# Optimization of MIG Welding Parameters to Control Quality of Welding

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*Abstract*— In the manufacturing industries welding plays a significant role and such industries require experienced manpower. Since to join metals and to have joints such that it can bear mechanical stresses with respect to the norms of industry standards and to have such welding joints industries requires greater control during the process. The welders play an important role and it again a problem to have sufficient qualitative manpower to obtain the desired process from them. Since MIG welding is popular in automotive and structural sectors so it is required to have to control the process of welding. In MIG welding there are number of input parameters used to control the welding process and so it is required to check and control its input parameters to get weld of desired qualities. In this paper we have discussed the optimization process for input parameters with respect to the quality of welding so that it can be greater help for welders to have control on the output quality of welding.

***Key words:*** Metal Inert Gas (MIG), Optimization, Weld Input Parameters, Artificial Neural Network (ANN)

## I. INTRODUCTION

In manufacturing and fabrications industries the Metal Inert gas welding (MIG) process is widely used since it is cost effective and highly productive. To manage the welding arc, it is require monitor during the welding. During the MIG welding process along with the input parameters there are lots of unwanted noise, heat and light occurs. These side effects can be utilized for monitoring the quality in MIG welding process and an experienced welder can identify the quality of welding during process[1]–[3]. The importance of this current and voltages in control welding processes has been known for a long time, but relatively few studies have been published in which weld qualities along with the input parameters such as current, voltage and travelling speed of welding and as well as side effect parameters such as heat considered as a source of information for monitoring the welding process[4], [5]. During welding process one can identify the quality of weld by looking at the weld performed on the job as show in the figure below.

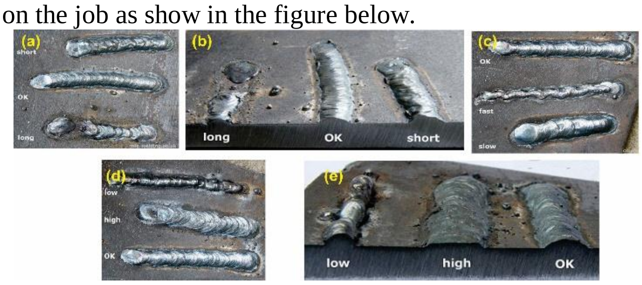



Fig. 1: shows (a)-(b). Arc length Fault (c)-(d). Travel Speed Fault (e). Current Setting Fault[6], [7]

Basically there are different types of weld occur on the basis of various parameters such as current flow, voltage, travelling speed, etc. The good and defective welding can be distinguished on the basis of following types:

Arc Length Faults: As shown in the figure (1 a) and (1 b) where arc length is short , perfect and long this kind of welding is occurs[1], [6].

Travel Speed Faults: As shown in the figure (1 c) and (1d) it occurs when the feeding rate of welding is varies[5], [8], [9].

Current Setting Faults: when there is a variation in current is also responsible for various kind of welding which as shown in the figure (1 e).

The physics of electric arc welding is highly complex in nature, which makes it difficult to develop a mathematical model to correlate the quality factors to the process variables or emissivity characters such as spectroscopic, arc sound etc. Now a day’s smart manufacturing process plays a significant role in industries to compete with high competition of high quality with controlled budget[1], [5], [10].

There are many researchers who have been doing various works in this significant field and doing several efforts to develop the prediction model to monitor and control the quality of manufacturing processes in industries. And in the field of joining technology of welding there is research still required to emphasis the smart production in industries[1], [10], [11].From the literature reviews indicated that there exist many computational intelligent techniques for automated weld quality control[12], [13].

It has found that there are various parameters in welding process which are useful to determine quality of welding either by using individually or there combinations for investigating often without limiting to one domain. Dimensionality reduction the use of dimensionality reduction is seen in the article by Shujuan Bi, Hu Lan, Hongyan Zheng and Lijun Liu , principal component analysis is used to eliminate redundant features from a larger set of descriptive parameters[14]. In the similar case for GTAW a large set of features extracted from wavelet decomposition is reduced using a generic algorithm[15].

It has found during literature survey that still more research is required to machine based to improve machine based quality control inspections techniques in welding technology. And for our proposed work the welding parameters such as current , voltage , feeding speed , sound and pictures can be consider for preparing data sets[8], [9], [13], [16].

J Mirapeix ,et.al. mentioned a new approach that allows automatic weld defect detection and classification based in the combined use of principal component analysis (PCA) and an artificial neural network (ANN) is proposed. The plasma spectra captured from the welding process is processed with PCA, which reduces the processing complexity, by performing a data compression in the spectral dimension. The designed ANN, after the selection of a proper data training set, allows automatic detection of weld defects. The proposed technique has been successfully checked.

Researchers have developed an analytical model to provide a theoretical background of the effect of pulse parameters on metal transfer in welding. And also investigated the same phenomenon with both time and frequency domain analyses to correlate it with metal transfer modes in welding[4], [17], [18].

## II. METHODOLOGY

The arrangement has made and collect the welding parameters during the welding, the data sets prepared from the 60 specimens welded under MIG welding with varying dimensions: 15cm × 3 cm × 0.5 cm, 15cm × 3 cm × 1 cm and 15cm × 3 cm × 1.2 cm. These 60 welding specimens were divided under three sections:

1) Good weld
2) Incomplete weld
3) Burn through

The arrangement of our welding as shown the figure below:

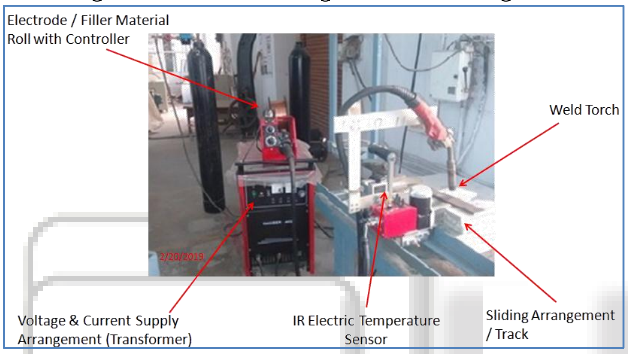



Figure 2: MIG Welding Arrangement at Laboratory

The qualities were inspected from the experienced layman during the process of welding. The input parameters collected as datasets and with help of decision model filtered the unwanted data and the significant data were correlates with respect to the three mentioned qualities of welding. It has found that the combinations of input parameters play an important role to check and control welding quality. And it is required for a layman to monitor all these parameters to obtain good welding. Our model helps them to understand and to optimize the input parameters to get the good welding quality as well as to avoid unwanted welds. The weld specimens are shown in the figure (3) with varying size and dimensions. The main important dimension which we varied is thickness of the specimen $t_1$=.5 cm, $t_2$=1 cm, $t_3$=1.2 cm.

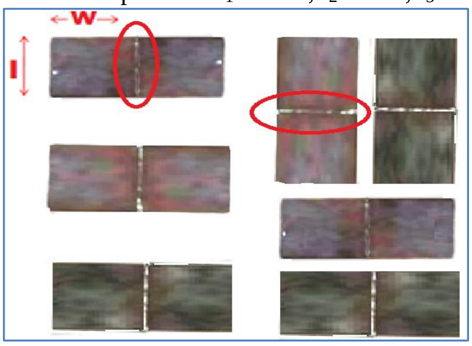
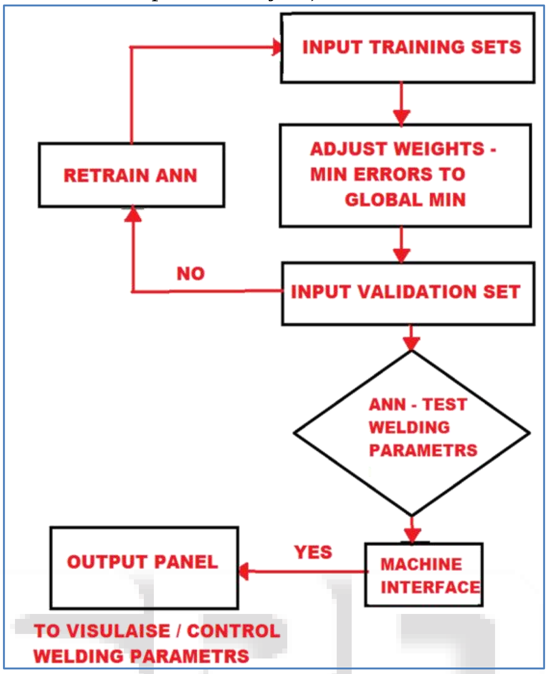



Fig. 3: Welding samples with varying dimensions and quality welds performed.

To get the feedback and to process with respect to the input and output modules the model which we have used Artificial Neural Network (ANN) is as shown in the following flow chart (1) which is used to predict the behavior of parameters vs. the welding qualities . To train the neurons we used the twenty – twenty –twenty data sets for various qualities of welding i.e. good, burn through and lack of fusion welds . The methodology as shown the flow chat (1) to access with ANN and to get the desired classified outputs so that the welder can get the control panel to have the desired welding quality with respect to dimension of the job specimen (thickness of weld plate to be join).

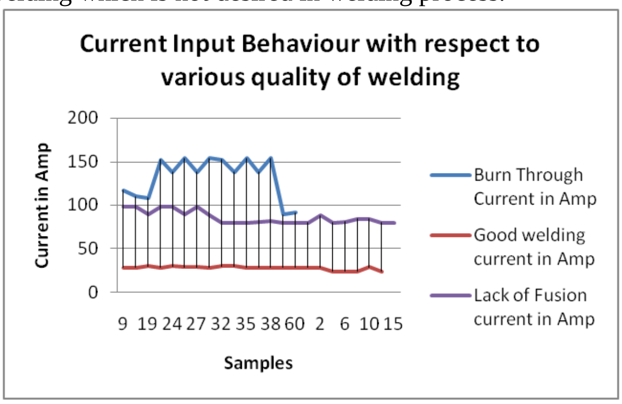



Flow Chart 1: ANN processing with respect to input welding parameters vs. output panel.

The output panel configured with the machine interface so that layman can control the input parameters with respect to the signals from ANN model.

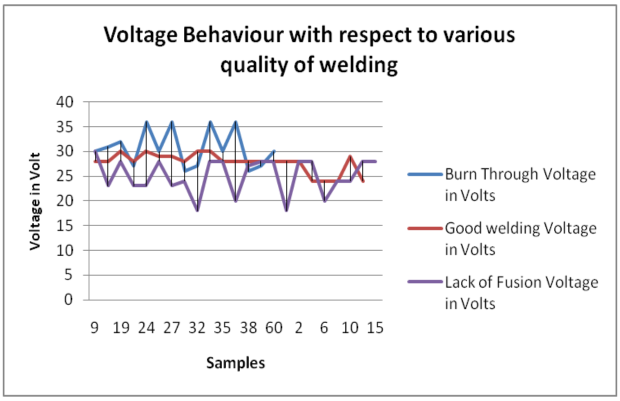
## III. RESULTS

It has identified that the input parameters affects the welding qualities and it is clear from the experiments that the current, voltage and travelling speed of the job to be weld affects the quality. As we can see from the figure (4 a) input current varies with respect to the quality of welding. The good weld required constant low current with respect to the thickness of plate to be weld and if the current is too high or sudden low down it is responsible for burn through and lack of fusion welding which is not desired in welding process.

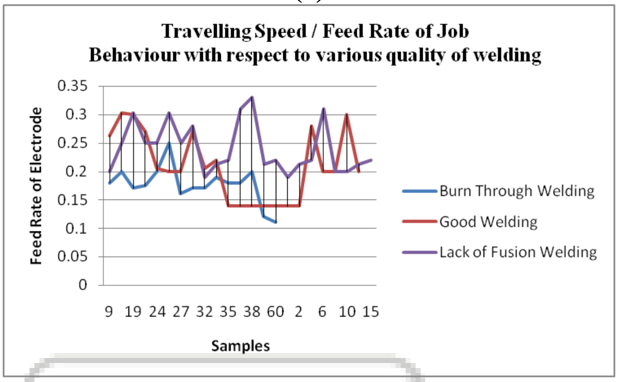



(a)




(b)




(c)

Fig. 4: (a) Current behavior (b) Voltage behavior (c) Travelling Speed vs sample of various weld qualities

Figure (4 b) gives the behavior of varying voltages with respect to the weld specimens. For good welding the average voltage as shown in the figure is required not too high not too low. Since it is visible from the graph that too high and too low nature of welding voltage results in not desired qualities of welding and it results in the cause of burn through and lack of fusion kind of welding.

Figure (4 c) gives the behavior of travelling speed of job specimen to be weld and it is clearly visible that the speed also affect the quality of weld which is shown in the figure (2c). It is desired to have constant speed during the welding process with respect to the thickness of job specimens and its clear that it is responsible for the quality of the welding.

## IV. Conclusion & Future scope

This model can help layman in MIG welding process by reducing effort with respect to take care about all parameters together parallel to the welding process and layman can easily check and control the quality of welds.

Since the model is based on Matlab software and machine interface was used so there is requirement for user to have familiar about Matlab software, it is one of the limitation with this process. Researchers can make in use of other parameters and also can prepare friendly Graphical User Interface systems to check and control this process with help of high level language like Java, php.

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