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WELD QUALITY PREDICTION OF SUBMERGED ARC WELDING PROCESS USING A FUNCTION REPLACING HYBRID SYSTEM

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Abstract:
Product variety, quality level and stiff competition have driven the manufacturing systems to be automated. Success of automation depends on effective and efficient decision making tools. This paper details about the development of intelligent decision making tool using a function replacing hybrid system for Submerged Arc Welding (SAW) process parameters to attain desirable weld quality. Experiments are designed according to Taguchi's principles and a multiple regression model is developed. Experimental data is supported with the data generated by regression model while developing the Neural Network model trained with Particle Swarm Optimization (NNPSO) technique. NNPSO model is found to be superior over in terms of computational speed and accuracy for the prediction of weld quality than the neural network model trained with traditional algorithm. The developed model is validated. The proposed method is flexible, competent, accurate, enhance automation, increase productivity, flexibility, safety and risky jobs is avoided by deployment of robots. Further, hardware controls are to be setup for online weld quality monitoring. Similar intelligent systems can be developed for real time monitoring and quality control of other welding process. This paper promotes manufacturers to develop unmanned factories to achieve the highest level for automation.

Key Words: Automation, Decision Making Tools, Function Replacing Hybrid System, Particle Swarm Optimization, Submerged Arc Welding, Weld Quality, Weld Bead Width

1. INTRODUCTION

To consistently produce high quality of weld, SAW requires skilled welding personnel with significant experience and a proper selection of welding parameters for a given task. Many attempts are made by researchers to establish the SAW process for a desired weld quality. Traditionally the desired welding parameters are obtained based from experience, charts or handbook values which are difficult, cumbersome and they does not ensure that the chosen welding parameters are optimal for the particular welding environment.

Later mathematical models have been developed to correlate the welding performance such as weld bead width, shape and size [1-5] with welding parameters. Multiple linear regression techniques were used to establish mathematical models for the weld bead geometry [6, 7]. Due to the inadequacy and inefficiency of the linear regression models to explain the nonlinear properties existing between the weld geometry parameters and welding parameters, intelligent systems such as ANN, fuzzy logic and expert system have been emerged. ANN is a good technique used to handle problems of nonlinearity. ANNs trained with back propagation algorithm [8-16] have been used to predict the weld bead geometry and penetration in shielded metal-arc welding process.

ANN and regression approaches were used to predict back-bead of gas metal arc [17] welding process. Data from regression analysis are used to train ANN with back propagation algorithm (NNBPA) to predict shear wave velocity from wire line log data for a carbonate reservoir [18]. In real-world applications, the back-propagation algorithm cannot guarantee an optimal solution since it may converge to a set of sub-optimal weights from which it cannot escape. Function replacing hybrid (FRH) can address this issue.

FRH is a hybrid system in which the principal function of a particular intelligent technique is replaced by another intelligent processing technique. A neural network combined with genetic algorithm is proposed [19] to determine the initial process parameters for injection moulding. GA-based neural network was used to model the explosive welding process [20], to optimize the design for a ball grid array wire bonding process [21], the electrical discharge machining process. [22], welding parameters [23] and neural networks trained by a genetic algorithm was used to predict machining forces [24].

PSO is used instead of back propagation algorithm in neural network for the prediction of tool life in turning operation [25].This paper details the design and development of a function replacing hybrid system to predict the weld parameters involved in SAW process. This hybrid system is composed of ANN trained with particle Swarm Optimization technique, which is a predictive neural network where weight updating is done using PSO algorithm. It scopes to build fast, accurate predictive networks.

2. DATA ACQUISITION

Experimentation is done on SAW is done using Taguchi method, a systematic application of design of experiments technique to improve the product quality. It uses a special design of orthogonal arrays to study the entire process parameter space with a small number of experiments. Orthogonal array is chosen based on the number of factors of interest and the number of levels of interest. An L8 orthogonal array is selected with number of factors involved is four and number of levels as two to conduct experiments in the semiautomatic SAW (SURARC of type XRCP 1200) machine. Single pass butt-welding is performed on the commercially available steel of IS 2062 grade (0.25%C, 0.20%Si, 0.75%Mn and balance Fe) (500 mm x 50 mm x 6mm) keeping the electrode positive and perpendicular to the plate. Electrode (diameter of 3.15 mm) utilized is AWS ER70S-6. The sizes of 10mm (width) samples are cut from the test piece. Then the specimens are cleaned, polished and etched. Profile projector is used to measure the weld bead width. Experimental observations for different combinations of weld parameters are shown Table I. Figure 1 shows the photographic views of weld samples. The dependency of weld quality to welding current, arc voltage, welding speed and electrode stick out is established using the multiple regression equation [26] for the SAW process.

Weld bead width,

$$mm = -34.833 + (6.667\times10^{-2} \times \text{welding current, ampere}) + (0.75\times\text{arc voltage, volts}) + (1.25\times10^{-2} \times \text{welding speed, mm/ min}) - (4.17\times10^{-2} \times \text{electrode sickout, mm}) \quad (1)$$

From the above equation, new values of weld bead width are generated to train the networks R^2 value for weld bead width is high which shows the strength on correlation of weld process parameters with weld bead width is significant.

Table I: Observed values from the test specimen.

Trial nos.	Weld bead width (mm)	Weld bead reinforcement(mm)	Depth of bead penetration (mm)	Weld bead hardness (H_RC)
1	13.0	2.0	3.0	37
2	11.0	2.0	3.5	40
3	12.5	3.0	3.5	42
4	13.5	1.5	4.0	34
5	14.5	2.0	5.0	52
6	14.0	2.5	4.5	48
7	14.5	2.0	4.0	49
8	15.0	3.0	3.5	48

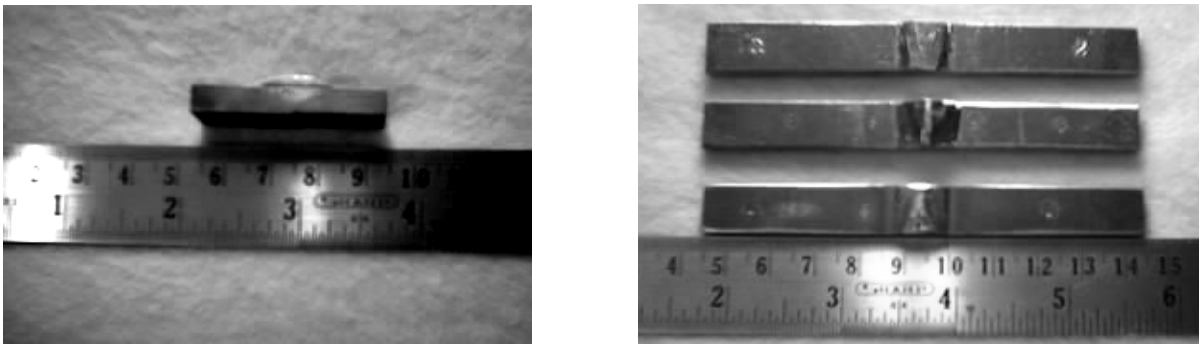

Figure 1: Photographic view of weld samples.

3. PREDICTIVE NEURAL NETWORKS

There are different algorithms to train ANN models. The most widely used method is back propagation algorithm. But is has limitations owing to the time taken to converge to a optimum solution and accuracy of result is less. This work exemplifies the use of PSO technique for weight updating in Neural Networks.

3.1 Development of NNBPA model

In submerged arc welding, the width of the weld bead is changed due to the complicated welding conditions, and accurate mapping is needed to produce the desired weld bead according to the welding parameters. Therefore, artificial neural network trained with back-propagation algorithm is used. The architecture of developed NNBPA is shown in Figure 2. It is feed forward back propagation network trained with Levenberg-Marquardt back propagation algorithm. The data set required for training the network is obtained using the experimental values together with data generated from regression analysis. The number of samples for training and testing are 51 and 5 respectively. The learning function is gradient descent algorithm with momentum weight and bias learning function. The number of hidden

layers and neurons are determined through a trial and error method, in order to accommodate the converged error. The structure of the proposed neural network is 4-12-9-1 (4 neurons in the input layer, 12 neurons in 1st hidden layer and 9 neurons in 2nd hidden layer and 1 neuron in the output layer) . With a learning rate of 0.55 and a momentum term of 0.9, the network is trained for 10000 iterations. The error between the desired and the actual outputs is less than .001 at the end of the training process. The back-propagation learning algorithm used in this neural network cannot guarantee an optimal solution since it might converge to a set of sub-optimal weights from which it cannot escape. Prediction technique using neural networks needs attention.

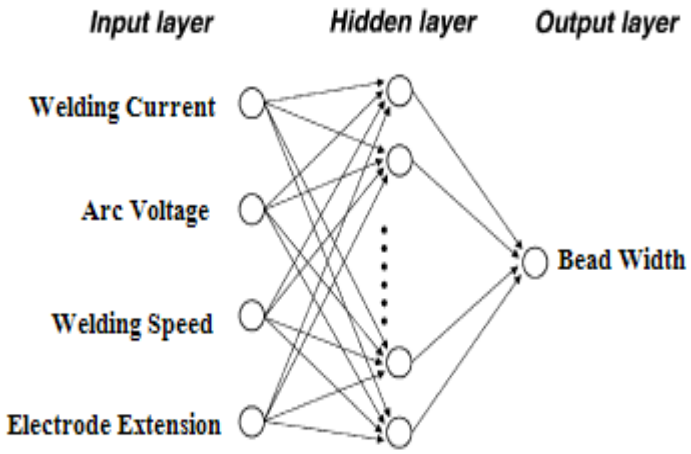

Figure 2: Architecture for the developed NNBPA model.

3.2 Development of NNPSO model

The scheme developed to predict weld quality in SAW process using NNPSO technique is shown in Figure 3. It is built using Matlab functions. The input weld parameters considered in the model are welding current, welding speed, arc voltage and electrode sickout with weld bead width, bead reinforcement, depth of penetration and weld bead hardness as outputs. The data required for training and testing the NNPSO model is taken from the experimental data in Table 1 supported with data from regression analysis. In this model, back propagation algorithm of neural network is replaced by PSO algorithm. Here the randomly

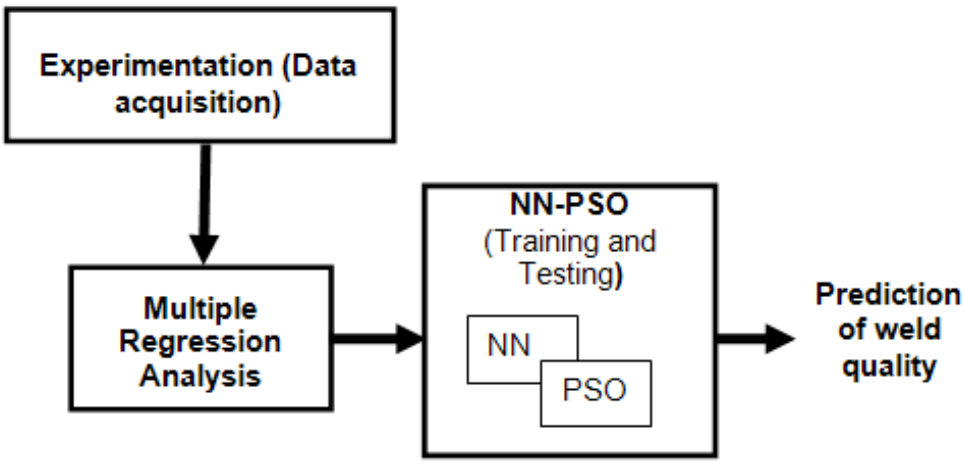

Figure 3: Proposed NN-PSO model for weld quality prediction.

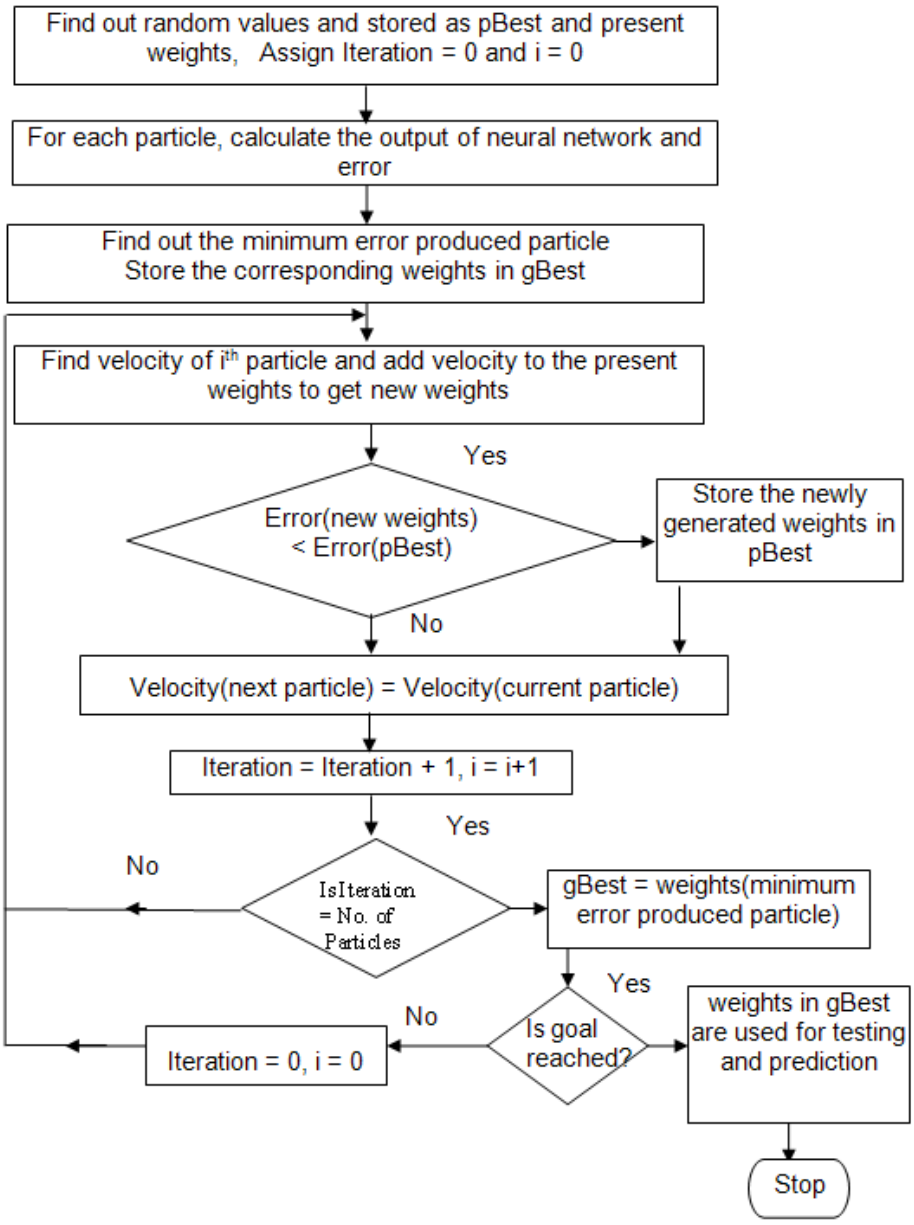

Figure 4: Flowchart for training the neural network using PSO algorithm.

generated weights are assigned in each link of neural network. In particle swarm optimization algorithm, pBest is the location of the best solution of a particle has achieved so far. gBest is the location of the best solution that any neighbour of a particle has achieved so far. Initially random numbers are generated for each particle and these random values are considered as pBest and present weights. Velocity is calculated using the equation 2 and added with the present weight in each link of neural network. For each particle, the newly calculated weights are compared with the pBest weights and the minimum error produced weights are stored in pBest. Initial velocity V is assumed to be 1 and gBest is the weights of minimum error produced particle. New weight is calculated as in equation 3.

$$V1 = W \times V + C1 \times Rand1 \times (pBest[w1]-present[w1]) + C2 \times Rand2 \times (gBest[w1] - present[w1]) \quad (2)$$

$$\text{New weight } wi = \text{current weight } w + \text{new } V1 \quad (3)$$

where C1 and C2 are two positive constants named learning factors (usually Cl= C2 = 2). Rand1 and Rand2 are two random functions in the range [0, 1]. W is an inertia weight to control the impact of the previous history of velocities on the current velocity. The operator W plays the role of balancing the global search and the local search; and was proposed to decrease linearly with time from a value of 1.4 to 0.5. As such, global search starts with a large weight and then decreases with time to favour local search over global search. When the number of iterations is equal to the total number of particles, goal is compared with the error produced by the gBest weights. If the error produced by the gBest weights are less than or equal to the goal, weights in the gBest are used for testing and prediction. Otherwise weights of minimum error are stored in gBest and the iterations are repeated until goal reached. The flow chart of the proposed NN-PSO model is shown in Figure 4.

4. RESULTS AND DISCUSSION

Interaction of weld parameters with the weld bead width has a complicated correlation and the results of analyzing the correlations are high. Since the width of the weld bead shows a linear pattern, in the regression analysis the input parameter is expressed in terms of linear equation as given in equation (1). The performance analysis of the developed ANN models to predict weld bead width in terms accuracy and speed are evaluated and compared. The comparison of measured values of weld quality with predicted values obtained from NNBPA and NN-PSO model is shown in Figure 5. The graph shows that the weld quality predicted by NNPSO are closer to the measured value and hence are found to be accurate than the predicted valued from NNBPA. Among the developed models, computational time needed for training the network using NNPSO is less compared with NNBPA. Hence the NNPSO model is found to be superior in computational efficiency than the other. The reason is that PSO stores the gbest as well as pbest solutions in memory. Each individual in the population tries to emulate the gbest and pbest solutions in the memory by updating the PSO equation. Results from Figure 6 shows that NNPSO needs only minimum number of epochs and hence computational time required is less. This is due to that in this proposed method, the random weights used for training the initial network was selected only based on the fitness function that generates the minimum error. So the number of epochs required for training the neural network is greatly reduced.

5. CONCLUSIONS

Prediction and determination weld quality is important for the process and product design of welded structures. The existing prediction measurement, techniques and methods are limited in application. Intelligent hybrid systems are being attempted to develop predictive neural networks. This paper proposes the development of a hybrid weld quality prediction system. The proposed predictive network is a Function Replacing Hybrid system build with the neural network trained by PSO technique. Developed NNPSO model will predict the requisite values of weld quality for given set of parameter combinations in real time with out any extensive and expensive computations. It is validated with the experimentation and proposed method is simple, economical, reliable competent, found fast and ease in prediction. With this encouraging result the prediction model can be further improved upon by including weld bead geometry and weld bead hardness as other influencing parameters on weld quality. Further, hardware controls are to be setup for online weld quality monitoring. Similar intelligent systems can be developed for real time monitoring and quality control of other welding process.

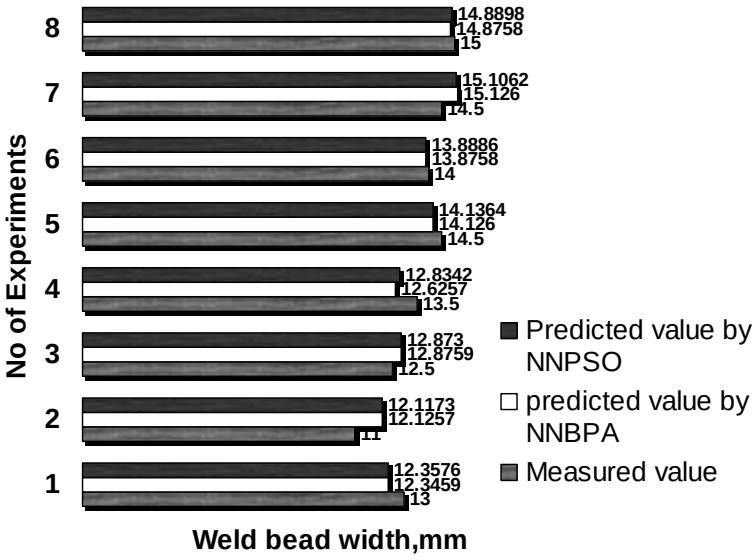

Figure 5: Comparison of weld bead width between measured and predicted values.

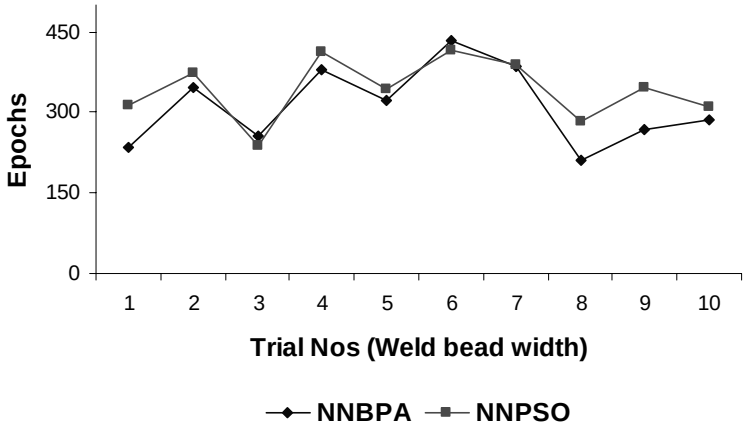

Figure 6: Comparison of performance between NNBPA and NNPSO model.

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