Prediction of Welding Parameters for Pipeline Welding Using an Intelligent System

I. S. Kim, Y. J. Jeong, C. W. Lee and P. Yarlagadda

Abstract

In this paper, an intelligent system to determine welding parameters for each pass and welding position in pipeline welding based on one database and FEM model, two BP neural network models and a C-NN model was developed and validated. The preliminary test of the system has indicated that the developed system could determine welding parameters for pipeline welding quickly, from which good weldments can be produced without experienced welding personnel. Experiments using the predicted welding parameters from the developed system proved the feasibility of interface standards and intelligent control technology to increase productivity, improve quality, and reduce the cost of system integration.

Key Words : Intelligent system, FEM, Neural network, C-NN model, Weld pool.

1. Introduction and background

Generally, determination of welding parameters for pipeline welding requires considerable expertise and very often needs the involvement of manufacturing. In many cases for pipeline welding process, information of material and process setting for material joining is based on the industry standards or the database provided by the related manufacturers. However, these data are available only for standard process conditions. If not, welding companies have to relay on expert to determine welding parameters, and the above method can be difficult to use the determination of welding parameters because they are only useful in selecting stored data and not for evaluating the effect of the variation of welding parameters on the weldability [1].

Recently, an Artificial Neural Network (ANN) for arc welding process modeling is outlined by Tarng and Yang [2]. The advantage of this approach is that modeling can be done using experimental data without having to make any simplifying assumptions. Recently, expert systems in arc welding process have been developed in order to improve the decision-making process within the different factors required in the welding technology. The expert systems developed include welding process selection, welding default diagnosis and welding material selection [3~5]. Furthermore, Park and Hwang [6] developed an expert system for CO_2 robotic arc welding to recommend the optimal values of welding parameters in the shipbuilding using the various artificial data processing methods, not pipeline welding. Tarng et al. [7] have recently been applied a fuzzy pattern recognition technique to classify aluminum weld quality based on the features on the weld geometry in GTA (Gas Tungsten Arc) welding. Recently, AI techniques have employed to determine the optimal welding parameters for various arc welding processes. However, these techniques have proven to possess only a limited range of applicability, and not led to predict welding parameters for pipeline welding system application.

This paper represents the development of a computer-based intelligent system for automatic determination of welding parameters within pipeline welding environment. The main objectives of the research work were to develop an AI algorithm for selection of optimal welding parameters, and integrate the intelligent system that utilizes a database and FEM model, two BP neural network models and C-NN model to determine and calculate the optimal welding parameters. This system might help the welder to select the optimal process parameters for different material properties, and to give users alternatives on how to control the welding quality.

2. Description of an intelligent system

The overall structure of an intelligent system for determination of welding parameters in pipeline welding is shown in Fig. 1. The intelligent system is divided into four components: (1) database and FEM (Finite Element Method) model; (2) BP (Back-Propagation) neural network model for welding parameters; (3) BP neural network model for welding quality; and (4) C-NN

I. S. Kim, Y. J. Jeong and *C. W. Lee* : Department of Mechanical Engineering, Mokpo National University, Jeonam, Korea
Email : ilsookim@chungkye.mokpo.ac.kr
P. Yarlagadda : School of Mech. Mfg. & Med. Engineering, Queensland University of Technology, Brisbane , Australia

(Corrective Neural Network) model. Firstly, base metal, welding process, bead geometry (top-bead width, top-bead height, back-bead width and back-bead height) were entered into the intelligent system by user, because they were determined material preparation and joint fit-up design. The database and FEM model calculate the pass number according to primary input parameters such as the material thickness, groove angle, material type, wire type and wire diameter. Then, the acceptable welding parameters (welding current, arc voltage and welding speed) for each pass and welding position are calculated in BP neural network model for welding parameters according to the pass number, material thickness, groove angle, material type, wire type and wire diameter. The bead geometry is predicted in BP neural network model for welding quality from the information on acceptable welding parameters and learning data. Also, the bead geometry entered by the user is compared with the predicted results. If the user's bead geometry is not matched the predicted bead geometry, C-NN model is processed to calculate a corrective coefficient using primary input parameters and secondly input parameters (joint type, groove type, gas flow rate, arc length, torch angle and surrounding gas type) in order to make correction of the predicted welding parameters based on the inputted bead geometry. The modified welding parameters are calculated to multiple the corrective coefficient and the predicted welding parameters. A detailed description of the developed system was referred to the relevant report [8].

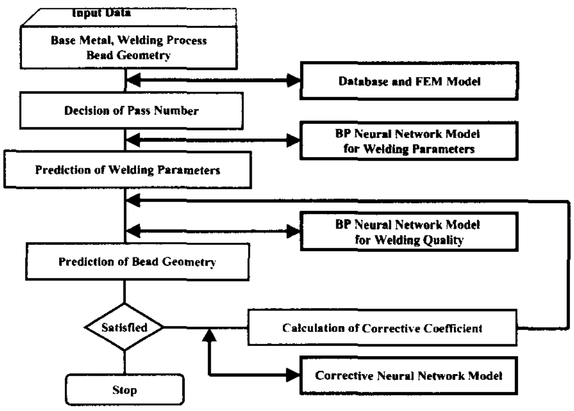


Fig. 1 The schematic diagram of the system for determination of process parameters

3. System implementation and validation

In this section, an implementation example is provided to illustrate how the proposed intelligent system can be usefully applied in a real-world automated pipeline environment using database that were collected from the pipeline welding. To demonstrate the feasibility of the methodology described in this paper, a prototype system, called Intelligent Welding Control System (IWCS) has been integrated. The developed system was implemented in Visual C++ program language, and run Windows 98. Fig. 2 shows the user interface and the corresponding input. On the following side of this widow, input parameters such as the material thickness, groove angle, material type, wire type and wire diameter will be input. Fig. 3 shows the contents of the initial welding parameters for each pass number and welding position determined by the developed IWCS system.

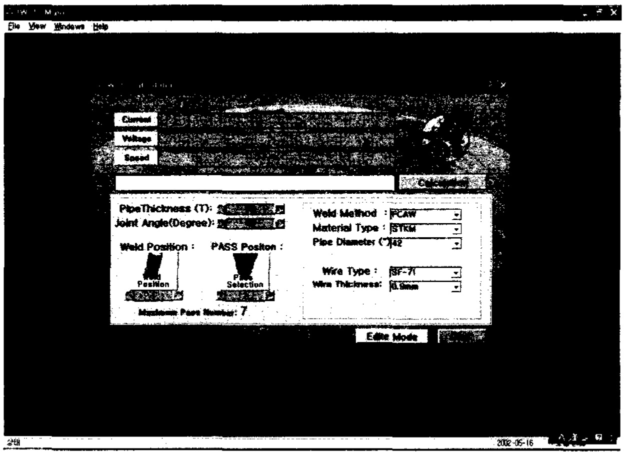


Fig. 2 User interface and the corresponding input

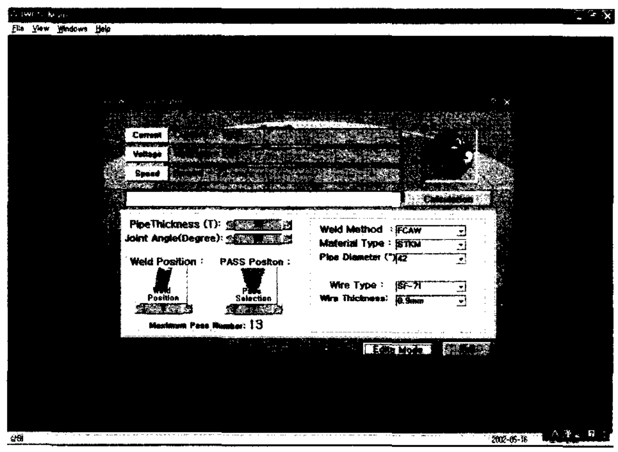


Fig. 3 Welding parameters determined by the developed system

These acceptable welding parameters are processed in off-line simulator to verify and check the associated welding quality in terms of welding geometry. Using the predicted welding parameter, off-line simulator is operated and checked welding position and value of optimal welding parameter depending on pass number and welding position. The detailed welding distortion and undercut size of the welding joining to control welding quality is beyond the scope of this software.

To verify the developed system, the experiments for STKM steel pipe with 42 inch and thickness 22 mm was carried out. The welding process selected for the experimental work was FCA (Flux Cored Arc) welding which favored to reduce the fabrication time and minimize distortion. To meet these goals and increase weld quality, the developed system was employed for determination of welding parameters. The pass number would be calculated from the database and FEM model, and shown in Fig. 4. The pass number requested is employed to predict welding parameters for each pass and welding position. The predicted welding parameters for pipeline welding is directly shown on the main screen and shown in Fig. 3. Using the predicted welding parameters, the experiment was carried out.

After welding, the workpieces were sectioned and prepared for examination by ASME SEC IX standard procedures. The samples were then examined by optical and scanning electron microscopy. Bead geometry (top-bead width, top-bead height, back-bead width and back-bead eight) was measured. Undercut and distortion were not found. Tensile test was conducted to evaluate the tensile strength of the joint.

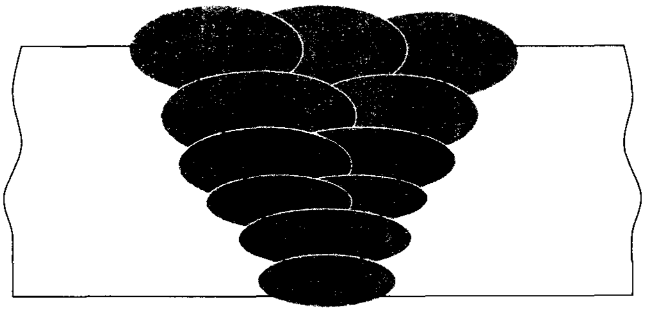


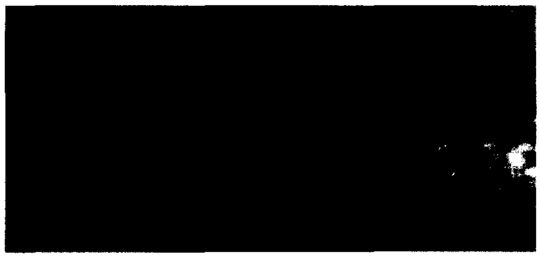
Fig. 4 Configuration of specimen for experiment

4. Results and discussion

It can be observed that there was no violation of the quality criteria in the validation test. Therefore, the optimal welding parameters for each pass and welding position recommended by the developed system can be contributed to good quality of the weld joint in pipeline. In the validation test, the developed system took less than 3 min including the time for user input to obtain a set of welding parameters corresponding to an the real welding problem. Therefore, the developed IWCS system can greatly reduce the time required to generate initial welding parameters for pipeline welding in comparison with the expert.

As a result, the weld quality using welding parameters determined from the developed system shows a uniform smooth weld with close ripples and good fusion shown in Fig. 5. The results of the joint tensile tests were Table 1. The most important observation, however, is that all fractures occurred away from the weld zone. This confirmed the joint strength of the selected visually sound welds was greater than that of the base metal. Since all specimens broke at positions away from the weld, the tensile property observed was thus that of the base material, and the values were reasonably uniform. It can be concluded the optimal welding parameters for each pass number and welding position calculated from the developed system do not affect the tensile strength of the specimens.

(a) Root pass



(b) Fill pass

Fig. 5 Surface appearance of bead geometry for validation of the developed system

5. Conclusion

Based on the preliminary results obtained from this research, the following conclusions can be drawn from this research;

1) One database and FEM model, two BP neural network models and a C-NN model to select welding parameters for each pass and welding position in pipeline welding can be integrated successfully.

Table 1 Tensile results of pipeline joint

Specimen No	Ultimate Total Load (ton)	Ultimate Unit Stress (kgf/mm2)	Character of Fracture of Location
1	18.65	57.74	Base Metal
2	18.3	56.03	Base Metal
3	18.55	57.77	Base Metal
4	18.74	57.04	Base Metal
5	18.4	57.65	Base Metal
6	18.45	57.12	Base Metal
7	18.5	56.98	Base Metal

2) The IWCS system has been verified with the results of experimental results. The weld quality using the predicted welding parameters determined from the developed system shows a uniform smooth weld with close ripples and good fusion. Joint strength of the selected welds was greater than that of the base metal.
3) The system proposed in this paper is able to determine welding parameters based on the primary and secondary input parameters and help in avoiding inappropriate welding design. Also, the developed system, which was designed to cover different materials, different types of welding process, has the potential to deal with complex products that are made up of multiple components.

The developed system should make use of CAD/CAM techniques. This would be useful to facilitate communication between user and the system, and to model the welding environment.

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