"Application of statistical and soft computing based modeling and optimization techniques for various welding processes" a review

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Abstract- Manufacturing systems such as welding processes are described by multiple input variables and multiple output parameter models having non-linear coupling. Various methods of obtaining the desired output variables through models to correlate input variables with output variables have been suggested by various researchers. In the present study, a review has been made on various statistical and soft computing techniques that have been employed for modeling and optimization of various welding processes by different researchers. This study predominantly focuses on the chronological order of the various research works.

Keywords: ***welding processes, mathematical model, design of experiments, Taguchi method factorial methods, response surface methods, PSO, ANN, GA, Fuzzy logic ,hybrid methods, optimization***

I. INTRODUCTION

Welding is a predominant manufacturing process having significant role in the repairs and hard facing of products as well. The demand for producing joints of dissimilar materials is continuously increasing due to their advantages, which can provide appropriate mechanical properties and good cost reduction. Welding processes developed with the advances of technology. Varieties of novel welding methods continue to emerge and are affirmed by industries. At the present time, welding process is divided into about 70% arc welding with the balance divided between resistance welding and oxyacetylene welding.[1].But there are many industries like automotive, which are actively considering the application of alternative welding processes that would enable the use of light weight and high performance materials, like, innovative solid state joining, laser welding, electron beam welding, friction stir spot welding etc.

Modern welding techniques are employed in the construction of numerous products. Ships, buildings, guided missiles, nuclear power plant parts, bridges are fabricated by welding processes. Welding is also used extensively in the manufacture of automobiles, farm equipment, home appliances, computer components, mining equipment and earth moving. Hundreds of products that we use in our daily life are also joined together by some type of welding processes. And the quality of the products is a vital factor for survival of concerned industry .The current understanding of the concept quality; is to be the leaders in satisfying the customers. It is possible only by innovations and process automation .Developments in welding processes is strongly related with the need to increase productivity without losing quality of the welds formed. Only targeting these aspects, companies can be competitive in the worldwide markets. Reduction in costs and enhanced quality are strongly related to technological innovations. And also to ensure high productivity as well as good quality of products, a manufacturing process needs to be automated.

The weld quality mainly depends on the mechanical properties, weld bead geometry, distortion of the welded joint and deposition efficiency. All of these quality characteristics are influenced by metallurgical characteristics and chemical compositions of the weld. These mechanical-metallurgical features of the weldment depend on the weld

bead geometry, which are directly related to welding process parameters. In other words, weld quality depends on welding process parameters. These parameters should be selected in a judicious manner to reach the desired quality dictated by the area of applications of the weldment. It is necessary to find an optimal process condition capable of producing desired weld quality and also to automate the welding process, a proper model has to be constructed and tested before implementing for on-line control. There is a natural quest for the researchers to establish input–output relationships of a process and an optimal determination of set parameters of a process nowadays a common industry activity. Various researchers have put in lot of efforts to achieve these things by making use of number of statistical as well as soft computing based techniques like DOE, Taguchi method, linear & curvilinear regression, Response Surface Methodology, grey relational analysis, PSO, ANN, GA and some of the Hybrid techniques. In this paper a comprehensive literature review of the application of these techniques is presented. The literature survey revealed the scarcity of review papers to give a total picture of research works carried out by various researchers. An attempt has been done to summarize the various optimization techniques utilized for the different welding processes and later to arrange the various research works in a chronological order to provide a solid data base for future research works.

II. Modeling and Optimization techniques

In the early days, welding was carried out manually so that the weld quality can be totally controlled by the welder ability. The welder, when welding, can directly monitor the flow pattern in puddle and make immediate adjustments in welding parameters to obtain good weld ability. To consistently produce high quality of weld, welding requires welding personnel with significant skill and experience. One reason for this is the need to properly select welding parameters for a given task in order to get a good weld quality which is identified by its micro-structure and the amount of spatter, and it relies on the correct bead geometry size. Therefore, the use of the control system in welding can eliminate much of the “guess work” often employed by welders to specify welding parameters for a given task. In addition, development of mathematical models is of specific importance that can be employed to predict welding parameters about arc welding process with respect to the work piece. Several methods have been tried by various investigators to predict weld quality in welding. These methods include theoretical studies, statistical analysis and artificial intelligence methods. Realizing the difficulties associated with theoretical estimation of input-output relationships of a real-welding process, various researchers have tried to get those through statistical analysis of the experimental data. These methods include linear regression, non-linear regression, response surface methodology, Taguchi methods, and others.

2.1 Design of Experiment (DOE)

Design of Experiment (DOE) is an experimental or analytical method that is commonly used to statistically signify the relationship between input parameters to output responses, whereby a systematic way of planning of experiments, collection and analysis of data is executed. DOE has wide applications especially in the field of science and engineering for the purpose of process optimization and development, process management and validation tests. In the process, a mathematical model can be developed by using analysis techniques such as ANOVA and regression analysis whereby the mathematical model shows the relationship between the input parameters and the output responses (Montgomery. 1991). Among the most prominently used DOE techniques are Response Surface Methodology with Central Composite Design, Taguchi’s method and Factorial Design. In DOE, synergy between mathematical and statistical techniques such as regression, analysis of variance (ANOVA), non-Linear optimization and Desirability functions help to optimize the quality characteristics considered under a cost effective process. ANOVA helps to identify the effect of each factor versus the objective function. Experimental design was first introduced in 1920s by R. A. Fischer who developed the basic principles of factorial design and the associated data analysis known as ANOVA during research in improving the yield of agricultural crops.

DOE became a more widely used modeling technique superseding its predecessor one-factor-at-time (OFAT) technique. One of the main advantages of DOE is that it shows the relationship between parameters and responses. In other words DOE shows the interaction between variables which in turn allows us to focus on controlling important parameters to obtain the best responses. DOE also can provide us with the most optimal setting of parametric values to find the best possible output characteristics. Besides, the mathematical model generated can be used to predict the possible output response based on the input values. Another main reason for using DOE is savings on time and cost in terms of experimentation. DOE can determine the number of experiments or the number of runs before the actual experimentation is done.

2.2 Factorial Method

Factorial design is used for conducting experiments as it allows study of interactions between factors. Interactions are the driving force in many processes. Vital interface may be unobserved without factorial design of experiments. In a hill factorial experiment, responses are measured at all combinations of the experimental factor levels. The combinations of factor levels represent the conditions at which responses are measured. Each experimental condition is called a "run" and the response measurement is called an "observation", while factorial design can be run on two-levels, three-levels and multi-level factorial. The entire set of runs is the "design". According to Myers and Montgomery (2002), Full Factorial Design is a design in which all possible combinations of the factor levels are fulfilled. The result from the hill factorial experiments would be more reliable, but conducting the full factorial experiments is costly and sometimes prohibitive.

2.3 Response surface methodology

Response surface methodology is an empirical modeling approach using polynomials as local approximations to the true input/output relationship. This empirical approach is often adequate for process improvement in an industrial setting. By careful design of experiments, the objective is to optimize a response (output variable) that is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. The relationship between the response variable of interest(y), and the input variables ($x_1, x_2, \ldots, x_n$) is usually not known. In general, the experimenter approximates the system function with an empirical model of the form: $y = f(x_1, x_2, \ldots, x_n)$ (1) where "f" is a first- or second-order polynomial. This is the empirical or response surface model. The variables are known as *natural variables* since they are expressed in physical units of measurement. In the RSM, the natural variables are transformed into coded variables which are dimensionless. The successful application of RSM relies on the identification of a suitable approximation for "f". The "f" function is a low order polynomial build with linear regression techniques. The necessary data for building the response models are generally collected by an experimental design. The most popular of the many classes of RSM designs is the central composite design (CCD).

2.4 Central Composite Designs

Central composite designs (CCDs) also known as Box-Wilson designs are appropriate for designing the full quadratic models described in Response surface models. There are three types of CCDs, namely, circumscribed, inscribed and faced as in Figure 1.

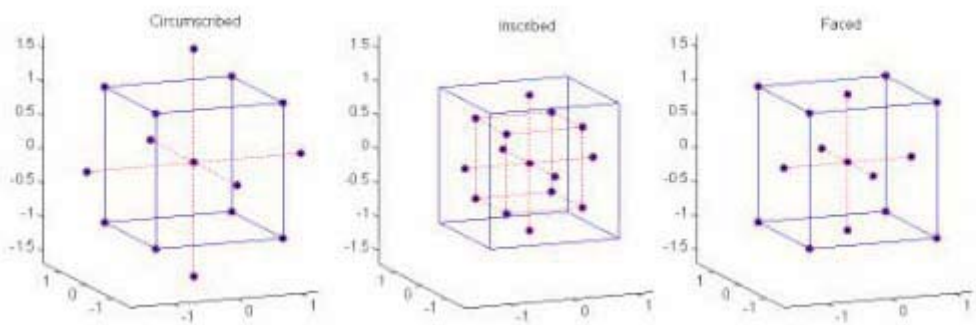

Fig. 1 Circumscribed, inscribed and faced designs

The type of CCD used (the position of the factorial and star points) is determined by the number of factors and by the desired properties of the design. A design is rotatable if the prediction variance depends only on the distance of the design point from the center of the design.

2.5 Taguchi method

The Taguchi method, a popular experimental design method, can overcome the shortcomings of full factorial design when doing fractional factorial design. The approach optimizes parameter design, but with fewer experiments. Traditional experimental design is used to improve the mean level of a process. In modern quality engineering, experimental design work is performed to develop robust designs to improve the quality of the product. Taguchi's parameter design is intended to yield robust quality by reducing the effects of environmental conditions and variations due to the deterioration of certain components. This high quality is achieved by the selection of various design alternatives or by varying the levels of the design parameters for component parts or system

elements. It can optimize performance characteristics by the settings of design parameters and reduce the sensitivity of the system performance to sources of variation. Taguchi proposed that engineering optimization of a process or product should be carried out in a three-step approach: system design, parameter design and tolerance design. In system design, the engineer applies scientific and engineering knowledge to produce a basic functional prototype design. The objective of the parameter design is to optimize the settings of the process parameter values for improving performance characteristics and to identify the product parameter valises tinder the optimal process parameter values (Ross. 1988). The steps included in the Taguchi parameter designs are: selecting the proper Orthogonal Array (OA) according to the number of controllable factors (parameters); running experiments based on the OA; analyzing data: identifying the optimum condition and conducting confirmation runs with the optimal levels of all the parameters. The main effects indicate the general trend of influence of each parameter. Knowledge of the contribution of individual parameters is the key to decide the nature of the control to be established on a production process. ANOVA is the statistical treatment most commonly applied to the results of the experiments to determine the percentage contribution of each parameter against a stated level of confidence (Ross. 1988).

2.6 The modified Taguchi method

Optimization of process parameters is the key step in the Taguchi method to achieving high quality without increasing cost. This is because optimization of process parameters can improve quality characteristics and the optimal process parameters obtained from the Taguchi method are insensitive to the variation of environmental conditions and other noise factors. Basically, process parameter design is complex and not easy to use. Especially, a large number of experiments have to be carried out when the number of the process parameters increases. To solve this task, the Taguchi method uses a special design of orthogonal arrays to study the entire process parameter space with a small number of experiments only. A loss function is then defined to calculate the deviation between the experimental value and the desired value. Taguchi recommends the use of the loss function to measure the deviation of the quality characteristic from the desired value. To consider several quality characteristics together in the selection of process parameters, the Taguchi method needs to be modified to evaluate several loss functions corresponding to different quality characteristics. In this method, a weighting method is used to integrate the loss functions into the overall loss function. The value of the overall loss function is further transformed into a signal-to-noise (S/N) ratio. Usually, there are three categories of the quality characteristic in the analysis of the S/N ratio, i.e. the lower-the-better, higher-the-better and the nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the quality characteristic, a larger S/N ratio corresponds to a better quality characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio. Furthermore, a statistical analysis of variance (ANOVA) has to be carried out to see which process parameters are statistically significant and the optimal combination of the process parameters can then be predicted. Finally, a confirmation experiment has to be conducted to verify the optimal process parameters obtained from the process parameter design.

2.7 Grey-based Taguchi method for parametric optimization

Taguchi's technique based on OA of experiments has been widely used in different fields of engineering to optimize the process parameters. The integration of DOE with parameter optimization of process can be achieved in the Taguchi method. An OA provides a set of well-balanced experiments, and Taguchi's signal-to-noise(S/N) ratios serve as objective functions for optimization. It helps to learn the whole parameter space with a small number. OA and S/N ratios are used to study the effects of control factors and noise factors and to determine the best quality characteristics for particular applications. However, Taguchi method was designed to optimize single-performance characteristics. Optimization of multiple performance characteristics is much complicated than single-performance characteristics. To solve the multiple performance characteristics problems, the Taguchi method is coupled with grey relational analysis. This grey-based Taguchi technique has been widely used in different fields of engineering to solve multi-response optimization problems. In Grey relational analysis, measured features of quality characteristics are first normalized ranging from zero to one and is known as Grey relational generation. Based on normalized experimental data, Grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall Grey relational grade is determined by averaging the Grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the Grey relational grade. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function is overall Grey relational grade. The optimal parameter combination is then evaluated for highest Grey relational grade. The optimal factor setting for maximizing overall Grey relational grade can be performed using Taguchi method.

2.8 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a stochastic population-based evolutionary computation technique. It has similarity with bird flocking, fish schooling or sociological behavior of a group of people and used to solve a variety of optimization problems. The population of solution is known as swarm, which is composed of a number of agents called particles moving around the search space to look for the best solution. Each particle is treated as a point in an N-dimensional space, which modifies its flying according to its own flying experience and that of other particles. Each particle keeps a track of its coordinates in the solution space, which are associated with the best solution in terms of fitness achieved so far by it is called personal best, Pbest. Another best value that is tracked by the PSO is that obtained so far by any particle lying in its neighborhood is called the global best, Gbest. The basic concept of PSO lies in accelerating each particle toward its Pbest and Gbest locations, with a random weighted acceleration at each time step.

2.9 Artificial intelligence (AI) techniques

The development of computer aided manufacturing systems such as welding process is evolving towards the phase of intelligent manufacturing systems. The system may be characterized by their ability to solve problems without either a detailed, explicit algorithm available for each solution procedure, or all the facts, mathematical relationships and models available in perfect arrangement and complete form for a deterministic and unique answer to be found. Some systems are capable of solving unprecedented and unforeseen problems within certain limit on the basis of incomplete and imprecise information. A tremendous amount of manufacturing knowledge is needed in an intelligent manufacturing system. Soft-Computing based techniques such as Genetic Algorithms (GA), Neural Network (NN), Fuzzy Logic (FL) and Hybrid systems are designed for capturing, representing, organizing, and utilizing knowledge by computers.

2.9.1 Genetic algorithms (GA)

GA's are a set of computer procedures of search and optimization based on the concept of the mechanics of natural selection and genetics. Holland made the first presentation of the GA techniques in the beginning of the 1960s and further development can be credited to Goldberg. The GAs operates over a set of individuals, usually represented by a binary string comprised between 0 and 1. This binary codification is randomly generated over the search space, where each individual represents a possible solution. When determining the solution within the search problem range, the genetic algorithm simultaneously considers a set of possible solutions. This parallel processing of the algorithm may prevent the convergence of one particular local extreme point. Another characteristic of these algorithms is only use the fitness value of each string; the fitness function does not need to be continuous or differentiable.

2.9.2 Artificial Neural Networks (ANN)

ANN is used in a variety of areas such as function approximation, classification, association, pattern recognition, time series analysis; signal processing, data compaction, non-linear system modeling, prediction, estimation, optimization and control. ANN models also provide effective solution approaches to problems faced in materials science. ANN models have a wide application area on casting, welding. An ANN is composed of simple elements operating in parallel inspired by biological nervous systems. The connections between elements largely determine the network function. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Neural networks trained to a particular input leads to a specific target output and also many input/response pairs are needed to train a network.

2.9.3 Neural network (NN) models

The use of NN models is vital in the modern manufacturing environment. NN are dynamic systems consist of processing units called neurons with weighted connections to each other. Neural networks can learn, remember and retrieve data. The significant functions of neural network are tackling non-linearity and mapping input-output information. The different types of neural networks in practice such as back-propagation neural network, counter propagation neural network and radial basis function neural network.

2.9.4 Back propagation neural network (BPNN) model

BPNN is a multiple layer ANN with input layer, output layer and some hidden layers between the input and output layers. Its learning procedure is based on gradient search with least mean squared optimality criteria.

2.9.5 Radial basis function neural network model

RBFNN is a feed forward multilayered network consists of three types of layers called input, hidden and the output layers. The number of nodes in the input layer is equal to the dimension of the input vector and in the output layers it is equal to the dimension of the output vector. In the hidden layer node not fixed and it depends on the application. Each of the nodes in the input layer is connected to all the nodes in the hidden layer through unit weights while each of the hidden layer nodes is connected to all the output layer nodes through weights. The input layer nodes do not carry out any computation. The input nodes pass the incoming input vector to the hidden nodes. The connections between hidden nodes and the input nodes (first layer connections) are not weighted. The connections between

hidden nodes and output nodes (second layer connections) are weighted and the output nodes are simple summation. Once the hidden units are synthesized, the second layer weights are computed using the supervised, normalized least mean square error rule. This procedure reduces the amount of computational time, since only the second layer weights are to be calculated using an error signal. RBFNN uses Gaussian activation function i.e., $f(x) = \exp(-x^2)$ and the response of such a function is non-negative for all values of x.

2.9.6 Fuzzy logic (FL)

The fuzzy logic controllers are special expert system that can be used to optimize desired values from the set of input and output variables. The set of values that is determined from experimental results. Fuzzy controllers are capable of utilizing knowledge elicited from human operators. A general fuzzy controller consists of four modules, fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification. A fuzzy controller operates by repeating a cycle of above four steps. In fuzzification, the measurements of all variables is taken are converted into appropriate fuzzy sets. These sets are numbers which represent linguistic labels such as approximately zero (AZ), positive small (PS), negative small (NS), positive medium (PM), negative medium (NM), positive large (PL), negative large (NL). Two conditions are monitored by the controller, an error (e) and the derivative of error (e′). Using values of e and e′, fuzzy controller produces values of controlling variable (v). The linguistic states are represented by a triangular shaped fuzzy numbers to get fuzzy quantization for variables e, e′ and v. The knowledge of control problem is formulated in terms of fuzzy inference rules.

2.10 HYBRID SYSTEMS

Each intelligent technique has certain strengths and weaknesses and they cannot be applied universally to every problem. This limitation is the central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques. The motivation for combining different intelligent techniques is multiplicity of application tasks, technique enhancement and realizing multifunctional tasks. Hence optimization techniques like GA and PSO algorithms are employed in development of neural network models.

In addition to the above techniques, several studies on the application of hybrid systems using fuzzy logic, neural network, and genetic algorithm, PSO in welding have been reported.

III Review of Previous Research Works in Chronological Order

Sunil et al. [2] employed fractional factorial technique for predicting weld-bead geometry in terms of penetration, weld width, reinforcement height and shape factor i.e. width to penetration ratio as affected by wire feed rate, arc voltage, nozzle to plate distance, welding speed, torch angle and gas flow rate in MIG welding of 100×250×13mm Al alloy 5083 flats adapting a bead on plate technique. Linear regression method was used for model developments & ANOVA, to test were used to test their adequacy

S.C Juang et al [3] described both back-propagation (BPNN) and counter-propagation (CPNN) networks for modeling TIG Welding process of pure Aluminum 1100 sheet of 1.6mm with a single pass with reasonable accuracy & found BPNN with better generalization & CPNN with better learning ability

Y.S. Tarng et al [4] described in application of Neural Network & Simulated annealing (SA) algorithm to model & optimize the GTAW process of pure 1.6mm aluminum 1100 sheet. As CPN is equipped with good learning ability, CPN is selected to model the process & SA applied to search for welding process parameter with optimal weld pool features

Ganjigatti et al [5] an attempt to determine input-output relationships of the MIG welding process by using regression analysis based on the data collected as per full-factorial design of experiments on the welding of structural steel plate of size 15 x 75 x 8 mm. The effects of the welding parameters and their interaction terms on different responses have been analyzed using statistical methods. Both linear as well as nonlinear regression analyses are employed to establish the input-output relations all three approaches of linear regression analysis have slightly outperformed the non-linear regression analysis in terms of average RMS deviation in prediction considering all the three responses together.

Kumar & Sundarajan[6] presented a methodology for the selection of welding process parameters for obtaining the optimum weld butt-joint ultimate tensile strength (UTS) of aluminum alloy (6061-T6) plates of 180mm×100mm×6.3mm size Considering weld-joint UTS as the quality characteristic in the selection of process parameters, the Taguchi method is used to analyze the effect of each individual process parameter and of their interaction and then to determine process parameters for the optimum weld-joint UTS. Analysis of variance (ANOVA) technique is applied to investigate which welding process parameter has significant effect on the weld-joint UTS. Experimental results are provided to illustrate the proposed approach.

Ganjigatti et al [7] attempted to establish input–output relationships in MIG welding process with bead on plate welding on structural steel of size 150 × 75 × 8 mm through regression analyses carried out both globally (i.e., one set of response equations for the entire range of the variables) as well as cluster-wise. It is important to mention that the second approach makes use of the entropy-based fuzzy clusters. The investigation is based on the data collected through full-factorial design of experiments. Results of the above two approaches are compared and some concluding remarks are made. The cluster-wise regression analysis is found to perform a slightly better than the global approach in predicting weld bead-geometric parameters

Vidyut Dey et al [8] could find back – propagation neural network (BPNN) to show better performance than genetic- neural (GA-NN) in predicting the bead profiles in Electron beam bead on plates welding of ASS

Park et al [9] conducted experiments on the laser welding AA5182 of aluminum alloy with AA5356 filler wire were performed with respect to laser power, welding speed, and wire feed rate. The experiments showed that the tensile strength of the weld was higher than that of the base material under certain conditions. Using the experimental results, a neural network model was proposed to predict the tensile strength. To optimize the process parameters, a fitness function was formulated, taking into account weld ability and productivity. A genetic algorithm was used to optimize the laser power, welding speed, and wire feed rate. The optimal value of these parameters was considered to be the proper process conditions in terms of weld ability and productivity

Vidyut Dey et al [10] carried out Bead-on-plate welds on 5.0 mm thick austenitic stainless steel plates of grade ASS-304 using an electron beam welding machine. Experimental data were collected as per central composite design and regression analysis was conducted to establish input–output relationships of the process. An attempt was made to minimize the weldment area, after satisfying the condition of maximum bead penetration. Thus, it was posed as a constrained optimization problem and solved utilizing a Genetic Algorithm with a penalty function approach. The Genetic Algorithm was able to determine optimal weld-bead geometry and recommend the necessary process parameters for the same

Kumar & Sundar rajan [11] studied the influence of pulsed welding parameters such as peak current, base current, welding speed, and frequency on mechanical properties such as ultimate tensile strength (UTS), yield strength, percent elongation and hardness of AA 5456 Aluminum alloy weldments. Regression equations were developed to predict the quality characteristics, i.e. ultimate tensile strength, yield strength, percent elongation, and hardness within the selected range of parameters

Sukhomay Pal et al [12] The optimal parameter setting for PMIGW process was selected by using grey-based Taguchi method so as to improve a cost function made of important welding quality parameters. An L25 orthogonal array was adopted to conduct the experiment. The multiple quality characteristic parameters were combined into one integrated quality parameter by using grey relational grade or rank. ANOVA was performed to find the impact of process parameters on the individual quality parameters and also on the overall grey relational grade. For the considered optimization problem, it is found that the pulse voltage and pulse frequency are the most influential factors affecting the weld quality, whereas other factors also have some contribution that cannot be altogether neglected.

Kumar & Sundarajan [13] observed improvement of mechanical properties of AA 5456 Aluminum alloy welds through pulsed tungsten inert gas (TIG) welding process. Taguchi method was employed to optimize the pulsed TIG welding process parameters of AA 5456 Aluminum alloy welds for increasing the mechanical properties. Regression models were developed. Analysis of variance was employed to check the adequacy of the developed models. The effect of planishing on mechanical properties was also studied and observed that there was improvement in mechanical properties and also with the use of obtained optimum conditions the mechanical properties were found to increase and developed regression models are useful for the automation of the process.

Amarnath & Pratihar[14] solved forward and reverse mapping problems of the tungsten inert gas (TIG) welding process using radial basis function neural networks (RBFNNs), which is required to automate the welding process. Radial basis function neural networks are able to solve the problems of forward and reverse mapping of the TIG welding process. The cluster-based approaches are able to outperform the non-cluster-based approaches in terms of accuracy in predictions

Kumar & Sundarrajan [15] made an attempt to study the effect of pulsed TIG welding process parameters on dilution and mechanical properties such as notch tensile strength, hardness, and impact toughness in as-welded condition. Pulsed TIG welds exhibited lower notch tensile strength and impact toughness than the parent metal due to inter dendritic network microstructure features. Taguchi method was used to optimize the pulsed TIG welding process parameters of heat-treatable (Al-Mg-Si) aluminum alloy weldments for maximizing the mechanical properties. An inverse relationship has been observed between the notch tensile strength and impact toughness.

Esme et al [16] showed that the tensile load ,heat affected zone and penetration, bead width and bead height of the weld bead in the TIG welding of 240 x 15 x 1.2 mm AISI 304 S.S plates are greatly improved by using grey relation analysis in combination with Taguchi method..

Senthil Kumar et al [17] using factorial experimental design(4 factors at 2 levels) reported the effects of pulsed current parameters such as peak current, base current, pulse frequency and pulse on time on tensile, impact and fatigue strength of AA 6061 aluminum alloy with TIG welding. Statistical tools such as Yate's algorithm, ANOVA and regression analysis were applied to develop the mathematical models to predict tensile, impact and fatigue strengths satisfactorily with confirmation tests.

Vidyut Dey et al [18] conducted Bead-on-plate welding on Al-1100 plates as per central composite design of experiments. Regression analysis was conducted to determine input– output relationships of the process. A constrained optimization problem was formulated to minimize weldment area, after ensuring the condition of maximum bead penetration. A binary-coded GA with a penalty term was used to solve the said problem. The GA was able to reach near the globally optimal solution, after satisfying the above constraints. Weld-bead profiles had been predicted using the neural networks. The GA-NN was found to perform better than the BPNN.

Karthikeyan et al [19] applied a central composite rotatable design with four factors and five levels were chosen to minimize the number of experimental conditions. An empirical relationship was established to predict the tensile shear fracture load of friction stir spot-welded rolled sheet of 2.7-mm thickness of AA2024 aluminum alloy by incorporating independently controllable FSSW process parameters. Response surface methodology (RSM) was applied to optimize the FSSW parameters to attain maximum lap shear strength of the spot weld.

S.V.Sapakal & M.T.Telsang [20] used L_9 OA to find the optimal process parameters for penetration & S/N ratio & ANOVA used for optimization of parameters.

Kundan Kumar et al [21] used RSM as a model for predicting the output responses of TIG welding (i.e. reinforcement height, weld bead width, metal deposition rate). w.r.t input namely current, voltage, and speed in welding of 150×50×48 AISI 304 L S.S with a single V-groove.

D.V.Kiran et al [22] used central composite rotatable design is SAW welding of 12mm thick HSLA steel to optimize weld bead mechanical properties.

P. Sreeraj et al [23] use a 5 level 5 faster full factorial design matrix based on central composite rotatable design technique to develop mathematical model to predict clad bead geometry of austenitic S.S deposited on 300×200×20 M.S plate of grade IS-2062 by GMAW. And later utilized ANN to predict clad bead geometry & applied GA model to optimize weld bead geometry.

P.K.Palani et al [24] utilized RSM to investigate the effect of welding parameters on TIG Welding of 75×75×3mm plates of Aluminum alloy 65032. Io speed, current & gas flow rate more input parameters & UTS & %elongation more output responses. ANNOVA was carried out to find optimum welding conditions to maximize T.S & % elongation.

IV.CONCLUSION

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. Using these plots, the best combination of factors to meet the desired goals can be predicted. RSM has an advantage over the Taguchi method in terms of significance of interactions and square terms of parameters. In RSM, only two control factors may be viewed at a time on a single contour plot even though more than about four responses on one graph become very difficult to interpret. However, since a response surface is available, an automatic optimizer can be used to help in determining the optimum setting for each response. In regard to ANNs, it was reported that ANNs perform better than the other techniques, especially RSM in the case of highly non-linear behavior. Also, RSM can be used to build an empirical model using a small number of experiments; however the accuracy of technique would be better for a larger number of experiments used to develop a model. In other words, the ANN model itself provides little information about the design factors and their contribution to the response, if further analysis has not been done. The

most popular ANNs are radial basis function neural networks, learning vector quantization neural networks, back-propagation and counter-propagation networks. The GA is a powerful optimization tool in irregular experimental regions. The main characteristic of GAs over the other optimization techniques is that they operate simultaneously with a huge set of search space points to find the optimal welding condition instead of a single point. But, this technique requires a good setting of its parameters and uses a large computational effort, and therefore a long run time. Further, this technique does not develop models. DOE allows the user to analyze importance of various factors and helps to identify important interactions among the factors. It doesn't predict the best factor levels to meet desired goals. A powerful optimization technique called Taguchi method which characterizes while improving the product quality and reliability at low cost. The optimization algorithm works based on calculating signal-to-noise (S/N) ratios for each combination and then the combination having a maximum S/N ratio is defined as the optimal setting. However, Taguchi's analysis approach of S/N may lead to non-optimal solutions, less flexibility and the conduction of needless experiments. Taguchi analysis can provide definitive information if there is only one response. But it does not deal with situations where a number of responses are to be optimized. The time required for conducting experiments using RSM is almost twice that needed for the Taguchi methodology. However, any one type of optimization methods such as Genetic Algorithms (GA), Particle Swami Optimization (PSO) etc. after selecting appropriate DOE for any method of welding phenomena. The different optimization methods reported in this survey are appropriate for modeling, optimizing, and predicting the different welding processes. The survey reveals the high level of interest in the adaptation of RSM and ANNs to predict response(s) and optimize the welding process. Adaptation of RSM and ANN's to predict and optimize the welding processes are preferred over adaptation of Taguchi method and ANN's because in RSM interaction, effects of multiple variables are available, but not in Taguchi method.

Literature review indicates that there is lack of comparative study carried out in regards the performance of the optimization methods, in other words for a given optimization problem which of the method would suit better. Combining two modeling and optimization techniques, such as RSM, NN, and NN-GA, would reveal good results for finding out the optimal welding conditions. Future work should focus on the application of these modeling and optimization techniques to find out the optimal welding combinations of parameters for a welding process.

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