THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

國家鋼結構工程技術研究中心香港分中心
Chinese National Engineering Research Centre For Steel Construction (Hong Kong Branch)

Address: Hong Kong Polytechnic University, Phase 8, Hung Hom, Kowloon, Hong Kong.
Telephone: (852) 3400 8451 Email: cnerc.steel@polyu.edu.hk Website: https://www.polyu.edu.hk/cnerc-steel/

Project Title:

To develop an Artificial Neural Network based Automatic Welding Defect Classification Methodology

Principal Investigator: **Dr. H.W. WAI**

Project Team Members: **Ir Alex W.H. CHOY, Dr. Mabel M.P. HO and Jason W.K. NGAI,**

Other Personnel: **Nurzhan IZDAUOV**

Project outline:

This project aims at developing a methodology, using artificial neural network (ANN) to process complex welding parameters and images, for detecting and classifying the welding defects which are perceived difficulty by the human eye.

MIG welding is one of the most widely used processes in the construction industry for the prefabricated structure. Using MIG welding mild steel as a case study for network training and validation could fully demonstrate and evaluate the characteristics of the developed welding defect classification methodology.

Under this project, an automated welding and monitoring system would be established to obtain the welding data and images for further processing and network training. Trial testing would be conducted to evaluate the performance of the methodology. Documentation would be compiled for technology transfer.

By adopting this new methodology for welding defect classification, the production efficiency and cost-effectiveness could be improved. This helps to expand the application of robotic welding and automated inspection through applying neural network in the construction industry and bring to the endless possibility in further research and development.

Scope of work

This project was divided into the following stages of activities:

- Stage 1- Develop the experimental testbed

  During this period, an automated MIG specimen welding system was designed and developed. The main components of an automated MIG specimen welding system include:

  1. An Industrial MIG Welder with calibrated control of filler feed rate, voltage, and current;
  2. An automated modular drive system to move the welding torch of (1) at preset velocity;
  3. Specimen fixtures are designed to position the parts for welding and secure the geometry of the product parts;
  4. Welding cameras to capturing the video image of weld pool locally & globally;
  5. A gas flow regulator to control the shielding-gas flow at preset rate;
  6. A process control and data logging system to control the operation of different components and capture the test data for further analysis.

- Stage 2- Building a quality dataset network training

  At this stage, an experimental methodology for building a dataset is established including

  - Define the specification of the weldment for test specimens
  - Setup the design of experiments
  - Develop the test run sequences
  - Establish welding procedures & Inspection methodology
  - Data pre-processing and conversion

- Stage 3- Develop the artificial neural network

  Data and images gathered during welding and testing of MIG welding mild steel are then employed for ANN training. The defect classification is carried out by ANN with backpropagation rule, where the input parameters are the welding parameters and the images of welding samples captured during welding. The accuracy of neural network is the index for evaluating the reliability of the proposed methodology. Improving the performance of the network would be needed through various methods such as expanding the data set.

Project progress

This project is progressing smoothly before middle of November. However, the scheduled was delay seriously because of the suspension of PolyU campus.

The detailed progresses of the project in 2019 are:

- Develop the experimental testbed and define the specification of the weldment for test specimens

  Figure 1 is the automated MIG welding testbed. The specimen geometry and preparation are conformed to ISO 9692-1 "Welding and allied processes — Types of joint preparation — Part 1: Manual metal arc welding, gas-shielded metal arc welding, gas welding, TIG welding and beam welding of steels". The material is 50mm × 140 mm × 6mm mild steel plate with one backing strip 25mm × 140 mm × 6mm.

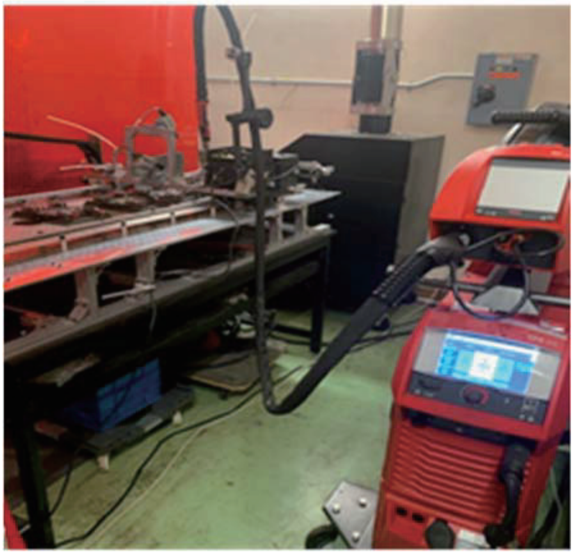


Figure 1. Automated MIG welding manufacturing system.

- Complete the design of experiments and develop the test run sequences

  According to the literature reviews, the most common MIG welding defects are porosity, lack of penetration, lack of fusion, burn through and under fill. To obtain an ANN model training with high accuracy, selecting a proper combination of parameters for the welding is a critical step. Statistically designed experiments that using trail run was processed to identify the crucial parameters which affect the predetermined type of defects. Using the one-factor-at-a-time (OFAT) experiments, the parameters including current, speed, voltage, gas flow, plate's gap, specimens' thickness were studied.

Statistically designed experiments that using design of experiment (DOE) was processed to prove the chosen parameters that affect the predetermined type of defects. In this study, DOE is for two purposes: to define the optimal experiments which maximize the accuracy on ANN model, and to minimize the number of necessary experiments for training and validating ANN model.

The parameters were further test the significance using DOE. Among these parameters, current, and speed and gas flow are the main factors which significantly affect the welding quality. The maximum and minimum of these parameters were also defined through OFAT. In this study 95% confidence was used therefore terms that have -value lower than 0.05 are significant. In this case, current, speed and gas flow as their p-value are 0.008, 0.001 and 0 respectively.

DOE was also applied to schedule the experiments and parameters systematically. The experimental parameters and the sequence were established using multilevel factorial design. Total run of the experiments is 256 including 3 factors, replicated by 4 and the number of level is 4.4.4. Another 64 specimens were planned to be run with random run order and parameter without controlling the range interval.

Table 1 shows the parameters used in this study and its range. The data logger recorded the current in a rate of 1 Hz and the set of data were averaged in 11 data per specimen. The input speed data was logged and the data from gas flow regulator was logged as the input of gas flow data. Videos were taken locally and globally through two welding cameras. 11 photos of each specimens were captured from video based on certain time interval and associated with the UT setup.

Table 1 the variances and the ranges for training.

Type of Variances	Unit	Lower range	Upper range	No. of records per specimen
Current	A	180	300	11
Speed	In/min	6	18	1
Gas Flow	l/min	3	18	1
Photo	-	-	-	11
Video	-	-	-	2

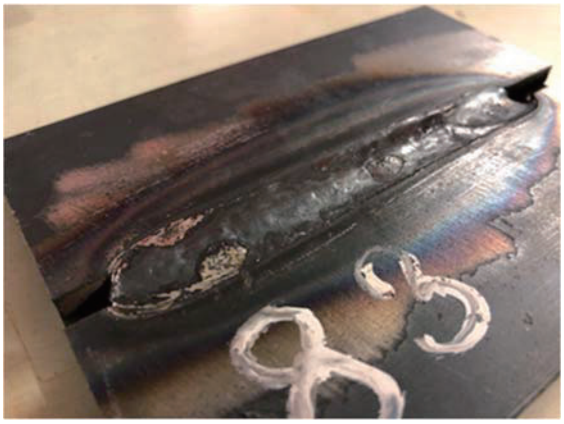
- Establish welding procedures& inspection methodology

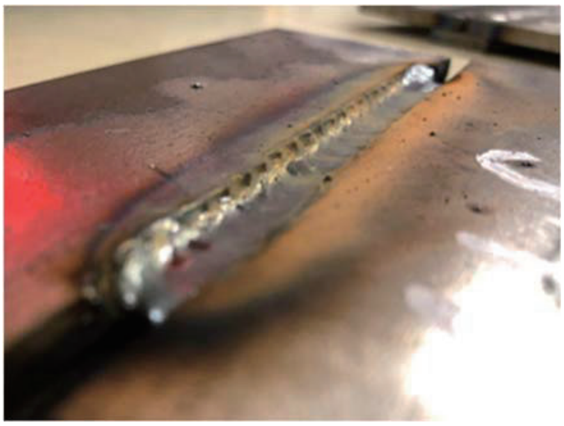
The procedures of specimens welding are as follow:

1. Clean the specimen to remove the oxide on the surface;
2. Set the part into the fixture and clamp it securely into place;
3. Select the appropriate program from the controller;
4. Set the welder, rectilinear and gas flow regulator in correct setting;
5. Press the "gas release" button on the welding to adjust the gas flow;
6. Cut the electrode wire with the electrode cutter;
7. Switch on the rectilinear while the arc starts;
8. Switch off the rectilinear when the weldment is finished;
9. Change the setting of the welder, rectilinear and gas flow regulator for next run order;
10. Collect the finished part and reload the work station for the next cycle;
11. Repeat step 1-9 until finished the final batch.

After the welding, the weldment width and height were measured. The defects including under fill and burn through were checked through visual inspection. Figures 2(a-d) show the specimens which were welded.

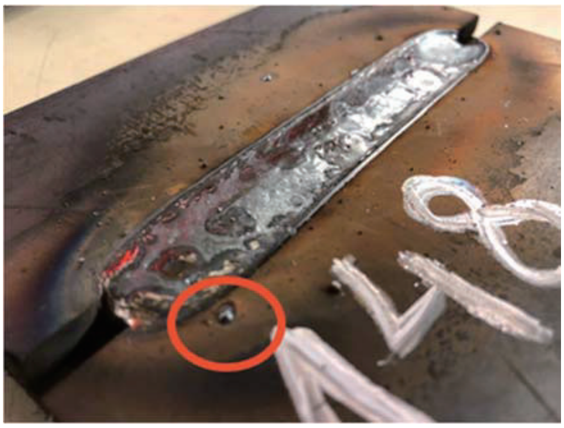
The UT scanning fixture was tailor-made. The SONATEST VEO +16:64 PAUT flaw detector was used with Olympus phased-array probe 5MHz, 16 element and 0.6 mm pitch probe. Sectional scan image in 10 mm were captured and stored for defect recognition.

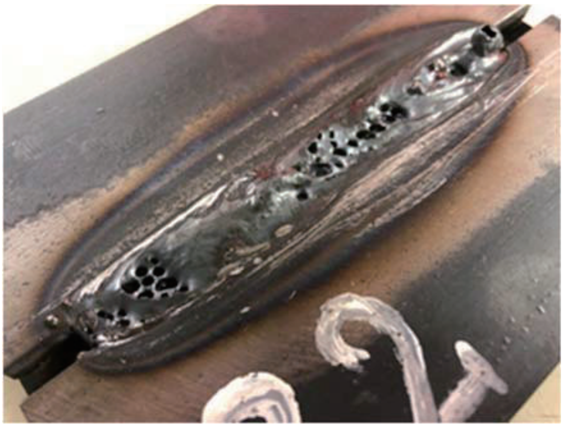




a) no visual defects

b) underfill





c) weld spatter

d) surface porosity

Figure 2. Welded specimens with corresponding defects

- <u>Develop the artificial neural network</u>

The first artificial neural network (ANN) model was developed for analysing and simulating the correction between the welding parameters and defects. The input parameters of the model consist of weld current, weld speed and gas flow. The outputs of the ANN model include clean weld, porosity, burn through, incomplete penetration and incomplete fusion.

Collection of the data was completed based on two data logs: machine log data and route card data. Machine log data including current, speed of the welding, time started and time of welding were obtained from the welding machine and the microcontroller. The route cards provide defect classification from the surface and ultrasonic inspection.

Three simple python scripts are written to configure the data to be suitable for the training process. One is used to extract the data from the welding machine's log. Second is used to create the needed quantity of snapshots for each of the specimens from video shot on outer cameras. The third script is used to make classification of pre-processed specimens for the training dataset. The dataset with 13 inputs and 4 outputs is collected, in which inputs include 11 data for current, 1 for speed and 1 for gas flow. Meanwhile, the outputs are classified as 1 or 0 for such defect as incomplete penetration, incomplete fusion, porosity, and under-fill.

In this project, multiple inputs-multi outputs and multiple inputs-single output approaches were developed and tested for network training. Multiple inputs-single output approach is the method when different structures are tested separately for each of the outputs

Multiple inputs-multi output approach targets to predict multiple outputs simultaneously. It subsumes learning problems in multiple disciplines and deals with complex decision making in real-world applications. Multiple inputs-multi output approach is the method of using a single neural network structure with similar activation functions, input numbers, hidden layers and nodes for all 4 outputs.

The structure of the multiple inputs-multi output network will be 13-x-4, where x stands for the number of hidden layers and nodes in that layers, while for the multiple inputs-single output it will be 13-x-1 and x is a variable that can be changed for better classification of each defect.

The 1st neural network was trained, and the results are discussed in details further. To date, 240 specimens were prepared and 160 specimens were inspected using Ultrasonic testing (UT). 90 specimens' defect classification was finished.

The multi-output neural network training for 90 specimens the highest accuracy achieved was 80.74 per cent under the 13-7-4 structure with a sigmoid activation function. The assumption was proved according to the results of this stage because the highest accuracy obtained from single-output neural networks was 85.186 per cent under structures 13-5-1, 13-6-1, 13-7-1 and 13-6-1 for incomplete penetration, incomplete fusion, porosity and underfill respectively. Table 2 shows the results obtained from the single-output approach. It is obvious that multiple inputs-single output approach is better and more accurate for the current dataset and observations, but it is slower compared to multiple inputs-multi output approach. Even though the number of epochs for multiple inputs-single output approach was three times less than for the multiple inputs-multi outputs, it took twice much time to execute the program for it. According to this fact, the implementation of real-time defect classification seems to get harder.

Table 2. The accuracy results for the single-output neural networks under different structures.

Structure	Activation	Epochs	Defect types			
			Inc. Pent	Inc. Fusion	Porosity	Underfill
13×3×1	sigmoid	800	77.038	68.890	87.408	86.670
13×4×1	sigmoid	800	76.296	58.512	88.888	91.112
13×5×1	sigmoid	800	80.002	74.074	85.928	89.630
13×6×1	sigmoid	800	79.260	76.296	87.410	93.336
13×7×1	sigmoid	800	75.556	68.146	91.110	87.408
13×8×1	sigmoid	800	75.556	69.630	88.890	89.630

Project deliverables

The research project will generate understanding and data on the application of robotic welding and automated inspection by applying a neural network in the construction industry. The four main expected deliverable of this projects are:

1. An automated MIG welding system with image capture function;
2. A data set of welding parameters, images with classified defects;
3. A trained neural network for MIG welding defect classification;
4. A technical file consisting of all project deliverables.

Project significance

The increasing application of robotic welding technology has led to accelerating the development of automated welding inspection. At present, qualified welder master and inspector are still needed for investigating the welded pieces and defining the different types of defects through visual inspection and other investigations such as ultrasonic testing, eddy current inspection and radiographic imaging. The investigation processes including inspection, examination and testing are time-consuming and labour intensive. Therefore, automated welding inspection has become necessary. However, automated defect inspection currently employed in the construction industry are either slow or limited in defect applicability.

ANN-based defect classification system with shorter inspection time and higher efficiency is crucially needed in the construction industry. The significance of outcomes of this project could also be extended to the automated inspection used in other welding technologies such as tungsten inert arc welding (TIG) and shielded metal arc welding (MMA) with various welding materials. Moreover, this project could further support and speed up the welding-related researches such as robotic welding and new welding material through reducing the efforts in defect detection and identification.

Future work

The following activities are planned for the remaining period of the project:

1. Level of consistency in surface defect detection methodology would be further validated using the industrial image processing system which supports interpreting and quantifying the information contained in the existing results.
2. Convolution Neural Network is planned to be implemented using snapshots and video records;
3. The data would be expanded to add diversity to the current data set.
4. ANN training using the same dataset would be carried on in order to compare the variances by altering the defect acceptance levels;
5. The behaviour of ANN model vs CNN model for the image and video processing will be tested and compared.
6. Reference standards for ultrasonic inspecting are used to validate that the equipment and the setup provide same results from day to day investigation under the same setting.