A STUDY ON WELDING CHARACTERISTICS OF MATERIALS FOR AUTOMOBILE SUB-FRAME

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ABSTRACT

Arc welding process, one of the most common joining processes in the metal industries was widely applied for facilities from Nano machines to highly-automated factories. More recently, products of piles and columns to support wind turbines has grown significantly in importance. A new algorithm that predicts the optimal welding parameters on a given bead geometry and accomplishes the desired mechanical properties of the weldment in order to make the automated GMA (Gas Metal Arc) welding process should be required. The developed algorithm should also make use of a wide range of material thicknesses and be applicable for all welding positions. 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 employing global regression analysis and cluster-wise regression analysis are proposed to be applicable to estimate the optimal welding parameters on the bead penetration area. For development of the proposed regression models, an attempt has been made to apply for a several methods. A full factorial design studying the effects of welding parameters on bead penetration area as a function of key output parameters with the lab-joint weld in the automated GMA welding process was carried out. The fitting of these models were checked and compared by using a variance test (ANOVA). Also the performance of the prediction of bead penetration area using the developed regression a model was verified the additional experiments.

Keyword: GMA (Gas Metal Arc) welding process, Global regression model, Cluster-wise regression model, Lab-joint welding, bead penetration area and Welding quality.

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1. INTRODUCTION
The optimization of welding process which selects the welding procedure and predicts bead geometry that will be deposited connected to the automatic arc welding process is recently increased. A major tasks involving optimization of arc welding process should define a welding procedure which can be shown to be the best with respect to some standard and chosen combination of welding parameters which give an acceptable balance between production rate and the scope of defects for a given situation [1]. Therefore, it can only be applied for small-lot production and production of a single part, even if the automated welding system provides the same time saving and precision welding [2]. A suitable process control algorithms that describe interaction of the welding parameters and their influence on optimal bead geometry to develop the automated arc welding process are required. However, it is not an easy task to apply them for various practical situations since relationship between the welding parameters and the bead geometry is non-linear.

Over the years, a various studies which included analytical [3-5], numerical [6-8], practical technologies [9-11] for developing the mathematical models have been studied. Most practical models were developed statically or experimentally, and attempted to decouple the welding parameters. However, decoupling of welding parameters is extremely difficult as each parameter has at least some effect on the others [10]. In recent years, AI(Artificial Intelligence) technology has been introduced a very powerful technique for developing a mathematical model to express interrelationship between the input and the output of complicated systems [12]. The major advantages of the technology in the domain of engineering design and group technology are its ability to store a large set of parameter patterns as memories for the system which can be later recalled. Park et al. [13] formulated a control system to perform real-time evaluations of the weld quality using fuzzy multi-feature pattern recognition with the measured signals. Tarng et al. [14] used a fuzzy clustering technique for classifying and verifying the quality of aluminum welds on the basis of bead geometry in Tungsten Inert Gas(TIG) welding process. Liao et al. [15] presented a welding flaw detection methodology which based on two fuzzy clustering methods, named fuzzy K-Nearest Neighbors(K-NN) and fuzzy c-means were studied.

Vitek et al. [16] employed the neural network to predict weld pool shape as a function of welding parameters for arc welding process, and explained that the developed neural network model is a viable technique for determining weld pool shape. Eguchi et al. [17] proposed not only the switchback method for achieving a stable back-bead geometry, but also an arc sensor to estimate the wire extension and the arc length by using measurements of both arc voltage and welding current. Jeng et al. [18] applied a BP(Back Propagation) and a LVQ(Learning Vector Quantization) neural network for the laser butt welding parameters and proved that both networks were very useful in selecting a suitable welding parameters and avoiding an inappropriate welding design. Kim and Jun [19] have made use of a BP neural network for determining bead geometry in the GMA welding process. The design parameters of the neural network model are chosen from the error analysis, and the proposed neural network model could predict bead geometry with reasonable accuracy. Li et al. [20] proposed a neural network model for on-line prediction of welding quality in the GMA welding process.

The situation has recently been altered with the advent of increasing computer efficiency and better understanding of the usefulness of statistically designed experimentation that is strongly related to factorial techniques which can reduce cost and provide the required information about the main and the interaction effects on the response factors [21]. The regression analysis, a statistical process for estimating the relationships among variables includes many techniques for modeling and analyzing several variables, when the focus is on relationship between a dependent variable and one or more independent variables. More
specifically, regression analysis explained how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Regression models for prediction are often useful even when the assumptions are moderately violated, even if they may not perform optimally. On the other hand, the methods with small effects or questions of causality which took the basis of observational data can especially give misleading results in many applications.

Recently, Chandel [22] first applied regression analysis technique in the 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. [23] 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 [24] showed a regression model for the selection of welding parameters by using a Taguchi method for obtaining the optimal bead geometry in the GTA welding process of stainless has been proposed. However, very limited studies of prediction of welding parameters on the optimal bead penetration area with lab-joint weld in the automated GMA welding process have been performed.

Therefore, the objectives of this paper present an intelligent model with lab-joint weld in the automated GMA welding process by regression algorithms in order to predict the optimal bead penetration area and investigate the effects of various welding parameters. Based on the experimental results, the two regression models which based on the global and cluster-wise regression algorithms have been developed for determining the suitable bead penetration area. These two kinds of 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 made use of global and cluster-wise regression algorithm to correlate 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 automated GMA welding process is considered as a multi-parameter process, it's quite difficult to find optimal parameters with lab-joint weld for good welding. According to previous studies [15], 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 penetration area for controlling welding quality. A schematic diagram of bead penetration area with a lap-joint weld in automated GMA welding process was presented in Fig. 2. In this study, the bead penetration area as welding quality was mainly considered.

Figure 1 A schematic diagram for relationship between input and output parameters

The concept of experimental design for establishing quantitative relationship between welding parameters and bead penetration area was utilized. Therefore, welding parameters with two or three levels were employed as shown in Table 1. All other parameters except these were not changed. The bead penetration area, an important role in determining the optimal welding conditions, is employed for studying the welding quality. A schematic diagram of bead penetration area with a lap-joint weld in automated GMA welding process was presented in Fig. 2. In this study, the bead penetration area as welding quality was mainly considered.
Table 1 Welding parameters and their levels for the study

<table>
<thead>
<tr>
<th>Serial NO</th>
<th>Welding parameter</th>
<th>Units</th>
<th>Notation</th>
<th>Level</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Welding voltage</td>
<td>V</td>
<td>V</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>19</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td>21</td>
</tr>
<tr>
<td>2</td>
<td>Arc current</td>
<td>A</td>
<td>I</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>130</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td>160</td>
</tr>
<tr>
<td>3</td>
<td>Welding speed</td>
<td>mm/mi</td>
<td>S</td>
<td>0</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>CTWD</td>
<td>mm</td>
<td>C</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>5</td>
<td>Welding angle</td>
<td>°</td>
<td>A</td>
<td>0</td>
<td>55</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>65</td>
</tr>
</tbody>
</table>

Statistically designed experiments that are based upon full factorial techniques, reduce costs and provide the required information about the main and interaction effects on the response factors [16]. The design matrix that has 72 experimental welding runs was made use of where each row corresponds to one experimental run with two replications. The experimental data that included five welding parameters on bead penetration area were obtained by using a welding robot. In this study, the mean of these replications was considered output parameters to apply for the development of two regression models. Fig. 3 shows a block diagram in the automated GMA welding process for this study.

Figure 2 A schematic diagram for measurement of bead penetration area

The 200x75x12mm AS 1204 mild steel and steel wire with a diameter of 1.2mm was used for the experiment. A series of experiments to quantify the welding quality in the automated GMA welding process were performed using different welding parameter. Data collection and evaluation has been carried out using the robot welding facility. After 72 welds, the plates were cut using a power hacksaw and the end faces to measure the bead penetration area were machined. Specimen end faces were polished and etched using a 2.5% nital solution to reveal grain boundaries and display the bead penetration area. An image analysis package called Image Analyst, was applied accurately for measuring bead penetration area. The results of the experiment were employed on the basis of development of two regression models with the global and cluster-wise regression algorithm in the automated GMA welding process.

Figure 3 Block diagram for automated GMA welding process for this study
3. RESULTS AND DISCUSSION

3.1. Development of global regression model

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 for performing regression analysis have been developed. Similar 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 methods in practice depends on the form of the data generating process, and how it relates to the regression approach being used.

In general, the development of formalized approach for procedure optimization should be included to establish combination of welding parameters which would produce good weld quality. Global regression analysis which based on experimental data collected from the full-factorial design of experiments has been done. In this study, the response function redefined by using input parameters represented as follows:

\[ Y = f(V, I, S, C, A) \]  

Also, all chosen welding parameters and interaction factors for developing the global regression model are given below:

\[ Y = k_0 + k_1V + k_2I + k_3S + k_4C + k_5A + k_6VI + k_7VS + k_8VC + k_9VA + k_{10}IS + k_{11}IC + k_{12}IA + k_{13}SC + k_{14}SA + k_{15}CA + k_{16}VIS + k_{17}VIC + k_{18}VIA + k_{19}VSC + k_{20}VSA + k_{21}VCA + k_{22}ISC + k_{23}ISA + k_{24}ICA + k_{25}SCA + k_{26}VISC + k_{27}VICA + k_{28}VSCA + k_{29}VISA + k_{30}ISCA + k_{31}VISCA \]

Where the coefficients \( (k_0, k_1, k_2, \ldots, k_{31}) \) of the above equation are determined using a least square technique.

The following global regression model for bead penetration area was developed and presented as follows:

\[ A_p = 11545 - 652.5V - 104.0I - 242.8S - 608.1C - 187.9A + 5.940VI + 13.71VS + 34.68VC + 10.62VA + 2.200IS + 5.486IC + 1.699IA + 12.82SC + 3.943SA + 10.30CA - 0.1253VIS - 0.3167VIC - 0.0961VSA - 0.7290VSC - 0.2226VCA - 0.5857VICA - 0.1164IS - 0.0359ISA - 0.09263ICA - 0.2174SCA + 0.006991VISC + 0.002043VISA + 0.01233VSCA + 0.005332VICA + 0.001968ISCA - 0.000113VISCA \]

Fig. 4 shows comparison between the measured and predicted bead penetration areas used the developed global regression model. As proved in Fig. 4, the dotted line presented the predicted bead penetration area using the developed global regression model as well as the solid line indicated the actual data obtained from automated welding operation. It was reasonable that the developed global regression model for predicting bead penetration area was approximately shown equal to those obtained by experimental results. To assess the accuracy in the developed global regression model, the performance for predicting bead penetration area is represented in Fig. 5. The straight line put on the measured bead penetration areas and the dash line represented the predicted results by the developed global regression model as presented in Fig. 5. It can be found that differences between the measured and predicted results was very small in cases of the whole trail numbers, but the predicted value in the case of trail number 6 was the same as the experimental one.

In order to statistically analysis the accuracy of the developed global regression model, errors of the predicted results was calculated by
Error = \( y_i' - y_i \)

Where \( y_i' \) the predicted values of bead penetration area are, \( y_i \) represent the experimental ones and \( i \) is the serial number of testing data.

Fig. 6 saw the error of the predicted bead penetration area using the developed global regression model. According to Fig. 6, it can also be observed that distributions of the predicted bead penetration area were quite close to the best fit line so that the predicted results were reasonable reliable. In addition, it was demonstrated that the numbers of errors generated from the developed global regression model increased along with the error increasing when the error was lower than 0. After the zero point, the numbers of errors presented to have a tendency of decreasing.

**Figure 4** Comparison between the measured and predicted bead penetration area

![Figure 4](http://www.iaeme.com/IJMET/index.asp)

**Figure 5** Performance of the developed global regression model

![Figure 5](http://www.iaeme.com/IJMET/index.asp)

**Figure 6** The error of the predicted bead penetration area using the developed global regression

### 3.2. Model Development of cluster-wise regression model

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 for performing regression analysis have been developed. Similar 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 methods in practice depends on the form of the data generating process, and how it relates to the regression approach being used.

A better alternative is to perform clustering and regression simultaneously, which can be achieved through cluster-wise regression. That is, the input–output hyperspace is divided into
a number of valid clusters which based on similarity, while cluster-wise regression analysis is done determining the input–output relationships. It is expected that the prediction of output through cluster-wise regression analysis would be better compared to that obtained by the global regression analysis [25]. Cluster-wise regression analysis can be applied for dividing the input–output space into a number of clusters which based on similarity. Once the clusters are obtained, cluster-wise regression analysis can be carried out to determine the input–output relationships. Linear regression analysis involving main factors can only 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 utilized identifying the cluster centers and grouping them into the clusters on the basis of the similarity measurement. 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 the basis of the minimum number of data points required to perform 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 centers, data points that belong to each cluster center and number of outliers by varying the T (threshold for similarity) from 0 to 1. Once the clusters are identified with the basis of this cluster-wise input–output relationships, statistical regression analysis is carried out. When the input–output relationships are established, the test scenarios are passed through the model. In addition, the minimum distance from the data point to an appropriate cluster center for identifying which cluster each of the test data points belongs is calculated. As soon as 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 model for bead penetration area for lab-joint welds in automated GMA welding process performed and the following equations are acquired for the different clusters as shown below:

- Cluster 1:
  \[ A_R = 25.70 - 0.3640V + 0.02700I - 0.3540S - 0.1240C + 0.007000A \]
- Cluster 2:
  \[ A_R = 25.93 - 0.3434V + 0.02648I - 0.3697S - 0.1141C + 0.006870A \]
- Cluster 3:
  \[ A_R = -3.3 + 0.581V + 0.0150I - 0.149S + 0.0206C + 0.0220A \]
- Cluster 4:
  \[ A_R = 20.23 - 0.0805V + 0.02884I - 0.3615S - 0.1150C + 0.01735A \]
- Cluster 5:
  \[ A_R = 25.452 - 0.355590V + 0.027222I - 0.35476S - 0.12352C + 0.00816A \]

To check the performance of the developed cluster-wise regression model, the above 8 test cases 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 center. Table 2 explains the belongingness of the test cases to different clusters. For example, 1st, 4th and 5th clusters contain 1 test case respectively, but 2nd and 3rd clusters centers have accommodated 2 and 3 test cases individually.
Table 2: Belongings of test cases to different clusters in the automated GMA welding

<table>
<thead>
<tr>
<th>Cluster center</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data set No.</td>
<td>5</td>
<td>6, 8</td>
<td>1, 3, 4</td>
<td>7</td>
<td>2</td>
</tr>
</tbody>
</table>

Fig 7 showed comparisons between the measured and predicted bead penetration area using the developed cluster-wise regression model. It was observed that the calculated values obtained using the developed cluster-wise regression model was approximately equal to those obtained by the experiment.

Fig. 7 Comparison between measured and predicted bead penetration area

Fig. 8 Performance of the developed cluster-wise regression model

Fig. 9 The error of the predicted bead penetration area with the developed cluster-wise regression model

Performance of the developed cluster-wise regression model for predicting bead penetration area is represented in Fig. 8. The maximum error was limited within 0.001mm. In the cases of trail number 1, 4, 5, and 7, the estimated value was almost the same as the experimental results as explained in Fig. 8. It can be clear that these errors generated from the developed cluster-wise regression model were reasonably small to be accepted in most cases of practical applications. Fig. 9 spotted the error of the predicted bead penetration area with the developed cluster-wise regression model. According to Fig. 9, the error of the predicted
bead penetration area with the developed cluster-wise regression model increased along with the error increasing when the error was lower than 0. Therefore, it can be concluded that the developed cluster-wise regression model might be applied for determining bead penetration area for lab joint for a given welding conditions.

3.3. Selection of the best regression model
To choose the most accurate regression model for prediction of bead penetration area in the automated GMA welding process, the 8 additional experimental data were employed. The experimental data in order to confirm the developed regression modes were represented in Table 3.

<table>
<thead>
<tr>
<th>Serial No.</th>
<th>Input Parameters</th>
<th>Output Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>V</td>
<td>I</td>
</tr>
<tr>
<td>1</td>
<td>17</td>
<td>110</td>
</tr>
<tr>
<td>2</td>
<td>17</td>
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<td>3</td>
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<td>110</td>
</tr>
<tr>
<td>7</td>
<td>19</td>
<td>120</td>
</tr>
<tr>
<td>8</td>
<td>19</td>
<td>120</td>
</tr>
</tbody>
</table>

First of all, the performance of cluster-wise regression model was compared with that of global regression model in terms of the percentage deviation in prediction of bead penetration area for 8 test cases indicated in Table 3. Fig. 10 indicated comparison of the above two regression models for predicting bead penetration area for 8 test cases. It was true that cluster-wise regression analysis has shown better performance compared to another one. The maximum values of the positive and negative deviation in predictions were found to be equal to 0.06522% and -0.05025% in cluster-wise regression analysis respectively.

Figure 10 Comparison of the developed regression models for percentage deviation

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:

\[
E_{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i')^2}
\]

Comparison between the developed global and cluster-wise regression models were plotted in Fig. 11. According to Fig. 11, the calculated values obtained using the developed
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cluster-wise regression model was universally lower than those by the developed global regression model. However, it is readily shown 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 for estimating bead penetration area as shown in Fig. 11. However, it was true that the RMS value generated from the developed global regression model was still reasonably small to be accepted in most cases of practical applications.

Figure 11 Comparison between the developed global and cluster-wise regression models

To compare the precision of two developed regression models, PAM(Predictive Ability of Model) [26], standard deviation and average error for bead penetration area using the two developed regression models have been performed and presented in Table 4. The two developed regression models have predicted very accurately. In the bead penetration area, the developed cluster-wise regression model didn't achieve 100% in PAM, but compared with the developed global regression model, the developed cluster-wise regression model is significantly improved accuracy. As shown in Table 4, bead penetration area was predicted very accurately more than minimum 75% in PAM which means that the prediction of the cluster-wise regression model had the most accuracy, specially showing 98.84% PAM in bead penetration area. In the comparison of standard deviation and average error, the predicted bead penetration area indicated the most concentrated distribution. Eventually, it turned out the developed cluster-wise regression model has a predictive ability that is superior to the developed global regression model as spotted in Table 4. Therefore, it can be clearly evident that the developed cluster-wise regression model was able to make use of predicting bead penetration area for given welding conditions and is capable of modeling of non-linear problem such as welding process.

Table 4 Performance of the two developed regression models

<table>
<thead>
<tr>
<th></th>
<th>The developed global regression model</th>
<th>The developed cluster-wise regression model</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAM (%)</td>
<td>100</td>
<td>98.8</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.0417</td>
<td>0.0407</td>
</tr>
<tr>
<td>Average error</td>
<td>0.0328</td>
<td>0.0318</td>
</tr>
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</table>

4. CONCLUSIONS

The two regression models to estimate optimal welding parameters on the required bead penetration area and investigate the effects of welding parameters on the bead penetration area in lab-joint weld in the automated GMA welding process has been developed. Experimental results have been employed for studying the optimal algorithm to predict the optimal bead penetration area by a global and cluster-wise regression analysis with lab-joint weld in the automated 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 to predict bead penetration 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 penetration area. It was obviously found that the developed cluster-wise regression model has the least RMS in the aspects of bead penetration area so that the optimal algorithm for prediction of bead penetration area was the cluster-wise regression model.

A rule-based expert system can be incorporated with the developed cluster-wise regression model to integrate an optimized system in the automated GMA welding process. It has been realized that with the use of the developed system, the prediction of bead penetration area becomes much simpler to even a beginner who has no prior knowledge of the automated GMA welding process and optimization techniques.

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