ABSTRACT

Arc welding plays an important role in manufacturing science. Despite the widespread use of arc welding for joining metals, control of most of the welding processes still requires a considerable amount of skill and experience on behalf of a human welder. Total automation of a welding process has not yet been achieved, largely because of the fact that the physics, which determines the success of any welding task, is not yet fully understood and quantified.

Arc welding is categorized into a number of processes, each of which is characterized by the nature of the applied welding methodology and the techniques required for carrying it out. It is to be noted that each of these processes is usually best suited for a particular type of application. Moreover, arc welding process utilizes the heat of an arc created between the electrode and the work piece to be welded, to melt the metal and join the pieces by fusion. Arc welding is used in nearly all applications in the metal fabrication industry. Common to all of the processes is the use of an electric arc, which provides heat to the welded joint. The purpose of welding is to apply this heat to melt the base metal, and the optional filler metal, and thus bring about coalescence of the joined metals. The present study concentrates on the two most commonly used types of arc welding processes, such as tungsten inert gas (TIG) and metal inert gas (MIG) welding processes.

In arc welding, the quality of a weld depends on the bead geometric parameters, such as height, width, penetration etc. Bead parameters, in turn, are dependent on the process parameters. Thus, input process parameters control the weld quality. It might be interesting, to investigate the input-output relationships in welding.

In the present work, attempts are made to predict weld bead geometry for a set of input welding parameters by

(1) Statistical analysis,

(2) Combined fuzzy clustering and statistical analysis ,

(3) Genetic-fuzzy system.

Moreover, the reverse process modeling (i.e., prediction of welding process parameters for a desired weld bead geometry) has been carried out using the genetic-fuzzy system.

In Chapter 1, a detailed literature survey has been carried out. The gaps in the literature have been identified and the aims and objective of the thesis have been stated.

Chapter 2 introduces different tools and techniques used in the present thesis. These include regression / statistical analysis based on full factorial design of experiments (including methodology for checking adequacy of the model and significance test), entropy-based fuzzy clustering, fuzzy logic techniques, genetic algorithms, genetic – fuzzy system and others.

Chapter 3 includes the data related to TIG and MIG welding processes, used for the purpose of analysis. The data related to TIG welding process have been extracted from a paper authored by *Juang et al.* [39]. Five welding parameters, such as speed, wire feed rate, % cleaning, gap and current are considered as the inputs to the process and the parameters related to weld bead geometry, like front height, front width, back height and back width are taken as the outputs. Two level full factorial design has been adopted here. As there are five inputs variables, data are to be collected for $2^5 =$ 32 combinations of the input variables. These 32 sets of data obtained from the above literature have been used for carrying out regression analysis and its performance will be tested on 36 test cases. The input parameters and their ranges selected in this study are shown in Table 1:

Experiments are carried out on the MIG welding set-up present in the Welding Laboratory of Mechanical Engineering Department, IIT Kharagpur. Six parameters, such as welding speed, arc voltage, wire feed rate, gas flow rate, nozzle-to-plate distance and torch angle are considered as the input variables of the process and there are three outputs of the process, namely weld bead height, bead width and penetration. As there are two levels of each variable, a total of $2^6 = 64$ combinations of input variables are to be considered, to ensure a full factorial design of experiments. Moreover, four replicates of the responses have been considered for each combination of input variables. Thus, a total of 64 × 4 = 256 experiments are conducted, which are utilized to build the model and statistically check its adequacy. To test the performance of the above model, 27 test cases have been generated at random.

In Chapter 4, regression analyses (both linear and non-linear) have been carried out, to determine the input-output relationships in TIG and MIG welding process, in the following ways:

1. Linear regression analysis considering all the terms,
2. Linear regression analysis considering significant terms only,
3. Linear regression analysis considering the main factors,
4. Non-linear regression analysis.

The adequacies of the established models are checked by using the analysis of variance (ANOVA) and the significance of each parameter including the interaction terms are analyzed with the help of significance test. In TIG welding process, it is impossible to carry out the ANOVA for checking the adequacy of the models considering all the terms, as only one value is available for each response for a set of input variables. The one way to achieve this is by using the probability plot and Pareto chart of effects to identify the significant and insignificant terms.

To evaluate the efficiency of the models, scatter plots of target and predicted values for different responses are prepared. The performances of three approaches of linear regression analysis and one approach of non-linear regression analysis have been compared in terms of average RMS deviation in predictions of the responses. It is to be noted that two approaches of linear regression analysis have shown slightly better performances compared to that of the non-linear regression analysis. It could be due to the fact that the input-output relationships of this process are not so much non-linear.

The above regression analyses are also carried out, to estimate the input-output relationships in MIG welding process. Besides the normal probability plots, Pareto plots and significance test, ANOVA is attempted to investigate the effect of different factors and check the adequacy of the model. Moreover, the performances of the models have been tested on 27 test cases, created at random. Comparisons are made of the different regression analyses (as mentioned above), in terms of average root mean square (RMS) deviation in prediction. It is interesting to note that linear regression analysis has shown slightly better performance compared to the non-linear regression analysis, while modeling the data related to both TIG as well as MIG welding processes. It could be due to the fact that the input-output relationships of the above two processes are not so much non-linear.

A new method of cluster-wise regression analysis has been proposed. The above regression analyses are carried out based on the experimental data collected in a particular fashion. It is to be noted that only two levels (high and low) of a variable have been considered while making the plan of experiments. Thus, there is a possibility that the model will be able to predict the responses accurately at the anchor points (with the help of which, the model has been built) but it may show poor performance at some other points. To overcome this, the input-output hyperspace has been divided into a number of clusters by using an entropy-based fuzzy clustering technique. After the clusters are obtained, linear regression analysis is carried out cluster-wise.

Similarly, cluster-wise regression equations are also obtained for the MIG welding process. The performance of these models are checked for 36 and 27 test cases created at random, for the TIG and MIG welding processes, respectively. It is interesting to note that in both the processes, the proposed method of cluster-wise regression analysis has performed slightly better than the previously found best linear regression analysis. It has happened due to the fact that the proposed method is local in nature, as a separate set of response equations has been derived for each cluster, whereas the regression analysis discussed in the earlier chapter is global in nature.

Regression analysis is carried out for one response at a time. Thus, the dynamic interactions among the responses (if any) are totally neglected. Moreover, in actual welding, all the responses related to the weld bead geometry are produced simultaneously, for a set of input parameters. Thus, response-wise regression analysis (i.e., by taking only one response at a time) may not be a very practical approach. To overcome this, a fuzzy logic-based expert system has been developed, in which there are dynamic interactions among the input and output variables. As a manually –

constructed fuzzy logic controller (FLC) may be far from being an optimal, a genetic algorithm (GA) has been used to optimize its knowledge base off-line. The knowledge base (KB) of an FLC consists of the membership function distributions of the variables and the rule base.

The genetic-fuzzy system has been developed by using four different approaches given below.

1. Approach 1: GA-based tuning of database (symmetric) and rule base of manually constructed fuzzy logic controller.
2. Approach 2: GA-based tuning of database (asymmetric) and rule base of manually constructed fuzzy logic controller.
3. Approach 3: Automatic design of database (symmetric) and rule base of FLC using a GA.
4. Approach 4: Automatic design of database (asymmetric) and rule base of FLC using a GA.

The optimized FLCs have been designed separately for the TIG and MIG welding processes by utilizing the above approaches, and their performances are tested on some random test cases. For TIG welding process, Approach 1 has given the best performance. In Approaches 2 and 4, the GA performs its search in a wider space compared to that in Approaches 1 and 3. Thus, in Approaches 2 and 4, the GA faces a more difficult task to reach the optimal solutions. In case of MIG welding process, Approach 4 has slightly outperformed other approaches. It happens due to the fact that Approach 4 has got the maximum search space and the GA is able to reach the optimal solutions through search. It has been observed that the FL-based expert system in unable to reach the accuracy level in prediction of the cluster-wise regression analysis, in most of the test cases but not all. It may happen due to the fact that in the above statistical analysis, the responses have been modeled separately, but a single FL-based expert system has been developed for all the outputs taken together. Thus, the FL-based expert system may not be able to reach the accuracy level of the said statistical method. But, the performance of the FLC can be improved by further modifying its KB.

The reverse modeling of arc welding processes, in which the welding parameters are to be determined for getting a set of desired weld bead parameters. It is often required to control a process on-line. It is to be noted that the reverse modeling involves inversion of the transformation matrix. The transformation matrix obtained from the regression analysis, may not be invertible always. Moreover, it may also be a non-square matrix, which cannot be inverted. Some researchers have tried to find pseudo-inverse of the non-square transformation matrix but it may result into a lot of error in prediction of welding parameters. In the present work, an attempt has been made to develop an FL-based expert system, to carry out the reverse modeling of both TIG as well as MIG welding processes. As it is found to be difficult to design the FLC manually, the whole task of designing the FLC is given to the GA, which through its search determines a good knowledge base of the FLC. Thus, two approaches have been developed, which are as follows

1. Approach 1: Automatic design of rule base and data base (symmetric) of FLC using a GA
2. Approach 2: Automatic design of rule base and data base (asymmetric) of FLC using a GA

The performances of both the approaches have been compared in modeling of TIG and MIG welding processes. Approach 2 is found to perform better than Approach 1, in both the cases. It is obvious because in Approach 2, the GA carries out its search in a wider space compared to that in Approach 1.