STM JOURNALS

Journal of
Polymer & Composites

ISSN: 2321-2810 (Online)
ISSN: 2321-8525 (Print)
Volume 11, Special Issue 6, 2023
DOI (Journal): 10.37591/JoPC

http://engineeringjournals.stmjournals.in/index.php/JoPC/index

Research JoPC

Conceptualization of An Intelligent Decision Framework for Control Factors and Weld Quality Prediction

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Abstract

To improve the robot's welding quality, control welding precision, optimize welding parameters, realize continuous welding quality database optimization, and increase welding defect detection, a fuzzy neural network-based intelligent decision-making system must be built. This study demonstrates how fuzzy control theory and BP neural networks may be used to identify welding issues and enhance process variables. The experimental findings indicate that, with seam classification accuracy close to 90%, enhancing welding parameters and performance is feasible and achievable. Neural networks, fuzzy controls, and expert systems are all used to describe welding process control. Utilizing intelligent welding controllers. Systems with intelligence can identify surface, volume, and linear welding faults. morphological (pits, undercuts, welds, surface cracks), volumetric (voids), or linear (such as slag, partial penetration, unfused, and fractures). Destructive testing benefits from data storage and visibility. Design and demand changes complicate production decisions. AI approaches like neural networks make online decisions. This article uses neural networks to predict SAW weld quality (SAW). Taguchi's principles are applied in experiments and equations. The use of experimental data and regression analysis in the development of neural network models. Considering the relative speeds and precisions of the models. NNPSO performs better than BPNN, RBFNN, and GA combined (NNGA). The created weld quality prediction technique contains online monitoring, and it is customizable, competent, and accurate. Additionally, the scheme is competent. Models are tested. The strategy that has been presented and developed will assist people in protecting themselves from robot risks.

Keywords: Welding quality, intelligent decision-making system, welding quality, welding precision, optimized welding parameters, fuzzy neural network

INTRODUCTION

Submerged arc welding requires better parameter monitoring and prediction to maintain consistent weld quality. The quality of the weld affects the product's toughness, hardness, and durability. Weld quality is impacted by factors like as weld bead geometry, deposition rate, hardness, etc. Welding velocity, arc voltage, and electrode protrusion are properties that are controlled by current. Good quality requires the proper welding process parameters [1]. SAW is frequently used by scientists. The parameters of submerged-arc welding were studied, as well as the weld deposit area, element transfer behaviour, weld-metal chemistry, bead width and height, dilution and bead geometry, and bead shape. Welding quality is investigated because it affects product safety and service life. A non-linear, time-dependent process is welding [1]. A robot welding quality intelligent Decision system was developed in order to inspect and optimise the parameters of robot welding. It gives location information as well as parameters for repeated processing, as well as optimizing the

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Received Date: June 21, 2023
Accepted Date: August 29, 2023
Published Date: September 11, 2023

Citation: Pradeep Kumar Singh. Conceptualization of An Intelligent Decision Framework for Control Factors and Weld Quality Prediction. Journal of Polymer & Composites. 2023; 11(Special Issue 6): S10–S19.

database for grinding and spraying. The AI welding inspection system is the superior option [2]. The elimination of manual inspections and erroneous assumptions results in an increase in both the efficiency and quality of welding. There aren't a lot of research, either domestic or foreign, that look into computer-aided welding systems [3]. Some of the topics that will be covered in this research are neural networks, fuzzy control, and expert systems. There are both pros and downsides. Logical reasoning is one of the expert system's strong points, but it has a slow learning rate, which makes fast time-varying system control challenging. The time required for fuzzy object control is significantly longer than that required for fuzzy information processing and decision making [4]. It also needs to have a faster learning rate and stay away from local optimization [5, 6]. Information in a distributed neural network storage system can both self-organize and self-learn. Welding is becoming more and more dependent on neural networks, expert systems, and fuzzy control as research into intelligent control continues to improve [7, 8]. Fuzzy, conventional, neural, or hybrid expert control systems are all possible. Neural networks, fuzzy computing, and expert systems can all be used to create intelligent controllers. These technologies will be used to create a control system that is responsive, self-improving, and quality-maintaining. Expert systems are needed for deep penetration, melt width control, arc stability management, weld seam tracking, and parameter optimization. controlled by fuzzy arc stability. Tracking of the weld seam, penetration depth, and melting width are provided by a neural network with fuzzy control. Weld monitoring requires "learning" neural networks and fuzzy controllers. Table I lists the system's intelligent controls. Consider the AWI-CSM welding material selection scheme [9]. Cranfi61dhats created a defect-predicting technique [10]. Unguided multi-layer self-organizing feature mapping network was created. By merging welding Decision results and welding process parameters, the preceding paragraph's welding system can be improved [11, 12]. Figure 1 shows the robot's laser tracking system. Because of its laser tracker, the robot can scan and weld online. BP neural network [13–15] outputs optimal welding process parameters by employing welding quality Decision system to detect welding process parameters and post-weld quality information.

The manufacturing floor can be set in real time with the use of simulation and analysis. In automated production, AI may learn new skills and adapt to changing conditions (ANN). It's used in manufacturing. ANN's adaptability, fault tolerance, noise resistance, and nonlinearity may tackle complex industrial problems. Neural networks can withstand noisy or missing input, and neurons work in parallel, increasing computing power. ANN learns input-output correlations. The network learns input-output relationships by altering its weights. Weights alter with network training. After training, the network's weights are frozen and it can make predictions. New data can improve ANN models. Optimize/allocate resources, find patterns, predict. ANN predicts weld quality, angular distortions, and laser beam butt welding. ANN training uses several regression equations. Multiphase propagation learning algorithm converges to sub-optimal weights. Radius Neural network clustering delivers back prop-like performance with less training time. Only a small fraction of RBFN's hidden units respond to input vectors due to localized receptive field representation [16–18]. This allows self-organizing algorithms to update such units without involving the network's output units. Each input vector modifies all unit weights in a back-propagation network. The learning goal for the hidden and output layers are separated by the hybrid two-stage training approach [19]. The RBF Neural network predicts EDM quality. Neural networks address numerous problems, but have limitations. One is NN-training. Back propagation ANNs and RBFNNs aren't ideal [20]

METHODOLOGY FOR INTELLIGENT DECISION MAKING DURING THE DEVELOPMENT PHASE

Welding faults, including volume, surface, and linear flaws, are all checked for by intelligent judging systems. Flaws can be categorised based on their volume (like voids), shape (such surface, undercuts, cracks pits), or orientation like linear defect (such as partial penetration, slag, fractures, unfused). Here, we provide a system for intelligent judgment-based non-destructive testing. It is preferable to destructive testing because of its high level of automation and the transparency of the data it collects. Figure 1 displays the input and output values. The creation of an intelligent Decision system for welding quality and the application of a fuzzy neural network method for fault identification in welding are both described. Data on the welding process, welding location, molten pool condition, and welding quality are all recorded when welding is complete. The welding procedure is then adjusted using this information, which enhances the finish quality of the weld. It enhances the quality of the welds, maintains the stability of the system, and provides consistent calibration for the grinding and painting processes.

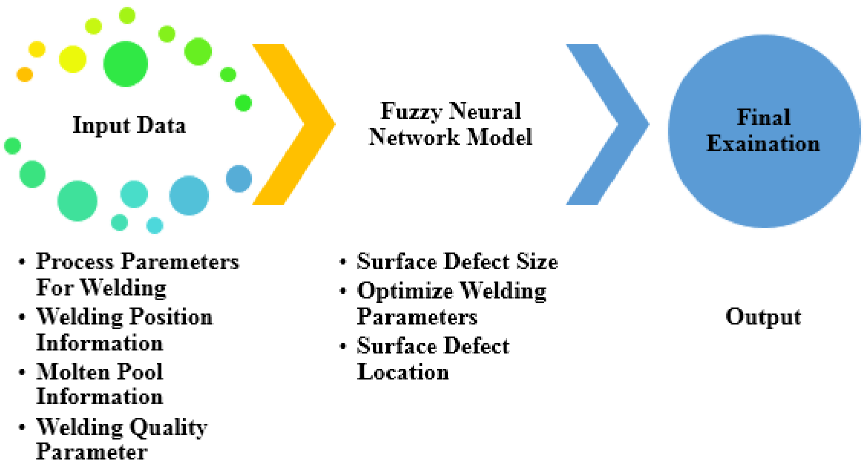

Figure 1. Intelligent Decision system input and output.

FUZZY NEURAL NETWORK APPLICATION

Fuzzy theory and neural networks are important for intelligent decision-making. The welding data visualization system uses neural networks for prediction, learning, and categorization. Figure 2 Weld Vision System uses a high dynamics spectrum camera imaging system to clearly view weld pools, welds, and torch and weld location while Figure 3 shows weld image acquisition. When welding equipment is running, it overcomes hard-to-see and hard-to-monitor difficulties, enhancing welding system reliability [17–19]. The technique works with any automatic welding equipment. Recording and replaying the welding process helps with quality traceability [20]. Figure 2 displays systems for intelligent Decision systems. Weld bead visualization devices capture real-time surface images. A standard weld library was generated using PCA and feature extraction. Image processing determines weld appearance, not features. Weld surface features and welding process parameters are recognised by a fuzzy neural network-based model. This model combines contour tracking and welding data to find faults. BP neural network identification determines defect site, weld edge, and weld defect causes. With defect identification data, a fuzzy neural network and fuzzy rule network are created. The model analyses data, finds welding faults in digital images, and enhances defect detection [21]. The method pinpoints grinding operations and improves welding process databases. Neuroarchitecture [22]. Nonlinear approximations, mapping, and fault tolerance don't require predetermined sample data in neural networks. The neural network's training delivers accurate predictions. BP's neural network performs poorly. Subjectivity creates fuzzy sets, membership functions, and rules. The fuzzy system learns to update membership and fuzzy rules. Fuzzy control translates an expert's control skills and knowledge into linguistic rules. Self-improving fuzzy control emerged. Experience-based fuzzy control. Complex uncertainty is difficult to regulate. Learning to control a precise system is challenging. Fuzzy system always improves membership function and fuzzy rules. Fuzzy theory and neural network self-learning improve knowledge expression and learning in intelligent Decision systems [23].

Deep learning's benefits in welding process control and weld flaw identification become obvious as real-time control precision and defect recognition accuracy improve. Robots and welding professionals are developing quality Decision technology as intelligent control, automatic welding, and robot welding improve. Fault-tolerant neural network reduces interference, improves soldering. Welding technology has included advances in computer science, automatic control theory, microelectronics, and power electronics. Neural networks are becoming more automated [24, 25]. Fuzzy control, which is an application of intelligent control theory, paves the way for the welding process to become more intelligent and to achieve improved welding quality.

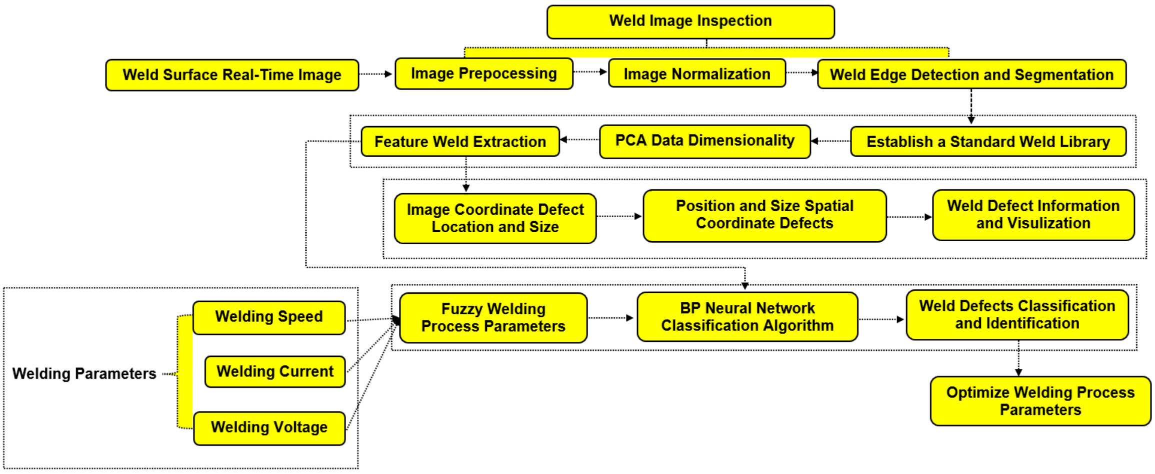

Figure 2. The Realization Process of Intelligent Decision System.

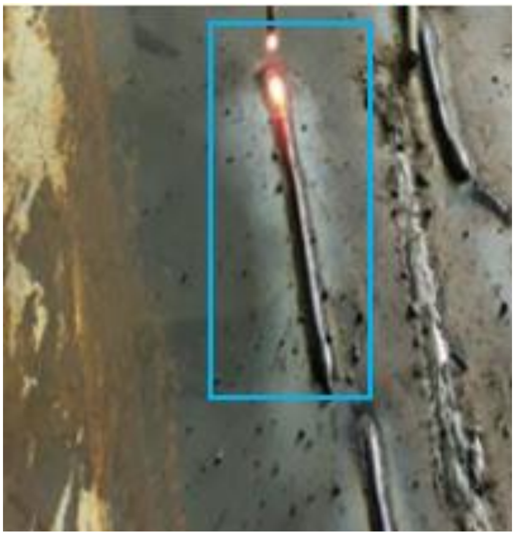

Figure 3. Weld image acquisition.

Data Acquisition

Taguchi's design of experiments was used to conduct the tests, and the L8 orthogonal array was used to collect data. There are four different variables, and two distinct stages. The experiments were carried out with the help of a semiautomatic SAW machine. (Figure 4). Two plates of IS 2062 grade (0.25%C, 0.20%Si, 0.75%Mn, and balance Fe) mild steel were welded together to form a square butt joint using a SAW machine with the electrode positive and perpendicular to the plate (500 mm 50 mm 6 mm). The 3.15-mm-diameter AWS ER70S-6 electrode was used for the welding. Figure 5 shows that samples were taken from the test item (width, 10 mm). Cleaning, polishing, and etching were done on the specimens in preparation for the examination. A profile projector was utilised to measure the weld bead geometry quantitatively (bead width, bead reinforcement and depth of penetration). Rockwell hardness testers were used to determine the weld bead's hardness, with the C scale being used. A diamond intender applied a 150 KgF stress to the weld bead's cross section for a few seconds. The results of the sample measurements are shown in Table 1.

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Volume 11, Special Issue 6
ISSN: 2321-2810 (Online), ISSN: 2321-8525 (Print)

Table 1. Observed value based on the experiment

I (current)	S (welding speed)	V (welding voltage	Average bead reinforcement, mm	Average bead Hardness H_RC	Average depth of Penetration mm	Average bead width, mm
390	410	26	2.50	51.0	4.25	14.7
370	420	25	2.00	43.0	3.50	12.5
380	400	26	2.50	44.5	4.25	14.0
360	400	26	2.25	40.0	3.75	13.0
370	410	25	2.00	38.2	3.45	12.5

Figure 4. Submerged Arc Welding for Experimental Study.

Figure 5. Weld samples by SAW (Submerged Arc Welding).

CREATION OF PROPOSED NEURAL NETWORK MODELS

Neural network models are designed and developed to manage a broad range of application tasks and attain multi-functionality.

BPNN (Back Propagation Neural Network) Model Construction

In Figure 6, we see the topography of the model used to forecast the geometry and hardness of weld beads. Using the Levenberg-Marquardt method, the network was trained to be a feed-forward back propagation model. To train and evaluate the BPNN model, experimental data and regression model data are mixed. The bias learning function employs momentum weighted gradient descent. The number of hidden layers and neurons needed to account for convergence error is determined by trial and error. The resulting 11-, 9-, and 4-layer neural networks (4 neurons in the input layer, 12 neurons in 1st hidden layer and 9 neurons in 2nd hidden layer and 4 neurons in the output layer). After 10000 training iterations with a 0.55 learning rate and 0.9 momentum term, the network is ready to use. After training, expected and observed outcomes differ by less than 0.001%.

Development of RBFNN (Radial Basis Function Neural Network) Model

Figure 7 illustrates the process of creating the RBFNN model for predicting weld quality. The RBFNN model is trained and evaluated using the regression analysis and experimental data presented in Table 1. Listed below are the RBFNN calculations. Each hidden unit's output, y, is calculated by comparing y to a parameter j in n dimensions. The sum of all inputs to radial basis neuron j.

RBFNN maintains a constant learning parameter. For adaptive problems, the learning parameter must be changed every iteration. Changing learning parameters through trial and error is inefficient. Therefore, the ability to adapt to changes in input parameters is essential. The variables error (e) and error rate of change (er) influence the learning parameter (ce).

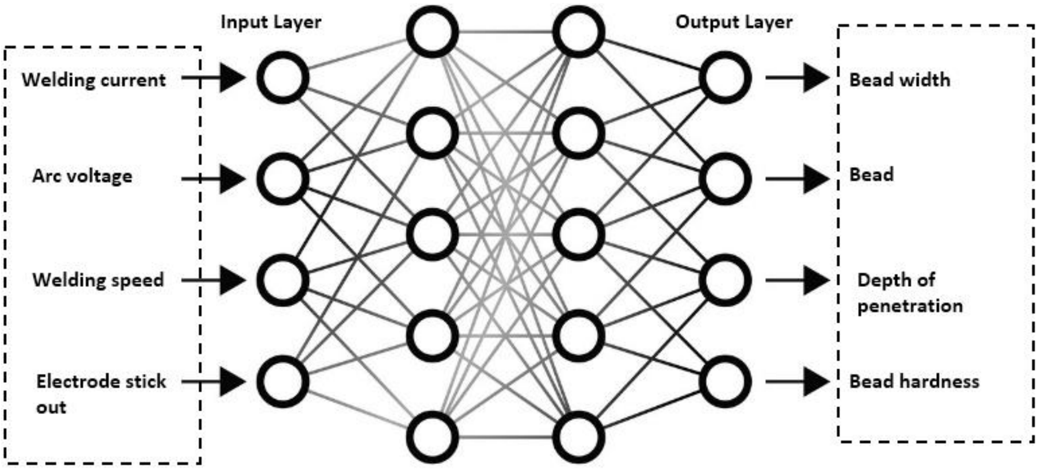

Figure 6. Developed structure of BPNN MODEL.

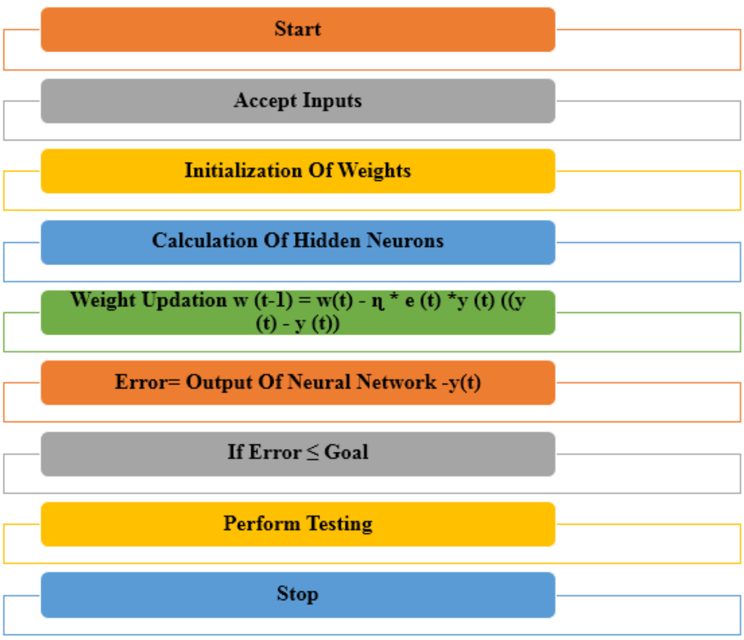

Figure 7. RBFNN model development for weld quality.

Journal of Polymer & Composites
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Modeling a Neural Network Using A Genetic Algorithm (NNGA)

Figure 8 show model's topography for predicting weld bead geometry and hardness. Levenberg-Marquardt feed-forward back propagation. The trained BPNN model uses experimental and regression data. Gradient descent, momentum weight, and bias are used by the function. In order to adjust for convergence error, you can alter the number of hidden layers and neurons. We created an 11-layer, 9-layer neural network with four inputs and four outputs, with four neurons in the input layer, twelve neurons in the first hidden layer, nine neurons in the second hidden layer, and four neurons in the final output layer. After various iterations with a 0.55 learning rate and a 0.9 momentum term, the network is ready. The expected and observed outcomes differ by less than 0.001% after training.

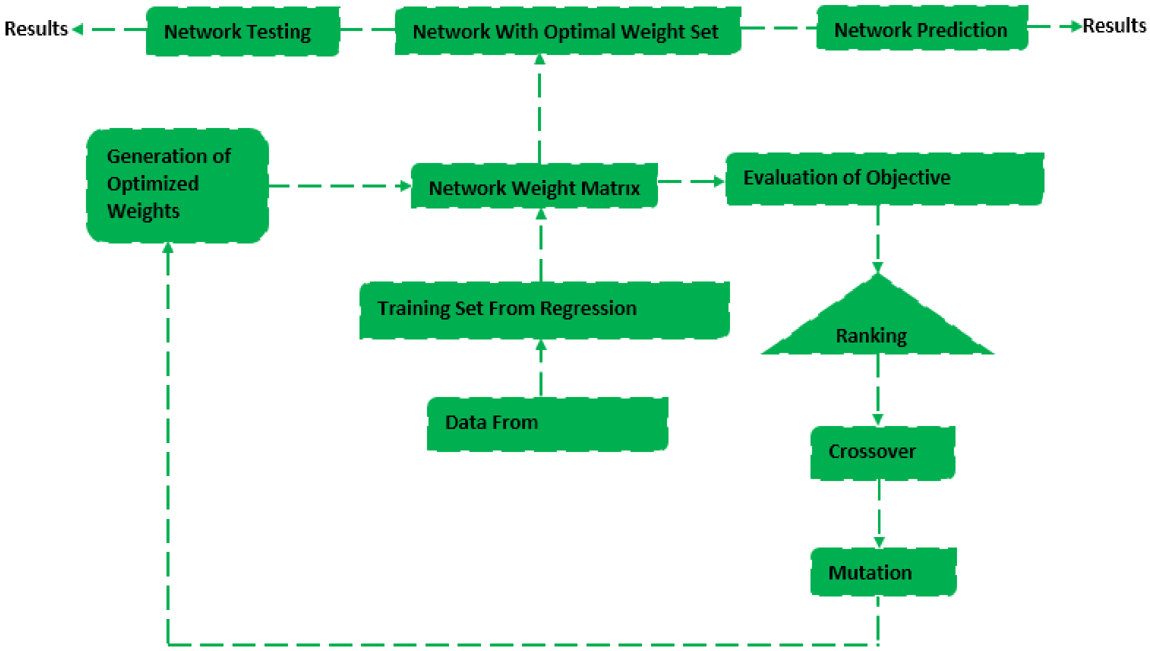

Figure 8. A Neural Network-Based Gauge Annotation Model to Predict Weld Quality.

The NNPSO (Neural Network based Particle Swarm Optimization)

The experimental data in Table 1 and extra data gained through regression analysis make up the data sets used in the training and testing of the NNPSO model. The PSO algorithm stands in for the traditional neural network's back propagation method in this model. As can be seen in Figure 7, the PSO technique is utilised to train the neural network. Table 2 displays the PSO-specific parameters that were employed in the analysis.

Table 2. Parameters used for PSO optimization

Dimension size	4
Velocity factors C1 and C2	1.5
Polulation size	40
Inertia weight	0.5–1.4
Number of iterations allowed	Total no. of particles

RESULTS AND DISCUSSIONS

Effective decision making determines an industry's success or failure. Intelligent decision-making tools improve decision making. Every process needs efficient decision-making tools. The best decision-making tool for a high-quality weld is described in this study. Taguchi's ideas are applied in SAW machine tests. Additional data are produced via experiments with several regression models. R2 > 0.8 is used to assess the accuracy of mathematical models. Correlation exists. Using experimental and regression data, neural network models are trained and tested. Figures 8 compare model results to experimental data. Microscopic analysis of test materials ensures weld quality. Even after metallographic etching, heat-impacted zones are hard to see using an optical microscope. When the weld was etched, corrosion rates changed between the fusion zone, heat-impacted zone, and base metal. 13 and 14 demonstrate metallographically etched welds. Heat-damaged zones were darker than nearby fusion zones and base metal, which had brilliant precipitates along their grain boundaries. In the base metal, lath-shaped precipitates are visible, and in the fusion zones, nodular precipitates High charge concentration and distinctive appearance made these precipitates stand out in SEM. Black and smooth, the base metal SEM image in its original form. As a result, in the weld that was obtained, SEM cannot identify the heat-impacted zone. - Pretreated welds, rather than ones that were received untreated, show solution and precipitation at the weld metal grain boundaries.

Model Accuracy

This method is validated by doing confirmatory tests. The results of the verifying tests are shown in Table 3. The network built with PSO has the lowest prediction error of all the models built using neural networks. Errors in output prediction are kept to 2% or below using the PSO-based neural network model that was created. The developed models' error percentage is [{Observed value-predicted value}/predicted value] × 100 as shown from Tables 4–6.

According to Tables 4–6, the error percentage for the generated models is [Observed value-predicted value/predicted value] x 100.

Table 3. Confirmatory experiment results

I	S	V	Average bead reinforcement, mm	Average bead Hardness H_RC	Average depth of Penetration mm	Average bead width, mm
390	410	26	2.50	51.0	4.25	14.7
370	420	25	2.00	43.0	3.50	12.5
380	400	26	2.50	44.5	4.25	14.0
360	400	26	2.25	40.0	3.75	13.0

Table 4. Results from the confirmatory experiments

RBFNN Model	NNPSO model	NNGA model	BPNN model
-5.21	-0.15	-3.27	-3.12
-0.798	0.088	-0.07	-2.54
1.838	-2.25	-1.74	-1.65
-3.68	-0.89	3.741	**3.258**

Table 5. Percentage error of weld bead reinforcement

RBFNN Model	NNPSO model	NNGA model	BPNN model
-7.33	1.65	-3.69	3.03
-5.70	0.057	0.100	-5.25
7.99	-0.234	-2.837	2.79
-5.93	-0.310	-8.312	1.323

Table 6. Percentage error of depth of penetration

RBFNN Model	NNPSO model	NNGA model	BPNN model
2.533	-0.70	-2.52	3.03
-0.28	0.057	1.596	2.10
-6.87	-0.23	-5.91	-0.234
-0.079	-1.35	6.92	1.323

CONCLUSIONS

With the use of an intelligent Decision system for welding quality, welding process parameters and surface quality can be evaluated more effectively, and the system can also offer suggestions for ongoing process correction. This methodology can serve as a scientific foundation for enterprise improvement management while also aiding in the standardization of processes and the enhancement of the quality of process design. Fuzzy control and neural networks operate together to maximise the strengths of both technologies, leading to enhanced intelligence, faster system identification, and better decisions. Further research is needed to test the validity of the fuzzy neural network stability analysis applied to weld seam tracking. By the use of regression analysis, we are able to define the connection between the input weld parameters such as bead width, reinforcement, penetration depth, and bead hardness and the resultant weld parameters. This enables us to use this information to train neural network models. It is determined whether or not the equations that were generated are accurate and reliable. It has been discovered that the output of neural networks trained with PSO appears to have an edge over the other models that have been established in terms of the amount of computational correctness as well as the amount of processing speed. Experiments designed to confirm something must first be carried out before it can be validated. Developing a model for the online weld quality monitoring procedure The inspection of weld samples using scanning electron microscopy, which displays a perfect grain structure, is one way to verify that the quality of welding is high. By establishing a connection between the SAW tools and a desktop or portable computer, the technology that has been proposed can be transformed into an in-process weld quality prediction system. Using the strategy that was suggested, manufacturing facilities can develop intelligent production systems, which enables them to achieve the highest possible degree of automation.

Abbreviations

BPNN: Back Propagation Neural Network

NNPSO: Neural Network based Particle Swarm Optimization

GA: Genetic Algorithm

NNGA: Neural Network based Genetic Algorithm

RBFNN: Radial Basis Function Neural Network

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