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A Review on Artificial Intelligence based Improved Welding Quality Prediction for Metal Inert Gas (MIG) Welding

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Abstract: Welding is widely used by manufacturing engineers and production personnel to quickly and effectively set up manufacturing processes for new products. The MIG welding parameters are the most important factors affecting the quality, productivity and cost of welding. This paper presents the influence of welding parameters like welding current, welding voltage, Gas flow rate, wire feed rate, etc. on weld strength, ultimate tensile strength, and hardness of weld joint, weld pool geometry of various metal material during welding. By using DOE method, the parameters can be optimize and having the best parameters combination for target quality. The analysis from DOE method can give the significance of the parameters as it give effect to change of the quality and strength of product.

Keywords: MIG, ANFIS, ANN, Welding Quality.

1. Introduction:

Metal Inert Gas welding as the name suggests, is a process in which the source of heat is an arc formed between a consumable metal electrode and the work piece, and the arc and the molten puddle are protected from contamination by the atmosphere (i.e. oxygen and nitrogen) with an externally supplied gaseous shield of inert gas such as argon, helium or an argon-helium mixture. No external filler metal is necessary, because the metallic electrode provides the arc as well as the filler metal. It is often referred to in abbreviated form as MIG welding. MIG is an arc welding process where in coalescence is obtained by heating the job with an electric arc produced between work piece and metal electrode feed continuously. A metal inert gas (MIG) welding process consists of heating, melting and solidification of parent metals and a filler material in localized fusion zone by a transient heat source to form a joint between the parent metals. Gas metal arc welding is a gas shielded process that can be effectively used in all positions. MIG Welding is a widely used industrial arc welding process needs a better prediction and monitoring of its parameters to produce consistent weld quality. Quality of welding plays an important role as it improves material strength, hardness and toughness of the product. Weld quality of a product is evaluated by different parameters like weld bead geometry, hardness, deposition rate etc. All these characteristics are controlled by weld parameters like welding speed, welding current, arc voltage and electrode stick out. To obtain good quality, is necessary to set the proper welding process parameters. Researchers attempted many techniques to establish MIG process. The effects of welding variables upon bead shape and size, bead width and height , dilution and bead geometry , weld deposit area, element transfer behavior and weld-metal chemistry in submerged-arc welding was explored. Also the effect of increasing deposition rate on bead geometry and flux component on softening temperature was examined [1] for MIG weld. Usually, the desired welding parameters are determined using traditional methods like welder's experiences, charts and handbooks (preferred values) which are simple and economical. However this does not ensure that the selected welding parameters result in satisfactory welding and this method is not applicable to new welding process. To overcome this problem, various methods of obtaining the desired output variables through models to correlate input variables with output variables have been developed. Fractional factorial techniques, Mathematical modeling, curvilinear regression equations, linear regression equations [2], response surface methodology [3], finite element modeling [3, 4], grey-based Taguchi method [5] and sensitivity analysis [6] were used to model MIG process. All These techniques are limited in application due to difficulties in modeling, time consuming and weighty. For this reason, inadequacy and inefficiency of the mathematical models to explain the nonlinear properties existing between the input and output parameters of welding lead to the development of intelligent modeling techniques. Precise simulation and analysis of the process needs attention which helps to predict the wide variety of process parameters to set the factory floor in real time.

2. Related Work:

MIG Welding (MIG) is one of the major metal fabrication techniques in industry due to its reliability and capability of producing good quality weld. The ability to join thick plates (as thick as 1.5 inch) in a single pass, with high metal deposition rate has made this process useful in large structural applications. Indeed various research works have been explored on various aspects of MIG welding, yet investigations are still being carried on to study the phenomenon that occurs during the process of submerged arc welding, and many other related matters, so that the process becomes controllable more precisely, and can be monitored well, both manually as well as automatically. In MIG welding, various process parameters interact in a complicated manner, and their interactions influence the bead geometry, bead quality as well as metallurgical characteristics and mechanical properties of the weldment. Acceptability of the weldment depends on various quality characteristics that confirm functional requirements of the welded joint in the intended area of application. In most of the cases, quality of the weld is left to depend on the past experience and working skill of operator. But, with the advent of automation, it is now possible to design a machine capable of selecting optimal process parameters to provide desired yield. Research in the field of MIG welding is not new.

Farhad Kolahan et al (2009), In this research a procedure was proposed to model and optimize weld bead geometry in GMAW process. Since, the relationships between bead geometry characteristics and welding output variables are complicated; a regression based method was employed to model the process. The experimental data for model development were gathered using the actual tests carried out by the authors. Along this line, using DOE approach and regression analysis, different mathematical models were developed to establish the relationships between welding input parameters and weld bead geometry outputs. A Simulated Annealing technique was developed to minimize the error function consisting of desired and calculated weld bead geometry. By minimizing such a function, the process parameters can be determined so as the resultant bead geometry has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately determine welding parameters so as a desired bead geometry specification is obtained.

Shahnwaz Alam et al (2012), showed that the two level full factorial designs are an effective tool for quantifying the main and interaction effect of variables on weld width. The developed model can be effectively used to predict the weld width in the MIG welding within the range of parameters used. Proposed models are adequate to predict the weld width with a confidence level of 95%. Weld width rapidly increases with voltage, slowly increases with current and wire feed rate and decreases with welding speed and nozzle to plate distance. The F-test indicates that the regression model as a whole is significant. Cross- validation test full-fills the validity of the models developed.

Karuna et al (2011), Here the combined effect of welding parameters on weld metal composition in MIG process was examined. Accordingly, the following conclusions can be drawn: It is interesting to note that chromium, molybdenum & silicon elements displaying a increasing trend & manganese element displaying a decreasing trend with an increase in any parameter, viz voltage, current & speed. An attempt was made to determine important welding parameters for composition of weld like Cr, Mn & Si in the MIG process. For controlling the weld metal composition, welding voltage is more effective than is welding current.

K. Lalitnarayan, et; al, (2011), showed that in gas metal arc welding where a gap exists, regression model questions of welding parameters which were thought to produce the desired geometry of the back-bead can be obtained. Both sides of the process regression model equation of the geometry parameters of the back-bead and welding process parameters are found and, after analysis it was found that whereas the correlation between parameters for the bead shape and welding process parameter has until now been
applied generally to bead-on-plate welding, this study extends the range of the research to the geometry prediction of the back-bead in butt welding where a gap exists. In order to obtain the geometry of the back-bead using the welding process parameters, the multiple regression analysis is modelled into a linear equation. The error rate of analysis had a maximum value of 9.5 percent. Also, the groove gap had the largest error rate for prediction, followed by the depth of the back-bead and the width of the back-bead. Thus, the groove gap was thought to be the most difficult parameter to predict. The multiple regression analysis of the welding process parameters which were though to produce the desired back-bead was modeled into a linear equation and the error rate of analysis was under 6.5 percent. Also, the normalized welding speed had the largest error rate for prediction, followed by the normalized arc voltage and the normalized welding current. In this case, the welding speed was thought to be the most difficult parameter to predict.

A. K. LAKSHMINARAYANAN et. al (2009), have described the use of design of experiments(DOE) for conducting experiments. Two models were developed for predicting tensile strength of friction stir welded AA7039 aluminium alloy using response surface methodology and artificial neural network(ANN). From this investigation important conclusions derived was that rotational speed is the factor that has greater influence on tensile strength, followed by welding speed and axial force. Further, a maximum tensile strength of 319 MPa is exhibited by the FSW joints fabricated with the optimized parameters of 1 460 r/min rotational speed, 40 mm/min welding speed and 6.5 kN axial force. The predictive ANN model is found to be capable of better predictions of tensile strength within the range that they had been trained. The results of the ANN model indicate it is much more robust and accurate in estimating the values of tensile strength when compared with the response surface model.

Suneel Ramachandra Joshi, (2014), The literature review provides insight into the application of DOE, ANN, GA, Taguchi method and other techniques for modeling and optimizing different welding processes. It was noted that RSM performs better than other techniques, especially ANN and GA, when a large number of experiments are not affordable. The trend in the modeling using RSM has a low order non-linear behavior with a regular experimental domain and relatively small factors region, due to its limitation in a model building to fit the data over an irregular experimental region. The main advantage of RSM is its ability to exhibit the factor contributions from the coefficients in the regression model. This ability is powerful in identifying the insignificant factors, main effect, insignificant interactions or insignificant quadratic terms in the model and thereby can reduce the complexity of the problem. But, this technique requires good definition of ranges for each factor to ensure that the response(s) under consideration is changing in a regular manner within this range. The most popular designs within RSM designs are the central composite design (CCD) and Box-Behnken design. RSM uses model to make contour plots of predicted behavior.

2.1 ANN approach:

Another approach used for modelling, simulation and prediction in MIG welding is the Artificial Neural Network. ANN creates a mapping between set of inputs and corresponding responses. ANN is very efficient to model and simulate process behaviour, while the nature of response variation, with varying inputs, is very much complicated. Depending on huge data set obtained from experiments (combination of inputs and outputs), ANN itself establishes a correlation among inputs and outputs, into its internal architecture, that consists of input, output, hidden layers and connection between the layers (nodes/neuron). ANN then predicts output for a given combination of factor settings (inputs). The perfection of network prediction or network performance depends on the data set used to train the network, and selection of its internal features viz. number of hidden layers, number of nodes in a layer, leaning rate, training algorithm, performance goal and so on. Adequate data set with optimal network architecture can predict results with minimum error. An important step in building the network is selection of input variables. In the field of welding, some studies have been made with the neurons of the input layer to receive the input process parameters, while the neurons of the output layer were used to send out the features of quality characteristics of the weldment viz. weld bead and HAZ geometry, mechanical properties of the weldment, metallurgical features of the weld metal as well as HAZ.

Hossein Towsyfyan et al(2013), In this study, three parameters including the current, speed and welding voltage were selected as the input variables and the weld bead penetration, width and height were modeled by the regression and neural network methods. Obtained results show that quadratic regression equations for bead weld penetration, width and height have the coefficients of determination 0.901, 0.6 and 0.739, respectively and they imply the accurate modeling, acceptable fitting and proper accuracy of quadratic model. Further, despite the accuracy of regression equations, designed neural network is significantly more accurate in predicting the weld bead geometry, so that the difference in relative error of two methods reaches 83%. Also by increasing the welding current, the weld bead penetration and height will be increased and the weld width will be reduced. By increasing the welding voltage, the weld bead penetration, height and width will be increased and by increasing the welding speed, the bead penetration will be decreased, while the bead width and height will be increased

Chandrasekhar Neelamegam et al(2013), HereGenetic algorithm in combination with ANFIS models has been used for optimizing the A-TIG welding process parameters to achieve the target weld bead geometry and HAZ width in RAFM steel. The methodology is imple- mented in two steps. First, independents ANFIS models were developed correlating the welding process parame- ters like current, torch speed and arc voltage with weld bead parameters like depth of penetration, bead width and HAZ width. Second, a GA code was developed to optimize the process variables to achieve the desired tar- get depth of penetration and HAZ width. The ANFIS models were used to evaluate the objective function in the GA code. A close agreement was achieved between the target and the actual values of depth of penetration and HAZ width. Thus, the present work shows that the GA has the capability to optimize and produce multiple sets of welding process parameters that can lead to the desired weld bead profile and HAZ width accurately in RAFM steel.

José Manuel Arroyo Osorio, et al(2007), have proposed a fuzzy logic method to suggest a reference tool geometry for different work-tool materials pairs by interpolating between empirically optimized tool geometries. With this method it is possible to suggest a tool geometry for not tested work-tool material pairs, diminishing the amount of experimental work necessary to optimize the tool tip geometry. The system can be improved by retraining it each time that the knowledge base of optimized tool geometries is increased or improved. In order to model the empirical knowledge about recommended cutting tool geometry, the reliable available data to train the fuzzy logic system was very few compared with the space of the problem, therefore was not made the normal procedure of using a percentage of the data to verify the system. Alternatively it was used a method found in the literature for tool geometry reliability evaluation.

I.U. Abhulimen et al(2014), revealed that the successful use of ANN to in predicting tensile and yield strength of TIG welded mild steel pipe joints and the results reported are in good agreement with other researchers. Predicted results shows a mean squared error of 34.2 for overall performance, a maximum and minimum absolute errors of 22MPa and 0.09 MPa respectively. Relative errors were 18% and 0.02% for largest and smallest errors respectively. The calculated average absolute error of 15.35% with an average percentage error of 3.5. These values are in agreement within the ranges of errors predicted by other researchers though they were conducted under different conditions. Barclay et al, (2012), reported a minimum percentage error of 0.0859 and a maximum absolute error of 0.0469 in predicting weld distortions using induced welding. They also recorded an average percentage error of 6.51%. Predicted values shows that tensile and yield strength as good as 508 MPa and 388 MPa can be achieved by a combination of certain factors as shown in the model.

P. Sreeraj et al (2013), showed that the developed model can be used to predict clad bead geometry within the applied limits of process parameters. This method of predicting process parameters can be used to get minimum percentage of dilution. In this study, ANN and GA were used for achieving optimal clad bead dimensions. In the case of any cladding process bead geometry plays an important role in determining the properties of the surface exposed to hostile environments and reducing cost of manufacturing. In this approach the objective function aimed for predicting weld bead geometry within the constrained limits.

Parth D Patel et al(2012), with the studies of MAG-CO2 welding technique and their test reports, they found that welding current has great impact on Hardness of Weld joint but other parameter like wire diameter of electrode and wire feed rate of electrode also play role in Weld Hardness. The tool use in this work NeuroXL Predictor proves as very handy tool for Different Welding Technique.The Artificial Neural Network has shown its effectiveness as a tool to predict various parameters in both MAG-CO2 and TIG welding technique.

J. Edwin Raja Dhas et al(2012), applied Taguchi method for experimentation. Relationship between the input weld parameters Weld bead width, weld reinforcement, depth of penetration and bead hardness and output weld parameters are modeled through regression analysis and additional data's are generated to train the neural network models. Validity of the developed equations is checked for adequacy. It is found that the result from neural network trained with PSO seems to have an edge over the other developed models in terms of computational accuracy and time. Confirmative experiments are done for validation. The developed model scopes for online weld quality monitoring system. To ensure high quality of welding SEM analysis is done on the weld samples indicating a good grain structure

Alice E. Smith et al (1993), demonstrated that neural networks can be comparable to Shewhart X-bar and R control charts for large shifts in mean or variance, and can out perform them for small shifts. For shape interpretation and prediction, networks performed best with minimal noise and maximum number of inputs. All neural networks proved capable of good quality decisions regarding pattern identification even in light of sparse and noisy data.

Literature summary

The critical review of the literature indicates that a lot of work has been done in the field of MIG Welding. Many investigators like Farhad Kolahan et al (2009), Shahnwaz Alam et al (2012), Karuna et al (2011), Hossein Towsyfyan et al(2013), Chandrasekhar Neelamegam et al(2013), etc., have studied the various responses like bead geometry, quality of weld, hardness and HAZ etc., and developed mathematical and theoretical models. The value and nature of the responses depend upon the range and selection of the input parameters i.e., current, voltage, electrode stick out, flux composition, travel speed, polarity etc. Many researchers Alice E. Smith et al (1993), J. Edwin Raja Dhas et al (2012), Parth D Patel et al(2012), P. Sreeraj et al (2013), José Manuel Arroyo Osorio, et al(2007), I.U. Abhulimen et al(2014), etc. have developed optimization models of the MIG welding process using the various like ANN, RSM, fuzzy logic etc.

3 Conclusion:

From the critical review of relevant literature, it has been found that no systematic work on an integrated approach of studying the effects of various welding process variables (welding current, voltage, welding speed, wire feed rate, nozzle-to-plate distance- all together) on bead geometric descriptors using full factorial technique and predicting the weld bead geometry using Artificial Neural Net work (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) has been found in the literature for MIG Welding.

Based on this literature review it has been found that a systematic work needs to be carried out to relate the welding parameters with weld bead geometry using Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Multiple Regression Analysis (MRA) on MIG Welding. Thus Mathematical relationships are needed to be developed between the welding process parameters viz. welding current, arc voltage, welding speed, wire-feed-rate, nozzle-to-plate distance and the important weld-bead geometrical variables viz. penetration depth, reinforcement height and weld width of the welded joint using full factorial design technique.

References:

[1] Shao-huaSui., Wei-weiCai., Zhi-qiang Liu, Tian-ge Song, & Zhang.(2006), "An Effect of MIG Welding Flux Component on Softening Temperature". International Journal of Iron and Steel Research.13(2): 65-68. http://dx.doi.org/10.1016/S1006-706X(06)60047-2

[2] Gupta, V. K. Parmar, R. S. (1986), "Fractional factorial techniques to predict dimensions of the weld bead in automatic MIG welding". Journal of Institution of Engineers.(70): 67-71.

[3] Yang, L.J. Chandel, R.S. Bibby, M.J(2003),. "Linear regression equations for modeling the submerged-arc welding process". Journal of Materials Processing Technology.39 (1-3): 33-42. http://dx.doi.org/10.1016/0924-0136(93)90006-R.

[4] Gunaraj, V. Murugan, N.(1999), "Application of response surface methodology for predicting weld bead quality in MIG welding of pipes". Journal of Materials Processing Technology.88 (15): 266-275. http://dx.doi.org/10.1016/S0924-0136(98)00405-1

[5] Wen, S.W. Hilton, P Farrugia, D. C. J.(2001) "Finite Element Modeling of MIG welding process". Journal of Material Processing Technology. (119): 203-209. http://dx.doi.org/10.1016/S0924-0136(01)00945-1

[6] Syrcos, G.P.(2003), "Die casting process optimization process using Taguchi methods". Journal of Materials Processing Technology. (135): 68-74. http://dx.doi.org/10.1016/S0924-0136(02)01036-1.

[7] Tarng, Y.S. Juang, S.C. Chang, C. H.(2002), "The use of grey-based Taguchi methods to determine MIG welding process parameters in hardfacing". Journal of Materials Processing Technology. (128): 1-6. http://dx.doi.org/10.016/S0924-0136(01)01261-4.

[8] SerdarKaraoglu. Abdullah Secgin, (2008), "Sensitivity analysis of MIG process parameters". Journal of Materials Processing Technology. 202: 500-507. http://dx.doi.org/10.1016/j.jmatprotec.2007.10.035.

[9] JANG, J-S. R., (1992), "Neuro-Fuzzy Modeling: Architecture, Analyses and Applications", P.hd. Thesis.

[10] JANG, J-S. R., (1993), "ANFIS-Adaptive-Network Based Fuzzy Inference System", IEEE Transactions on Systems, Man and Cybernatics, 23(3), pp 665-685.

[11] Anurag, R. Sharma, " Load Forecasting by using ANFIS", International Journal of Research and Development in Applied Science and Engineering, Volume 20, Issue 1, 2020.

[12] R. Sharma, Anurag, " Load Forecasting using ANFIS A Review", International Journal of Research and Development in Applied Science and Engineering, Volume 20, Issue 1, 2020.

[13] R. Sharma, Anurag, " Detect Skin Defects by Modern Image Segmentation Approach, Volume 20, Issue 1, 2020.

[14] Anurag, R. Sharma, " Modern Trends on Image Segmentation for Data Analysis- A Review", International Journal of Research and Development in Applied Science and Engineering, Volume 20, Issue 1, 2020.

[15] JANG, J-S. R., SUN, C.-T., (1995), "Neuro-fuzzy modeling and control", Proceedings IEEE,. 83 (3), pp 378–406.

[16] Shahnwaz Alam, et.al.,(2012), " Prediction of the Effect of MIG Welding Process Parameters on Weld Bead Width for MS 1018 Steel", IJEIT,Volume 1, Issue 5, 97-104.

[17] Alice E. Smith, "X-Bar and R Control Chart Interpretation Using Neural Computing", Revised for International Journal of Production Research March, 1993.

[18] Wladislav Sudnik, "ARC WELDING", InTech, Janeza Trdine 9, 51000 Rijeka, Croatia, Copyright © 2011 InTech

[15] Hossein Towsyfyan, Gholamreza Davoudi,P PBahram Heidarian Dehkordy and Ahmad Kariminasab 6TDepartment of Manufacturing, Technical and Vocational University, Ahvaz, Iran, " Comparing the Regression Analysis and Artificial Neural Network in Modeling the MIG Welding (MIG) Process", Research Journal of Applied Sciences, Engineering and Technology 5(9): 2701-2706, 2013