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Citation	Transactions of JWRI. 2010, 39(2), p. 127-129
Version Type	VoR
URL	https://doi.org/10.18910/5373
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Prediction of hardness in HAZ of low-alloy steel produced by temper bead welding using neural network†

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KEY WORDS: (Hardness prediction) (Temper bead welding) (HAZ) (Neural network) (FEM)

1. Introduction

Low alloy steel A533B is widely employed in building PWR reactor vessels. However, the excellent mechanical properties of the base metal will be altered after experiencing thermal cycles imposed by welding process, and the increase of hardness always happens in weld heat affected zone (HAZ) [1]. Therefore, post weld heat treatment (PWHT) is required to eliminate the residual stress and decrease the hardness.

Temper bead welding technique is in practice one of the effective repair welding methods instead of PWHT when PWHT is difficult to perform [2]. When temper bead welding is applied, it's very important to select the proper thermal cycle during temper bead welding in order to obtain high tempering effect. Hardness is one of the key criteria to evaluate the tempering effect by temper bead welding. Therefore a prediction method using Neural Network has been investigated to predict the hardness in HAZ of A533B, when temper bead welding is applied.

2. Experimental

The base metal is low alloy steel A533B and the filler material is Inconel690. Samples (5×5×5mm) were heated by a high frequency induction heating device to simulate as-welded and temper-processed HAZ. The multi-pass welded samples (100×33×120mm) were produced by TIG welding. The 1st layer in the welds contained 4 pass beads, and 5 pass and 3 pass in 2nd and 3rd layer, respectively. The Vickers hardness was measured for the specimens after polishing and etching with 3％ nital solution. The thermal cycles in multi-pass welds were calculated by House Code FEM software.

3. Results and discussion

As to long-term operation in the tempering temperature range, the "Larson-Miller parameter (LMP)" is a useful means for predicting the lifetime of material. LMP which is derived based on the Arrhenius rate equation is expressed as a function of time and temperature, as follows

$$P=T(\log t + C) \quad (1)$$

where T is the temperature in degrees Kelvin, t is the time in hours and C is a material specific constant often approximated as 20 for steel [3].

LMP can be used only for the iso-thermal heat treatment with constant tempering temperature. Therefore it cannot be applied for tempering during the thermal cycle process. In order to apply LMP for thermal cycle processes, the thermal cycle was divided into such minute sections as to be assumed as an iso-thermal heat treatment with short holding time. The whole tempering effect during thermal cycle process is considered as the sum of minute sectioned iso-thermal heat treatment. LMP during thermal cycle process can be calculated by following method.

The LMP of 1st cycle at T_1 with holding time t_1 is equal to that at T_2 with equivalent holding time $t_{1,2}$, shown as

$$P_1 = T_1(20 + \log t_1) = T_2(20 + \log t_{1,2}) \quad (2)$$

Thus, the equivalent holding time $t_{1,2}$ at T_2 can be obtained as

$$\log t_{1,2} = \frac{T_1}{T_2}(20 + \log t_1) - 20 \quad (3)$$

Then the LMP of 1st and 2nd pass can be expressed as

$$P_2 = T_2[20 + \log(t_{1,2} + t_2)] \quad (4)$$

Similarly, the LMP from 1st pass to 3nd pass can be obtained as

$$P_3 = T_3[20 + \log(t_{2,3} + t_3)] \quad (5)$$

In turn, the LMP from 1st pass to nth pass can be expressed as

$$P_n = T_n[20 + \log(t_{n-1,n} + t_n)] \quad (6)$$

where T_n is the temperature of the nth pass, t_n is the holding time of the nth pass, and $t_{n-1,n}$ is the equivalent holding time from 1st to (n-1)th pass at the temperature of T_n. The LMP during thermal cycle calculated by the newly proposed method is designated as Thermal Cycle Tempering Parameter (TCTP). **Figure 1** shows the relationship between hardness of the specimens and TCTP of 2nd and 3rd thermal cycle. A good linear

† Received on 30 September 2010
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*** The Kansai Electric Power Co., Inc., Japan

Transactions of JWRI is published by Joining and Welding Research Institute, Osaka University, Ibaraki, Osaka 567-0047, Japan

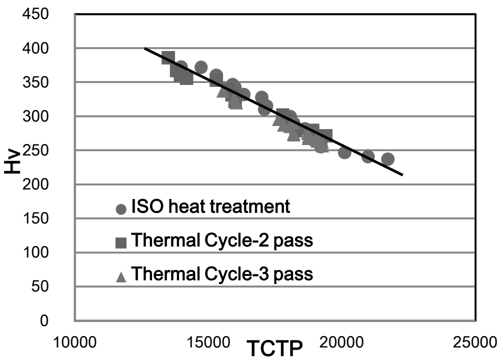

Fig.1 Relationship between TCTP and Hardness of multi-pass thermal cycle

relationship can be seen between the hardness of the specimens and TCTP. Hardness of the iso-thermal heat-treated specimens is also on the same line. This shows that the newly proposed TCTP can be applied to the hardness change in tempering during both thermal cycle process and iso-thermal heat treatment.

"Neural Network" (NN) [4], is a mathematical model or computational model that has been used to model complex relationships between inputs and outputs or to find patterns in data. Radial Basis Function (RBF) is a powerful technique for interpolation of multidimensional space in NN. The output $O(x_i)$ of the network is thus

$$O(x_i) = \sum_{j=1}^{n} w_j h_j(x_i) = \sum_{j=1}^{n} w_j \exp\{-(x_i - c_j)^2/r^2\} \quad (7)$$

where *n* is the number of neurons in the hidden layer, c_i is the center vector for neuron *i*, and w_i are the weights of the linear output neuron. The weights w_i, c_i, and r are determined in a manner that optimizes the fit between $O(x_i)$ and the data.

Based on the experimentally obtained hardness data base and the relation between hardness and TCTP, the hardness prediction system of multi-pass thermal cycle was constructed. For example, **Fig. 2(**a) and (b) respectively represent the calculated 3D and 2D-contour figure of the complex relationship between hardness and T_{p2}/ CR_2 of 2-pass thermal cycle when T_{p1} is 1350℃ and CR_1 is 91℃/s.

The thermal cycles in welds during multi-pass welding were calculated by House Code FEM. **Figure 3** demonstrates the calculated peak temperature distribution in the section of 1-layer and 3-layer welds. On the basis of the calculated thermal cycle parameter, the hardness in the HAZ was calculated, and the predicted hardness distribution is shown in **Fig. 4**. The predicted hardness and the experimental results are shown in **Fig. 5.** The predicted hardness (red marks) well agreed with the measured hardness (blue marks), indicating that the prediction system was useful and effective.

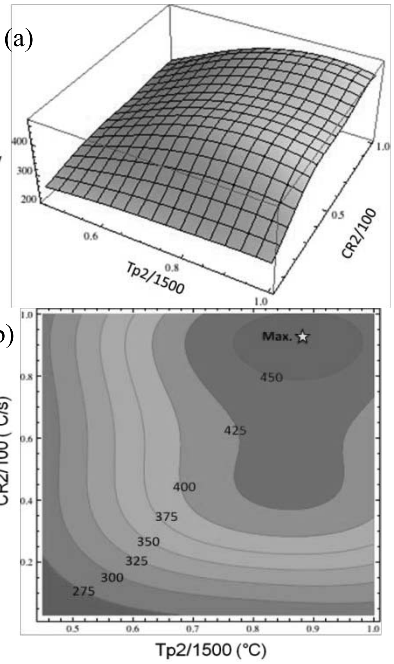

Fig. 2 Hardness prediction system of 2-Pass thermal cycle: (a) 3D figure and (b) 2D-Contour figure (Tp1=1350℃,CR1=91℃/s)

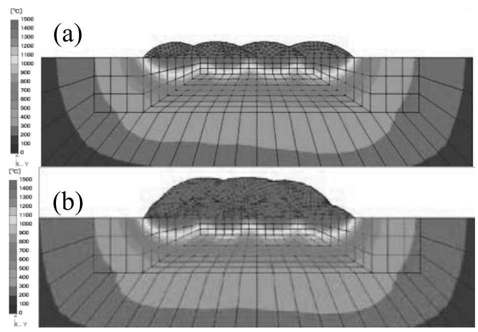

Fig. 3 Peak temperature distribution of (a) 1-Layer and (b) 3-Layer multi-pass welding

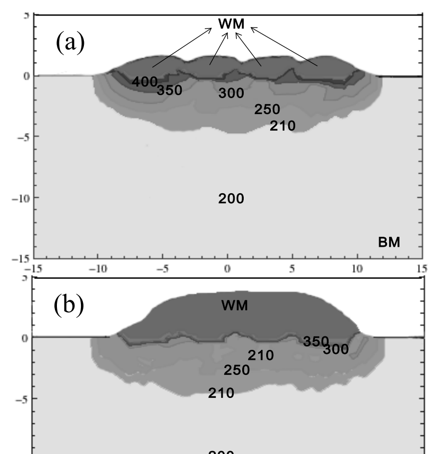

Fig. 4 Hardness distribution in HAZ of multi-pass welding: (a) 1-layer and (b) 3-layer

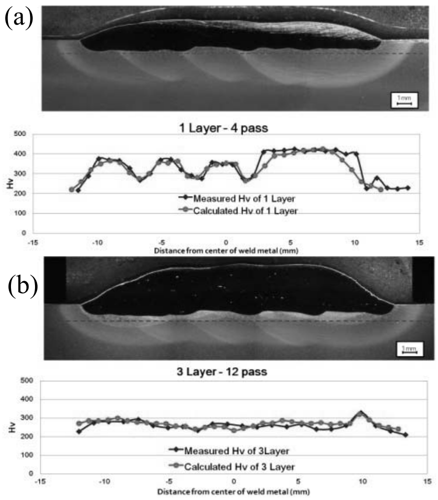

Fig. 5 Comparison between measured and calculated Hv of (a) 1-layer and (b) 3-layer

4. Conclusions

(1) Thermal Cycle Tempering Parameter (TCTP) calculation method for multi-pass thermal cycles process has been proposed based on LMP.

(2) On the basis of experimentally obtained hardness data base and thermal cycle parameters calculated by FEM, the hardness distribution in HAZ was predicted using Neural Network.

(3) The predicted hardness was found in good accordance with the experimental result. It follows that the proposed prediction system is effective for estimating tempering effect in multi-pass welding.

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