A Study on Global and Cluster-wise Regression Model in the Automatic GMA welding

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Abstract. The automatic welding system is presently made use of high volume production industries even if the cost of the related equipment is justified by the large number of pieces to be made. Also, the detailed movement devices with the predetermined sequences of welding parameter and the use of timers to form the weld joints were required. A new mathematical model that predict the optimal welding parameters on a given bead geometry and accomplish the desired mechanical properties of the weldment to make the automatic GMA (Gas Metal Arc) welding process should be needed. The developed model should be employed a wide range of material thicknesses and be applicable for all welding positions as well. In addition, the algorithm must be available in the form of mathematical equations which can be programmed easily to the robot and give a high degree of confidence in predicting the bead dimensions. In this study, two regression models with global regression and cluster-wise regression are proposed to be applicable for prediction of optimal welding parameters on the bead reinforcement area. For development of the proposed regression models, an attempt has been done for applying to a several methods. A series experiments to research the effects of welding parameters on bead reinforcement area as a function of key output parameters for the lab-joint weld in the automatic GMA welding process was performed. Not only the fitting of these models was checked and compared by using a variance test (ANOVA), but also the prediction of bead reinforcement area using the developed regression models were carried out the basis of the additional experiments.

1. Introduction
The Metal Inert Gas (MIG) welding process, occasionally called GMA welding process, is a welding process that produces coalescence of metals by heating with a welding arc between a continuous filler metal electrode and the workpiece [1]. Even if the automatic welding system provides the same time saving and precision welding, it can only be applied for small-lot production and production of a
single part [2]. A suitable process control algorithm that describe interaction of the welding parameters and their influence on optimal bead geometry in order to develop the automatic arc welding process are required. Nevertheless, it is quite difficult task to apply them for various practical situations because relationship between the welding parameters and the bead dimensions is non-linear. Jeng et al. [3] applied for the laser butt welding process using a BP (Back Propagation) and LVQ (Learning Vector Quantization) neural networks, and proved that both neural networks were very useful in determining the suitable welding parameters and avoiding inappropriate welding design. Kim and Jun [4] have made use of a BP neural network for determining bead geometry in GMA welding process. The design parameters of the neural network model are chosen from the error analysis, and the proposed neural network model could be estimated bead geometry with reasonable accuracy. Li et al. [5] proposed a neural network model for on-line prediction of welding quality in GMA welding process.

Chandel [6] first applied regression analysis technique in GMA welding process and indicated the developed regression models derived from experimental results could be utilized for predicting the bead geometry fairly accurately. Yang, et al. [7] extended the related algorithm for prediction of weld deposit area and presented the effects of welding parameters on the weld deposit area. Juang and Tarng [8] demonstrated the selection of welding parameters by using a Taguchi method for obtaining the optimal bead geometry in the Tungsten Inert Gas (TIG) welding process of stainless.

To develop the automatic GMA welding process, the mathematical models should be required to select bead geometry as welding quality. No matter how, only a very few studies of prediction of welding parameters on the optimal bead reinforcement area for lab-joint weld in the automatic GMA welding process have been done.

This paper presents an intelligent model for the lab-joint weld in the automatic GMA welding process by regression algorithms for estimating the optimal bead reinforcement area and studying the effects of various welding parameters. Based on the experimental results, the two regression models with the global and cluster-wise regression analysis algorithms have been developed to predict the suitable bead reinforcement area. These two kinds of developed models are verified by data obtained from additional experiments with lab-joint welds and compared. Finally, predictive behaviors and advantages of each model are discussed.

2. Experimental Works
Experiments were designed for developing the two regression models which based on global and cluster-wise regression analysis algorithm for correlating independently controllable welding parameters. The experimental design provides the smallest number of treatment combinations with which the main effect of a factor and the interaction between the factors can be defined. Since the automatic GMA welding process is considered as a multi-parameter process, it’s hard to find optimal welding parameters with lab-joint weld for good welding. According to previous studies [9], five welding parameters included welding voltage, arc current, welding speed, CTWD (Contact Tube Weld Distance) and welding angle were selected as the input parameters and the response was bead reinforcement area to control welding quality in this research. Figure 1 shows a schematic diagram for relationship between input and output parameters with lab-joint weld in the automatic GMA welding process.

![Figure 1. A schematic diagram for relationship between input and output parameters](image)

The bead reinforcement area is made use of studying the welding quality. A schematic diagram for measurement of bead reinforcement area with a lap-joint weld in the automatic GMA welding
process was presented in figure 2. In this study, the bead reinforcement area as welding quality was mainly considered.

Statistically designed experiments that are based upon full factorial techniques, reduce costs and supply the required information about the main and interaction effects on the response factors [10]. The design matrix that has 72 experimental welding runs was used where each row corresponds to one experimental run with two replications. The experimental results that included five welding parameters on bead reinforcement area were obtained by using a welding robot. In this study, the mean of these replications was considered output parameters to utilize the development of two regression models. The results of the experiment were employed on the basis of development of two regression models which based on global and cluster-wise regression analysis algorithms in the automatic GMA welding process.

\[ \text{A}_R = \text{6615} - \text{639.3V} - \text{47.29I} - \text{140.5S} - \text{447.0C} - \text{110.7A} + \text{2.654VI} + \text{7.885VS} + \text{24.78VC} + \text{6.167VA} + \text{1.016IS} + \text{3.362IC} + \text{0.7873IA} + \text{9.435SC} + \text{2.360SA} + \text{7.188CA} - \text{0.05713VIS} - \text{0.1860VIC} - \text{0.04385VIA} - \text{0.5257VSC} - \text{0.1321VSA} - \text{0.3978VCA} - \text{0.0751521ISC} - \text{0.01697ISA} - \text{0.053201ICA} - \text{0.1526SCA} + \text{0.003966VISC} + \text{0.000948VISA} + \text{0.008489VSCA} + \text{0.002933VICA} + \text{0.001140ISCA} - \text{0.000063VISCA} \]  

(1)

Figure 2. A schematic diagram for measurement of bead reinforcement area

3. Results and Discussion

3.1 Development of global regression model

In general, regression analysis is widely applied for understanding among which the independent variables are related to the dependent variable, and exploring the forms of these relationships. Many techniques to do regression analysis have been developed. Familiar methods such as linear regression and ordinary least squares regression are parametric, in that the regression function is defined in terms of a finite number of unknown parameters that are estimated from the data. The performance of regression analysis methods in practice depends on the form of the data generating process, and how it relates to the regression approach being used. Furthermore, the development of formalized approach for procedure optimization should be included to establish combination of welding parameters which would produce a good weld quality. Global regression analysis has been developed the basis of the experimental results. The following global regression model for bead reinforcement area was developed and presented as following:

The performance of the developed global regression model for predicting bead reinforcement area were showed figure 3. As indicated in figure 3, not only the straight line put on the measured bead reinforcement areas, but also the dash line represented the predicted results by the developed global regression model. It can be found that differences between the measured and predicted bead reinforcement areas were very small in cases of the whole trial numbers even if the maximum error was limited within 0.4mm. Figure 4 showed the error of the predicted bead reinforcement area using the developed global regression model. As shown in figure 4, it can also be indicated that distributions of the predicted bead reinforcement area were quite close to the best fit line so that the estimated results were reasonable reliable.
3.2 Development of cluster-wise regression model

Usually, accuracy of prediction of the output obtained by regression equations is depended on being higher or lower at the anchor points which used in the analysis. In this work, each welding parameter has been considered at its two levels for the global regression analysis. Hence, the error in prediction might be more or less deviate from their respectively expected values. In order to solve this problem, a cluster-wise regression analysis model was developed for this work. Cluster-wise regression analysis can be applied for dividing the input–output space into a number of clusters based on similarity. Once the clusters are obtained, the regression analysis can be carried out to determine the input–output relationships. Linear regression analysis involving main factors only can be adopted for this purpose. Initially, 72 sets of input–output data are randomly generated by selecting the input parameters lying within their respective ranges and using the output equations obtained above to determine the outputs. The technique is employed for identifying the cluster centres and grouping them into the clusters on the basis of the similarity measure. The minimum number of data sets in each cluster has been kept fixed to 8.3% (6 data sets out of 72) and it has been decided by the basis of the minimum number of data points required to carry out the linear regression analysis.

Moreover, the minimum number of data required for the regression analysis should be at least one greater than the number of input parameters. The parametric study is performed identifying the optimal number of cluster centres, data points that belong to each cluster centre and number of outliers by varying the T (threshold for similarity) from 0 to 1. When the clusters are identified by the basis of this cluster-wise input–output relationships, statistical regression analysis is performed. As the input–output relationships are established, the test scenarios are passed through the model. Furthermore, the minimum distance from the data point to an appropriate cluster centre in order to identify which cluster each of the test data points belongs is calculated. Once the cluster is identified for each test case, its outputs are predicted by using the linear regression equations corresponding to that particular cluster. Cluster-wise regression analysis for bead reinforcement area with lab-joint welds in the automatic GMA welding process carried out and the following equations are obtained for the different clusters as shown below:

- Cluster 1:
  \[ A_R = 25.70 - 0.3640V + 0.02700I - 0.3540S - 0.02700I + 0.3640V - 25.70 \]

- Cluster 2:
  \[ A_R = 25.93 - 0.3434V + 0.02648I - 0.3697S - 0.02648I + 0.3434V - 25.93 \]

- Cluster 3:
  \[ A_R = -3.3 + 0.581V + 0.0150I - 0.149S + 0.0206C + 0.0220A \]
- Cluster 4:
  \[ A_R = 20.23 \times 0.0805 + 0.028841 - 0.3615 - 0.1150C + 0.01735A \]  \[(5)\]

- Cluster 5:
  \[ A_R = 25.452 - 0.355590V + 0.02722I - 0.35476S - 0.12352C + 0.00816A \]  \[(6)\]

The 8 test cases to check the performance of the developed cluster-wise regression model are passed through the regression equations. A particular test case is the first checked for its belongingness to a particular cluster by considering its Euclidean distance from the cluster centre. Table 1 indicates the belongingness of the test cases to different clusters.

| Table 1. Belongings of test cases to different clusters in the automatic GMA welding |
|---------------------------------------------------------------|
| Cluster center | C1 | C2 | C3 | C4 | C5 |
| Data set No.    | 5 | 6, 8 | 1, 3, 4 | 7 | 2 |

**Figure 5.** Performance of the developed cluster-wise regression model for predicting bead reinforcement area

**Figure 6.** The error of the predicted bead reinforcement area with the developed cluster-wise regression model

Figure 5 represented performance of the developed cluster-wise regression model for predicting bead reinforcement area. As plotted in figure 5, performance of the developed regression model in order to estimate bead reinforcement area is excellent. It was noticed that differences between the measured and predicted bead reinforcement area was almost same in cases of the whole trial numbers even if the maximum error was limited within 0.04mm. Figure 6 demonstrated the error of the estimated bead reinforcement area with the developed cluster-wise regression model. Therefore, it can be concluded that the use of the developed cluster-wise regression model was able to predict bead reinforcement area with lab-joint weld for a given welding conditions.

### 3.3 Selection of the best regression model

To select the most accurate regression model for prediction of bead reinforcement area in the automatic GMA welding process, the 8 additional experiments were carried out. The convergence criterion for the developed regression models was determined by the average RMS error between the desired output value \( y_i \) and predicted output value \( y'_i \) for the prediction as following:

\[ E_{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y'_i)^2} \]  \[(7)\]
Figure 7. Comparison between the developed global and the developed cluster-wise regression models

Figure 7 plotted the comparison between the developed global and cluster-wise regression models in order to determine bead reinforcement area. The calculated values obtained using the developed cluster-wise regression model was universally lower than those by the developed global regression model as explained in figure 7. However, it is readily clear that the fitting on the experimental data of the cluster-wise regression model with the RMS value of 0.0021 is better than the developed global regression model to determine bead reinforcement area. No matter how, it was shown that the RMS values generated from the developed global regression model was still reasonably small to be accepted in most cases of practical applications.

4. Conclusions
The two regression models to determine the optimal welding parameters on the required bead reinforcement area and investigate the effects of welding parameters on the bead reinforcement area in lab-joint weld in the automatic GMA welding process has been proposed. Experimental results have been applied for developing the optimal algorithm to predict the optimal bead reinforcement area by a global and cluster-wise regression analyses in lab-joint weld in the automatic GMA welding process. The developed global and cluster-wise regression models were made comparing to the target value generated from additional experiment. Both of them were proved to be capable of predicting bead reinforcement area within an acceptable range of error. However, the developed cluster-wise regression model has yielded the slightly better predictions compared to the developed global regression model. A comprehensive analysis was further made for finding the optimal algorithm for prediction of bead reinforcement area. It can be concluded that not only the developed cluster-wise regression model has the least RMS in the aspects of bead reinforcement area, but also the selection of the most accurate regression model for prediction of bead reinforcement area was the cluster-wise regression model.

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