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Abstract

The weld bead geometry is the important information for determining the quality and mechanical properties of the weldment. The welding process parameters or variables that affect the weld bead geometry in the conventional arc welding process include the following: the welding voltage  $U$ , the welding current  $I$ , the wire feed speed  $WFS$ , the contact tip to work distance  $D$ , and the welding speed  $S$ . Modeling and predicting the weld bead geometry play an important role in welding process planning, to determine the optimal welding process parameters for achieving the improved weld quality. There have been lots of efforts and studies to develop modeling solutions and simulations to determine the weld bead geometry (Height  $H$  and Width  $W$ ) from the welding process parameters ( $U$ ,  $I$ ,  $WFS$ ,  $D$ ,  $S$ ) as the inputs. The welding process parameters can be determined based on the experiences, and the conventional analysis of variance (ANOVA); however, the high welding quality and accuracy are not always obtained. With the advancement of computer vision technologies, digital images from cameras and videos can be used for training the deep learning models, to accurately identify and classify objects. The digital images for evaluating the welding quality and the characteristics of welding objects can be captured via the use of the high-speed camera, and there are emerging data acquisition systems that can handle a huge dataset. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) model is proposed to determine weld bead geometry from the main welding process parameters  $U$ ,  $I$  and  $S$ . The proposed ANFIS model was successfully developed for the first basic investigations, as the foundation for further developments of innovative robotic welding systems which can be used for higher educations or research in Smart Manufacturing, with potentials for industrial applications.

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(separated by '-')            GMAW - metal inert gas welding - MIG

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# Prediction of the Welding Process Parameters and the Weld Bead Geometry for Robotic Welding Applications with Adaptive Neuro-Fuzzy Models

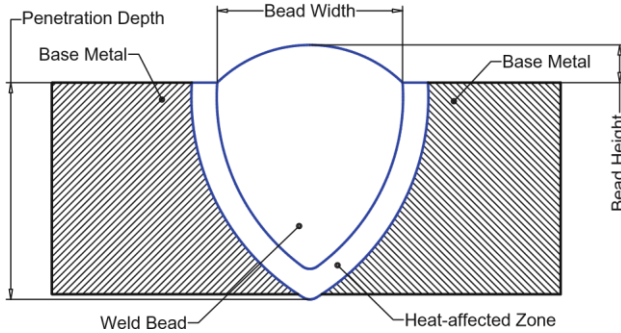
## 1 Introduction

The welding robots have been playing an important role in manufacturing industries. The combination of the advanced welding and robotic technologies leads to the emerging wire-arc additive manufacturing (AM) [1], which is one of the key-enabling technologies for Rapid Manufacturing and Cloud Manufacturing, through the capability of making functional parts and added-value products with the short Time-to-Market, as well as personalized and mass-customized design features. Under the impacts of Smart Manufacturing and Industry 4.0 [2–4], there have been an emerging need of investigating optimizations of process parameters for manufacturing processes, including determination of optimal parameters in the wire arc additive manufacturing in particular and the welding and machining processes in general [1, 5–12, 16], to predict and enhance the quality of the welding, AM and machining processes, as well as developing the effective computer aided process planning (CAPP), based on the big data analytics, Artificial Intelligence (AI), machine learning and simulations.

The weld bead geometry is the important information for determining the quality and mechanical properties of the weldment. Figure 1 presents the typical weld bead geometry, including bead height, bead width, and the depth of penetration. The welding process parameters or variables that affect the weld bead geometry in the conventional arc welding process include the following: the welding voltage  $U$ , the welding current  $I$ , the wire feed speed WFS, the contact tip to work distance  $D$ , and the welding speed  $S$ . Modeling and predicting the weld bead geometry play an important role in welding process planning, to determine the optimal welding process parameters or welding parameters for achieving the improved weld quality.

There have been lots of efforts of innovating the welding technologies, and developing simulations and optimizations of the welding process. With the advancement of computer vision technologies, digital images from cameras and videos can be used for training the deep learning models, to accurately identify and classify objects. Therefore, the digital images for evaluating the welding quality and the characteristics of welding objects can be captured via the use of the high-speed camera, and there are emerging data acquisition systems that can handle a huge dataset. Zhuohua *et al.* (2018) proposed a vision-based method for three-dimensional (3D) control in the robotic welding with the steel sheets, based on the digital images from passive vision sensors, in which the process parameters can be monitored, and the role of process parameters and their relationships are investigated [7]. There are different sensing

technologies that are used for data collection and evaluation of the weld pool state in the primary arc welding process for precision joining of metals [8]. 3D vision sensing technologies can be used to develop imaging and measurement systems for evaluation of welding quality and determination



**Fig. 1.** A typical weld bead geometry which is affected by the welding process parameters, including the welding voltage, the welding current, the wire feed speed, the contact tip to work distance, and the welding speed.

of welding parameters, especially for optimal dynamic modeling and penetration control strategies in gas tungsten arc welding (GTAW), to predict the depth of penetration with the *adaptive neuro-fuzzy inference system* (ANFIS) models [9, 10]. Huabin *et al.* (2009) developed a neural network (NN) model to calculate the full penetration state for the closed-loop control of robotic arc welding systems [11]; in which the welding current, welding voltage, weld pool geometry and changing ratio of bead width act as input for the back side bead width output related to the depth penetration; and the neuron network (NN) works on 1,000 training datasets and 200 testing datasets. D. T. Thao *et al.* (2014) reported the use of experimental data and analysis of variance (ANOVA) to describe the formular of the bead width from different tool tip distance  $T$ , gas flow rate  $G$ , welding speed  $G$ , arc current  $I$ , welding voltage  $V$ , to predict process parameters on top-bead width in robotic Gas Metal Arc (GMA) welding process [12], in which the genetic algorithm (GA) was utilized to estimate the coefficients of an intelligent model. Jamie *et al.* (2016) proposed an architecture based on an artificial neural network (ANN), to learn welding skills automatically in industrial robots, in which an optic camera and a laser-based sensor were used to measure the bead geometry (width and height), and a real-time computer vision algorithm was developed to extract training patterns in order to acquire knowledge to later predict specific geometries of the weld bead [13]. A deep learning approach can be used to estimation of the bead parameters in welding tasks; Soheil *et al.* (2015) presented the ANN algorithm which was applied to capture the response of 2 outputs (depth of penetration, bead width) with 4 hidden layers, 4 input parameter (voltage, current, traveling speed, wire speed); and it was reported that, the deep learning approach could reduce the error of RMS (Root-Mean-Square) bead parameters remarkably [14].

This study aims to investigate solutions for predicting the welding process parameters and the weld bead geometry for robotic welding applications based on the adaptive neuro-fuzzy models. Firstly, the structure of a digital twin model mentioned in [15] is used for

conducting the experiments and obtaining the datasets. Then, the ANFIS model is developed with the use of the obtained datasets, to estimate the weld bead width from the key welding process parameters as the inputs: the welding speed  $S$ , the welding voltage  $U$ , and the welding current  $I$ . In this way, the relationships between the welding process parameters and the weld bead geometry can be determined, and the welding process parameters can be optimally computed for robotic welding process planning and related applications in Smart Manufacturing.

The rest of the paper is organized as follows. Section 2 presents the materials and methods, with the focus on obtaining the datasets for the experiments, and then predicting the weld bead geometry based on the ANFIS model. Section 3 presents the results and discussions. Finally, Sect. 4 presents conclusions and further work.

## 2 Materials and Methods

### 2.1 Datasets for the Bead Width Obtained from the Experiments

<sup>A03</sup> The welding experiments were done by using the welding robot system RV-12SD integrated with the welding equipment Jassic Mig 250 A (Fig. 2).



**Fig. 2.** The integrated welding robot system

For the experiments, the straight welding butt joints are taken into account. The two welded parts are put together in the same plane. The welding seam is 10 cm long. The main welding parameters for the experiments are as follows:

- Welding speed  $S$ : 18–30 cm/min
- Welding voltage  $U$ : 20–25 V
- Welding current  $I$ : 150–250 A
- Welding wire diameter: 1.6 mm
- The welding nozzle's distance: 10 mm

The output geometry of the weld bead includes the bead width  $W$  and the bead height  $H$  which are extracted by the vision-based edge detecting method with the use of the laser projection beam. In the Labview system, the output geometry can be conveniently calculated with the use of the Vision Assistant tools. The bead width is calculated as the average value computed along to the whole welding seam. Tables 1 and 2 presents the

data obtained from the experiments, Table 1 is data from wide range of inputs and Table 2 is narrow range.

**Table 1.** The datasets obtained from the experiments with the large varied speed. S, I, U, W are the welding voltage, the welding current, the welding speed and welding bead width respectively.

S (Cm/min)	I (Ampe)	U (Volt)	W (mm)	S (Cm/min)	I (Ampe)	U (Volt)	W (mm)
18	150	20	6.48	22	220	25	8.50
18	180	20	7.07	22	250	25	9.04
18	200	25	9.02	19	150	20	6.30
18	220	25	9.44	19	180	20	6.88
18	250	25	10.04	19	200	25	8.77
30	150	20	4.97	19	220	25	9.18
30	180	20	5.42	19	250	25	9.76
30	200	25	6.91	24	150	20	5.58
30	220	25	7.24	24	180	20	6.09
30	250	25	7.69	24	200	25	7.76
20	150	20	6.14	24	220	25	8.13
20	180	20	6.70	24	250	25	8.64
20	200	25	8.54	26	150	20	5.35
20	220	25	8.93	26	180	20	5.84
20	250	25	9.50	26	200	25	7.45
22	150	20	5.84	26	220	25	7.80
22	180	20	6.37	26	250	25	8.29
22	200	25	8.12	22	220	25	8.50

**Table 2.** The datasets obtained from the experiments with the smaller varied speed. S, I, U, W are the welding voltage, the welding current, the welding speed and welding bead width respectively.

S (Cm/min)	I (Ampe)	U (Volt)	W (mm)
28	150	20	5.15
28	180	20	5.62
28	200	25	7.17
28	220	25	7.50
28	250	25	7.98
18	140	20	6.27
18	170	20	6.88
18	190	25	8.80
18	210	25	9.23
18	240	25	9.84

20	140	20	5.94
20	170	20	6.52
20	190	25	8.33
20	210	25	8.74

*(continued)*

**Table 2. (continued)**

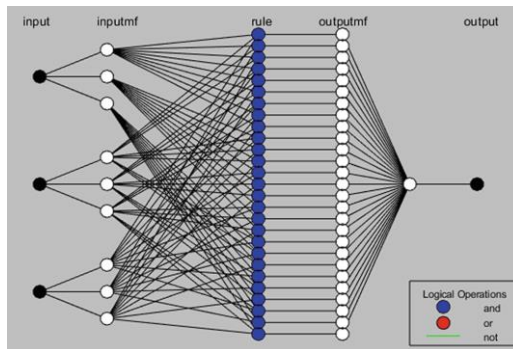
S (Cm/min)	I (Ampe)	U (Volt)	W (mm)
20	240	25	9.32
28	150	20	5.15
28	180	20	5.62
28	200	25	7.17
28	220	25	7.50
28	250	25	7.98

## 2.2 Development of the ANFIS Model for Predicting the Weld Bead Geometry

The ANFIS model has the input membership functions, the output membership functions and the rules (the Sugeno rule). The datasets are divided for the training, in which 70% of the dataset are for training and 30% of the dataset are for testing.

Figure 3 presents the ANFIS model structure. The input of the ANFIS model include the following: the welding voltage U, the welding current I, and the welding speed S. The output of the ANFIS model is the welding bread width W.

Figures 4, 5 present the membership functions for the welding voltage U, the welding current I and the welding speed S respectively.



**Fig. 3.** The ANFIS model in which the output is the welding bread width W, and the inputs include the welding voltage U, the welding current I, and the welding speed S.

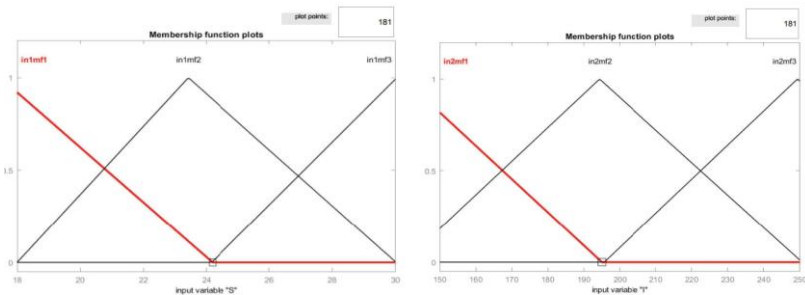


Fig. 4. The membership function for the welding speed S and current I

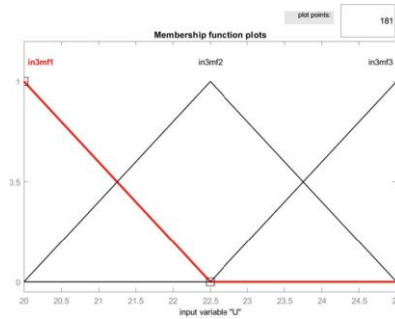


Fig. 5. The membership function for the welding voltage U

### 3 Results and Discussions

The designed ANFIS model has been trained with Epoch = 100. After training process, the training error value was reduced and less than  $2.82 \times 10^{-3}$ , which is acceptable and less than the allowable error of a welding seam geometry (Fig. 6).

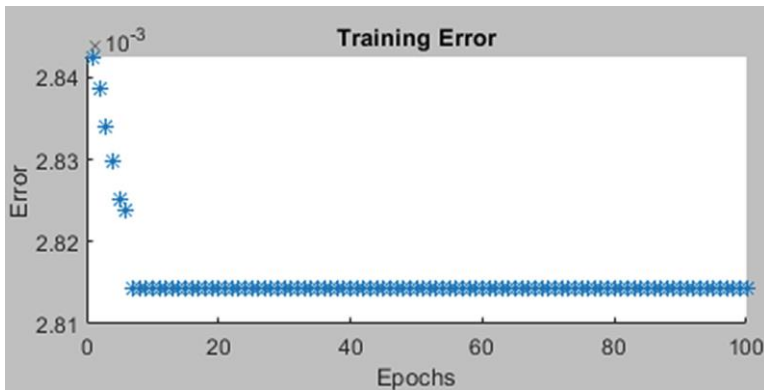
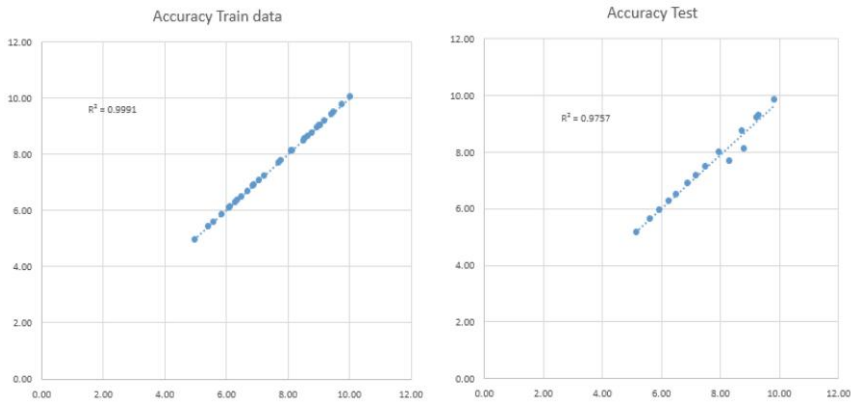


Fig. 6. Training error after 100 epochs

It has shown that, for the training data, the accuracy  $R^2 = 0.9991$ ; for test data,  $R^2 = 0.9757$ . See Fig. 7.



**Fig. 7.** Accuracy estimation

To validate the designed ANFIS model, the flowing demonstration was carried out and the performance of the trained model was evaluated with respect to background and knowledge of the welding process. In this manner, the inputs  $S = 25$  cm/min and  $U = 24$  V were kept as constants, and the welding current  $I$  was increased steps by steps as

**Table 3.** Effect of the welding current  $I$  and speed  $S$  on the welding bead width  $W$

$I$ (Ampe)	$W$ (mm)
180	3.29
185	3.7
190	4.11
195	4.51
200	4.56
205	4.61
210	4.66
220	4.77
225	4.82
230	4.87

a

$S$ (cm/min)	$W$ (mm)
20	5.09
21	4.97
22	4.85
23	4.74
24	4.63
25	4.56
26	4.45
28	4.29
29	4.21
30	4.15

b

shown in Table 3a. As shown in Table 3a, when the welding current  $I$  increased from 180 A to 230 A, the bead width  $W$  of the welding seam also increased from 3.29 mm to 4.87 mm. It is clearly seen that when the input  $I$  is increasing the output  $W$  is increasing, accordingly, which is matching with the physical characteristics of a welding process.

In another demonstration, the effect of the welding speed  $S$  on the welding bead width  $W$  was investigated to validate the designed ANFIS model. In this case, the constant inputs were  $I = 200$  A, and  $U = 24$  V. When the input  $S$  increased, the obtained output values  $W$  decreased as shown in Table 3b. This behavior of the model is suitable with the welding performance of a welding process.

The solution with ANFIS model has ability to estimate the non-linear behavior of welding process. The result depends on the amount and reliability of data set. There are some small errors but the average error still stays under considerable. Furthermore, if data is calibrated and sharpened the model could work exactly for better precision.

## 4 Summary, Conclusions and Future Work

The weld bead geometry is the important information for determining the quality and mechanical properties of the weldment. The welding process parameters or variables that affect the weld bead geometry in the conventional arc welding process include the following: the welding voltage  $U$ , the welding current  $I$ , the wire feed speed  $WFS$ , the contact tip to work distance  $D$ , and the welding speed  $S$ . Modeling and predicting the weld bead geometry play an important role in welding process planning, to determine the optimal welding process parameters for achieving the improved weld quality. In the robotic GMAW or MIG welding, a robotic welding system basically consists of two functional units: the robot arm and a GMAW or MIG welding station. A robot arm automatically moves the robotic welding torch, following the programmed toolpath only; meanwhile, the welding process is controlled independently by a GMAW welding station, with the relevant welding process parameters. There have been lots of efforts and studies to develop modeling solutions and simulations to determine the weld bead geometry (Height  $H$  and Width  $W$ ) from the welding process parameters ( $U$ ,  $I$ ,  $WFS$ ,  $D$ ,  $S$ ) as the inputs. The welding process parameters can be determined based on the experiences, and the conventional analysis of variance (ANOVA); however, the high welding quality and accuracy are not always obtained, especially when there are additional constraints and technical requirements. With the advancement of computer vision technologies, digital images from cameras and videos can be used for training the deep learning models, to accurately identify and classify objects. The digital images for evaluating the welding quality and the characteristics of welding objects can be captured via the use of the high-speed camera, and there are emerging data acquisition systems that can handle a huge dataset. This study presents an ANFIS model-based approach to determine weld bead geometry from the main welding process parameters  $U$ ,  $I$  and  $S$ . The ANFIS model was successfully developed for the first basic investigations, as the foundation for further developments of innovative robotic welding systems which can be used for higher educations or research in Smart Manufacturing, with potentials for industrial applications.

Further studies will focus on enhancements of the ANFIS model-based solutions and predictive models for effectively determining the welding process parameters, with

the real-time monitoring of the weld bead geometry and data collections for Digital Twins and Smart Manufacturing applications, as well as to extend the robotic welding applicationstotheemergingwire-arcAM,whichisoneofthekey-enablingtechnologies for Rapid Manufacturing and Cloud Manufacturing.

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