, “Mathematical & ANN Modeling of ND:YAG Laser welding of Thin SS Sheets”, International Journal for the Joining of Materials, (2006), Volume 18 No. 3/4, pp 99-104.

[12] Bhuvanasekaran G., Balasubramanian K.R. and Sankaranarayanaswamy K, “Analysis of Laser welding parameters using Artificial neural network”, International journal for the joining of Materials, (2006), Volume 18 No.3/4, pp 99-104. ISSN 0905-6866.

[13] Banakar Nagaraj Dr. and V.Venkata Ramana, “Analysis and Optimization of Laser Beam Weld Bead Parameters: A Proposal”, International Journal of Mechanical Engineering Research & Applications (IJMERA), (2013), ISSN: 2347-1719, Vol. 1 Issue 4.

[14] G. Casalion, and F.M.C. Minutolo, “A model for evaluation of laser welding efficiency and quality using an artificial neural network and fuzzy logic”, J of Engineering Manufacture, (2004), Vol. 218, part B, pp. 1-6.

[15] Y.H. Wei., H.K.D.H Bhadeshia, and T. Sourmail, “Modeling mechanical properties of welds in plates of commercial titanium alloys”, Transactions of the Nonferrous Metals Society of China, (2005), Vol. 15, 70--74.

[16] S. Malinov., W.Sha. and J.J. McKeown, “Modeling the correlation between processing parameters and properties in titanium alloys using artificial neural network”, Computational materials science, (2001), 21, 375-394.

[17] Z. Sterjovski., D. Nolan., D. Dunne. and J. Norrish, “Predicting the HAZ hardness of pipeline and tap fitting steels with artificial neural networks”, in Proceedings of the 4th Inter. Conf. on pipeline technology, University of Wollongong, NEW, Australia, (2004), pp. 1233-1245.

[18] Z. Sterjovski., D. Nolan., K.R. Carpenter., D.P. Dune. and J.Norrish, “Artificial neural network for modelling the mechanical properties of steels in various applications”, J. of Materials Processing Technology, (2005), Vol. 170, No.3, pp. 336-544.

[19] M. Murugananth., S.S. Babu. and S.A. David, “Optimization of shielded metal arc weld metal composition for charpy toughness”, Welding Journal, AWS, (2004), pp. 267-s-276-s.

[20] Y. Wei., H.K.D. Bhadeshia. and T. Sourmail, “Mechanical property prediction of commercially pure titanium welds with artificial neural network”, J. of Material Science Technology, (2005) Vol. 21, n. 3, pp. 403-407.