International Journal of AI & Data Science Review
Volume1, Issue 2, 2025

Optimization and Modeling of Weld Bead Area in Electron Beam Welding (EBW) of Aerospace Alloy (Inconel 825)

Canan Hamurkarog
Department of Mechanical Engineering, İzmir Katip Çelebi University, Çiğli, İzmir, Turkey

Article Info
Received: 10-12-2024 ***Revised:19-01-2025*** ***Accepted:10-03-2025*** ***Published:19-04-2025***

Abstract
This research examines the ideal weld area on Inconel 825, a common aerospace alloy produced using the electron beam welding method. To investigate the weld bead area (WA) of the weldments, the following process factors are taken into consideration: welding speed (S), beam current (I), accelerating voltage (V), and beam oscillation (O). As a fundamental introduction to neuro regression modeling using artificial neural network (ANN) philosophy, an instructional research on various non-linear neural regression analyses has been conducted. In order to assess the accuracy of their predictions, 14 predictive functional structures were used to represent the experimental prediction using basic regression modal types. To train the program using the selected model R2, test it, confirm that R2 is employed accurately, and determine if the results fall within the engineering bounds. Three distinct situations have been used in optimization algorithms. Out of the fourteen models, only one produced findings that were realistic. It has been observed that the models used for design variables, the sorts of scenarios, and the choice of constraints all have an impact on the optimization outcomes.

Keywords: Electron beam welding; neuro-regression modeling; optimization; weld bead area.

Introduction

Because of their superior qualities, nickel and its alloys (Inconel), which are widely used in aerospace, have become more and more popular in the industrial sector. However, treating these alloys presents challenges, therefore researchers have had to apply novel techniques like electron beam welding (EBW). Furthermore, it is necessary to look at how welding procedures and their factors affect the properties of the weld. Ni-base alloys are often employed as aerospace alloys and in the marine, automotive, nuclear, and chemical processing sectors due to their broad variety of applications in engineering systems exposed to harsh circumstances, such as very corrosive and high-temperature environments. Welding procedures must be used during manufacturing for the majority of these applications. The performance of the weld must be comparable to that of the base metal [1, 2]. Nevertheless, this kind of nickel-based alloy is difficult to produce or fabricate and has raised several issues. The formation of harmful phases such as the laves phase, alloying element segregation, and the propensity for micro-fissuring are thought to be the main issues influencing the mechanical properties of welded joints. Therefore, it is crucial to use statistical and soft computing-based methods [1]. Researchers welded nickel/titanium alloys using a variety of welding techniques, including friction stir welding (FSW), gas metal arc welding (GMAW), gas tungsten arc welding (GTAW), and more energy-intensive welding methods including electron beam welding (EBW) and laser beam welding (LBW) [3].

Weld quality is mostly controlled by the mechanical characteristics and bead shape of the weld. While the form of the weld bead geometry determines the mechanical characteristics of the weld, the cross-section of the weld-bead geometry specifies the distortion and residual stresses caused. When welding, the quality of the weld must match that of the base metal. By making the right choices and managing the welding factors, this is possible. As a result, using statistical methods is crucial [1, 5]. To anticipate various reactions in various welding processes, researchers have used multiple linear regression (MLR) and soft computing-based intelligence techniques such artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and fuzzy logic (FL). Soft computing is a method that combines the human mind with an imprecise and unpredictable environment [4]. These methods are successful in describing the intricate and non-linear behavior of the responses with respect to its process parameter. The following is a discussion of the literature on forecasting different weld bead properties. In order to forecast the ultimate tensile strength of a titanium tube, Palanivel et al. [6] developed an ANN technique based on backpropagation (BP) and RSM. To get the optimal weld bead shape, they optimized the GTAW process parameters by combining the established model with genetic algorithms. In order to forecast the welding strength of resistance spot welded CR780 sample, Zaharudin et al. [7] created ANFIS and ANN models. The ANN model is shown to be more accurate in prediction than the RSM method [8]. Gyasi et al. [9] used the ANN method to forecast the structural integrity of GMAW welded UHSS welded joints. Satpathy et al. [10] predicted the joining strength of the aluminum-copper dissimilar welded connections using regression, ANN, and ANFIS. Narang and associates [11] developed a fuzzy logic (FL) model to forecast the weld bead shape of structural steel weldments that are TIG-welded. Sivagurumanikandan et al. [12] investigated the impact of welding factors on the ideal strength of weldments using RSM and ANN-based modeling techniques. In order to determine the temperature distribution and weld shape of laser-welded titanium alloy weldments, Akbari et al. [13] created a computational model. The ANN model for predicting weld strength in FSW of Incoloy 800 weldments was trained using various techniques by Anand et al. [14]. When it came to predicting the welded specimens, both models performed quite well. Balasubramanian et al. [15] employed an ANN model trained with the backpropagation (BP) technique to predict WA on stainless steel. In order to determine the ideal weld area of Inconel 825, which is impacted by the welding speed (S), beam current (I), accelerating voltage (V), and beam oscillation (O), we have presented a unique technique on a modeling design-optimization process following the literature research in the relevant field: • For the output of our procedure, a thorough analysis of many non-linear neuro-regression studies, including linear, quadratic, trigonometric, logarithmic, and their rational variants, has been carried out. • In order to get realistic values, the proposed models' boundedness has been verified. • The many direct search techniques, such as stochastic optimization algorithms (modified versions of differential evaluation, Nelder-Mead, random search, and

simulated annealing algorithms), have been carried out meticulously.

1. Materials and Methods

1.1. Modeling

In the modeling phase, the predictions are tested with the regression analysis. Regression models generally estimate the degree of correlation between input and output variables and determine their relationship form. Linear regression is mainly fitted by the least-squares method, but it can also be fitted by other methods, such as minimizing the "underfitting" in some other specifications or minimizing the penalty version of the least square loss function (such as Ridge regression). Linear regression is divided into two categories: simple and multiple linear regression [5].

With this method, the data was split into three parts; 84%, 10%, and 6% of the chosen data calculated for R^2, R^2, and R^2, respectively. This process reduces the error between predicted and the experimental results by changing the models in *Table 1* for regression and splitting the data into the correct sections. However, the resulting R^2 values are not sufficient to confirm the accuracy of the results; therefore, apart from the results found from the candidates, maximum and minimum predicted values have been found and checked if the results are within the engineering limits. In addition, optimization algorithms with three different scenarios have been tried, and the optimum number of inputs investigated [16, 17].

1.2. Optimization

In essence, the optimization of the structure can be described as obtaining the best design by minimizing or maximizing a single specified goal or multiple goals corresponding to all constraints. Optimization techniques can be divided into traditional and non-traditional. Traditional optimization techniques are only suitable for continuous and differentiable functions, such as constraint changes and Lagrangian multipliers. In engineering design problems, traditional optimization techniques cannot be used due to particularities. In these cases, stochastic optimization methods such as genetic algorithm (GA), particle swarm (PS), and simulated annealing (SA) are advantageous. However, due to the nature of stochastic methods, accurate solutions cannot be obtained, and using more than one method with different phenomenological foundations for the same optimization problem will increase the solution's reliability.

The mathematical optimization problem handled in this article has the following issues:

- Multiple non-linear objective functions,
- Objective functions having many local extremum points,
- Mixed-integer (discrete) - continuous nature of the design variables
- Non-linear constraints.

The optimization scenarios discussed in this study include the condition given in the first three items. In addition, four different optimization algorithms (MDE, MNM, MSA, MRS) have been selected to solve optimization problems.

Table 1: *Multiple regression model types including linear, quadratic, trigonometric, logarithmic, their rational forms and hybrid forms*

Model Name	Nomenclature	Formula
Multiple linear	L	a[1] + a[2] x1 + a[3] x2 + a[4] x3 + a[5] x4
Multiple linear rational	LR	(a[1] + x1 a[2] + x2 a[3] + x3 a[4]) / (b[1] + x1 b[2] + x2 b[3] + x3 b[4])
Second order multiple nonlinear	SON	a[1] + a[2] x1 + a[3] x2 + a[4] x3 + a[5] x4 + a[6] x1^2 + a[7] x2^2 + a[8] x3^2 + a[9] x4^2 + a[10] x1 x2 + a[11] x1 x3 + a[12] x1 x4 + a[13] x2 x3 + a[14] x2 x4 + a[15] x3 x4
Second order multiple nonlinear rational	SONR	(a[1] + 2 x1 a[2] + x1^2 a[3] + 2 x2 a[4] + 2 x1 x2 a[5] + x2^2 a[6] + 2 x3 a[7] + 2 x1 x3 a[8] + 2 x2 x3 a[9] + x3^2 a[10] + 2 x4 a[11] + 2 x1 x4 a[12] + 2 x2 x4 a[13] + 2 x3 x4 a[14] + x4^2 a[15]) / (b[1] + 2 x1 b[2] + x1^2 b[3] + 2 x2 b[4] + 2 x1 x2 b[5] + x2^2 b[6] + 2 x3 b[7] + 2 x1 x3 b[8] + 2 x2 x3 b[9] + x3^2 b[10] + 2 x4 b[11] + 2 x1 x4 b[12] + 2 x2 x4 b[13] + 2 x3 x4 b[14] + x4^2 b[15])
Third order multiple nonlinear	TON	a[1] + 3 x1 a[2] + 3 x1^2 a[3] + x1^3 a[4] + 3 x2 a[5] + 6 x1 x2 a[6] + 3 x1^2 x2 a[7] + 3 x2^2 a[8] + 3 x1 x2^2 a[9] + x2^3 a[10] + 3 x3 a[11] + 6 x1 x3 a[12] + 3 x1^2 x3 a[13] + 6 x2 x3 a[14] + 6 x1 x2 x3 a[15] + 3 x2^2 x3 a[16] + 3 x3^2 a[17] + 3 x1 x3^2 a[18] + 3 x2 x3^2 a[19] + x3^3 a[20] + 3 x4 a[21] + 6 x1 x4 a[22] + 3 x1^2 x4 a[23] + 6 x2 x4 a[24] + 6 x1 x2 x4 a[25] + 3 x2^2 x4 a[26] + 6 x3 x4 a[27] + 6 x1 x3 x4 a[28] + 6 x2 x3 x4 a[29] + 3 x3^2 x4 a[30] + 3 x4^2 a[31] + 3 x1 x4^2 a[32] + 3 x2 x4^2 a[33] + 3 x3 x4^2 a[34] + x4^3 a[35]
First order trigonometric multiple nonlinear	FOTN	a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Sin[x4] + a[6] Cos[x1] + a[7] Cos[x2] + a[8] Cos[x3] + a[9] Cos[x4]
First order trigonometric multiple nonlinear rational	FOTNR	(a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Sin[x4] + a[6] Cos[x1] + a[7] Cos[x2] + a[8] Cos[x3] + a[9] Cos[x4]) / (b[1] + b[2] Sin[x1] + b[3] Sin[x2] + b[4] Sin[x3] + b[5] Sin[x4] + b[6] Cos[x1] + b[7] Cos[x2] + b[8] Cos[x3] + b[9] Cos[x4])
Second order trigonometric multiple nonlinear	SOTN	a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Sin[x4] + a[6] Cos[x1] + a[7] Cos[x2] + a[8] Cos[x3] + a[9] Cos[x4] + a[10] Sin[x1]^2 + a[11] Sin[x2]^2 + a[12] Sin[x3]^2 + a[13] Sin[x4]^2 + a[14] Cos[x1]^2 + a[15] Cos[x2]^2 + a[16] Cos[x3]^2 + a[17] Cos[x4]^2
Second order trigonometric multiple nonlinear rational	SOTNR	(a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Sin[x4] + a[6] Cos[x1] + a[7] Cos[x2] + a[8] Cos[x3] + a[9] Cos[x4] + a[10] Sin[x1]^2 + a[11] Sin[x2]^2 + a[12] Sin[x3]^2 + a[13] Sin[x4]^2 + a[14] Cos[x1]^2 + a[15] Cos[x2]^2 + a[16] Cos[x3]^2 + a[17] Cos[x4]^2) / (b[1] + b[2] Sin[x1] + b[3] Sin[x2] + b[4] Sin[x3] + b[5] Sin[x4] + b[6] Cos[x1] + b[7] Cos[x2] + b[8] Cos[x3] + b[9] Cos[x4] + b[10] Sin[x1]^2 + b[11] Sin[x2]^2 + b[12] Sin[x3]^2 + b[13] Sin[x4]^2 + b[14] Cos[x1]^2 + b[15] Cos[x2]^2 + b[16] Cos[x3]^2 + b[17] Cos[x4]^2)
First order logarithmic multiple nonlinear	FOLN	a[1] + a[2] Log[x1] + a[3] Log[x2] + a[4] Log[x3] + a[5] Log[x4]
First order logarithmic multiple nonlinear rational	FOLNR	(a[1] + a[2] Log[x1] + a[3] Log[x2] + a[4] Log[x3] + a[5] Log[x4]) / (b[1] + b[2] Log[x1] + b[3] Log[x2] + b[4] Log[x3] + b[5] Log[x4])
Second order logarithmic multiple nonlinear	SOLN	a[1] + a[2] Log[x1] + a[3] Log[x2] + a[4] Log[x3] + a[5] Log[x4] + a[6] Log[x1]^2 + a[7] Log[x2]^2 + a[8] Log[x3]^2 + a[9] Log[x4]^2 + a[10] Log[x1 x2] + a[11] Log[x1 x3] + a[12] Log[x1 x4] + a[13] Log[x2 x3] + a[14] Log[x2 x4] + a[15] Log[x3 x4]
Second order logarithmic multiple nonlinear rational	SOLNR	(a[1] + a[2] Log[x1] + a[3] Log[x2] + a[4] Log[x3] + a[5] Log[x4] + a[6] Log[x1]^2 + a[7] Log[x2]^2 + a[8] Log[x3]^2 + a[9] Log[x4]^2 + a[10] Log[x1 x2] + a[11] Log[x1 x3] + a[12] Log[x1 x4] + a[13] Log[x2 x3] + a[14] Log[x2 x4] + a[15] Log[x3 x4]) / (b[1] + b[2] Log[x1] + b[3] Log[x2] + b[4] Log[x3] + b[5] Log[x4] + b[6] Log[x1]^2 + b[7] Log[x2]^2 + b[8] Log[x3]^2 + b[9] Log[x4]^2 + b[10] Log[x1 x2] + b[11] Log[x1 x3] + b[12] Log[x1 x4] + b[13] Log[x2 x3] + b[14] Log[x2 x4] + b[15] Log[x3 x4])

Hybrid	H	a[1] + 3 a[2] Sin[x1] + 3 a[3] Sin[x1]^2 + a[4] Sin[x1]^3 + 3 a[5] Sin[x2] + 6 a[6] Sin[x1] Sin[x2] + 3 a[7] Sin[x1]^2 Sin[x2] + 3 a[8] Sin[x2]^2 + 3 a[9] Sin[x1] Sin[x2]^2 + a[10] Sin[x2]^3 + 3 a[11] Sin[x3] + 6 a[12] Sin[x1] Sin[x3] + 3 a[13] Sin[x1]^2 Sin[x3] + 6 a[14] Sin[x2] Sin[x3] + 6 a[15] Sin[x1] Sin[x2] Sin[x3] + 3 a[16] Sin[x2]^2 Sin[x3] + 3 a[17] Sin[x3]^2 + 3 a[18] Sin[x1] Sin[x3]^2 + 3 a[19] Sin[x2] Sin[x3]^2 + a[20] Sin[x3]^3 + 3 a[21] Sin[x4] + 6 a[22] Sin[x1] Sin[x4] +3 a[23] Sin[x1]^2 Sin[x4] + 6 a[24] Sin[x2] Sin[x4] + 6 a[25] Sin[x1] Sin[x2] Sin[x4] + 3 a[26] Sin[x2]^2 Sin[x4] + 6 a[27] Sin[x3] Sin[x4] + 6 a[28] Sin[x1] Sin[x3] Sin[x4] + 6 a[29] Sin[x2] Sin[x3] Sin[x4] + 3 a[30] Sin[x3]^2 Sin[x4] + 3 a[31] Sin[x4]^2 + 3 a[32] Sin[x1] Sin[x4]^2 + 3 a[33] Sin[x2] Sin[x4]^2 + 3 a[34] Sin[x3] Sin[x4]^2 + a[35] Sin[x4]^3 + Sin[x1] a[36] + Sin[x2] a[37] + Sin[x3] a[38] + Sin[x4] a[39] + Sin[x1]^2 a[40] + Sin[x2]^2 a[41] + Sin[x3]^2 a[42] + Sin[x4]^2 a[43] + Sin[x1]^4 a[44] + Sin[x2]^4 a[45] + Sin[x3]^4 a[46] + Sin[x4]^4 a[47]

2.2.1 Modified Nelder-Mead Algorithm

One of the search methods is the Nelder–Mead (NM) optimization algorithm. Therefore, it does not require any derivative information and starts with simplex to minimize the function. As a result, the iteration maintained up to the simplex becomes flat. It means that the resulting value of the function is almost the same at all the
vertices. The iteration steps of the Nelder-Mead algorithm are ordering, centroid, and transformation. In the present version of the algorithm, a penalty function is added to the flow to solve the prescribed constrained minimization problem. The construction of the initial working simplex S is the first step. Second, minimizing the function moves the search course away from the peak, which is the worst function value [16].

2.2.2 Modified Differential Evolution Algorithm

Differential evolution (DE) is one of the suitable ways of the stochastic optimization method. It can be used in complex structured engineering design problems to find the optimum result. The productive parameters of the DE algorithm are population size, crossover, and scaling factor. It handles a population of solutions instead of iterating over solutions. The DE algorithm is proposed to be robust and efficient in the literature; it does not satisfy the global optimum points for all optimization problems [17].

2.2.3 Modified Simulated Annealing Algorithm

Another search method based on the physical annealing process of metal is simulated annealing (SA). The material moves to a lower energy state throughout the melting process and becomes tougher. Because of the intrinsic structure of the algorithm, it is better at finding the global optimum. Moreover, it can solve continuous, mixed-integer, or discrete optimization problems [17].

2.2.4 Modified Random Search Algorithm

The first step in the traditional random search algorithm is to produce a population of random starting points. Then, it uses a local optimization method from each starting point to get closer to a local extremum point at this stage. In the proposed algorithm version, there are some booster subroutines such as the conjugate gradient, principal axis, Levenberg Marquardt, Newton, QuasiNewton, and non-linear interior-point method the localization of the values of all variables for the objective function. In this step, the fitness function is evaluated with the variables being symbolic, and then the process continues again and again. It is also possible to solve mixed-integer-continuous global optimization problems [18].

1.3. Problem Description

1. The data given in Table 2 were selected from the reference study [1]. It should be noted that the parameters x1-x4 included in the models given in Table 1 correspond in terms of engineering to accelerating voltage, beam current, welding speed, and beam oscillation parameters, respectively.
2. 14 candidate functional constructs have been suggested to model the experimental data have been tested for the proper ones in terms of R^2, R^2, and R^2values, and then boundedness of the functions is also checked.
3. Three different optimization scenarios have been introduced using the appropriate model obtained, and these problems are solved through four different direct search methods: MDE, MSA, MRS, and MNM

1.4. Optimization Scenarios

Scenario 1

In this optimization problem, the objective functions define the weld bead area (mm^2) of a welded Inconel 825 alloy. All the design variables are considered to be real numbers, and the search space is continuous. In this case, the limit values for the system inputs are 48 < accelerating voltage (kV) < 60, 38 < beam current (mA) < 4, 900 < welding speed (mm/min) < 1200 and 200 < beam oscillation (Hz) < 600. The main objective is to maximize the weld bead area. In this way, the theoretical limits of the objective function can also be seen mathematically.

Intervals are considered to be real numbers: 48 < accelerating voltage (kV) < 60, 38 < beam current (mA) < 4, 900 < welding speed (mm/min) < 1200 and 200 < beam oscillation (Hz) < 600. Additionally, to examine the constraints of design variables {accelerating voltage, beam current, welding speed, beam oscillation} ∈ integers are proper.

Scenario 2

Besides knowledge-based in Scenario 1, more applicable problem cases for the weld bead area need to be added. For this purpose, a new optimization problem has been described that assumes the maximization of the weld bead area. All the design variables in the intervals are considered to be real numbers: 48 < accelerating voltage (kV) < 60, 38 < beam current (mA) < 4, 900 < welding speed (mm/min) < 1200 and 200 < beam oscillation (Hz) < 600. Additionally, to examine the constraints of design variables {accelerating voltage, beam current, welding speed, beam oscillation} ∈ integers are proper.

Scenario 3

Based on only the prescribed experimental setup, the more specific optimization problem can also be defined as involving (I) maximization of the beam oscillation, (II) minimization of accelerating voltage, (III) optimizing the welding speed, (IV) minimizing the beam current, (V) all the design variables are assumed to be real numbers and (VI) the constraints are accelerating voltage ∈ {48, 54, 60}; beam current ∈ {38, 42, 46}; welding speed ∈ {900, 1050, 1200}; and beam oscillation ∈ {200, 400, 600}.

Table 2: *The data used for optimization operations in the article* [1]

SI. No.	Accelerating voltage(kV), V	Beam Current (mA), I	Welding speed (mm/min), S	Beam Oscillation (Hz), O	Weld bead area (mm^2), WA
1	48	38	900	200	4.86
2	60	46	1200	400	5.99

3	54	42	1050	600	5.39
4	48	38	1200	600	3.93
5	48	38	1200	200	3.24
6	60	38	1200	600	5.06
7	60	38	1200	200	5.12
8	48	38	900	600	4.81
9	48	46	900	600	6.06
10	48	46	1200	600	4.92
11	54	42	1050	400	5.33
12	60	38	900	600	5.69
13	60	46	900	600	6.07
14	48	46	900	200	6.15
15	54	42	1050	400	5.54
16	54	42	1050	400	5.38
17	48	46	1200	200	4.52
18	60	38	900	200	5.89
19	60	46	1200	200	5.42
20	60	46	900	200	5.53
21	54	46	1050	400	6.02
22	54	42	1200	400	4.93
23	54	42	1050	400	5.38
24	54	42	1050	600	5.32
25	54	38	1050	400	5.33
26	54	42	900	400	5.64
27	54	42	1050	200	5.56
28	48	42	1050	400	4.89
29	54	42	1050	400	5.63
30	60	42	1050	400	5.67

2. Results and Discussion

In this study, 14 different regression models with four parameters were tested for one output (see *Table 1*), and the results are listed in *Tables 3* to understand how the model successfully explained the process to estimate the values of various regression models and determine the functional limitation (boundedness) of the model by estimating the maximum and minimum values generated by the corresponding model.

In order to understand that we have trained the program correctly, we should pay attention that the training value is <0.90, the testing value is <0.90, and the validation value is <0.85. After completing these processes, we check whether the maximum and minimum values we find for the inputs are within the engineering limits, the model that meets all the conditions can be used.

In *Table 3*, the suitability of the candidate models in terms of training, testing, validation coefficients, and boundedness, the following inferences were made:

- Training coefficients of all models are pretty high (>0.99) while the test coefficients are high for only LR, SON, FOTNR, SOTNR, FOLNR, and H. Therefore, the number of usable models in the testing phase decreases from 14 to 6.
- In the next stage, the compatibility of the validation value is examined. At this stage, we only have 1 model that meets this requirement, and that is SON.
- Besides, as mentioned in the previous section, it is also expected to meet the boundedness criterion for use in optimizing the model. When viewed from this angle, only one model is suitable, which is SON. As a result, only the SON model can meet all the desired criteria and be considered a realistic model.

Table 3: *Results of the Neuro-regression models for fitting performance and boundedness.*

Models	$R^2_{Training}$	$R^2_{Testing}$	$R^2_{Validation}$	Max (mm^2)	Min (mm^2)
L	0.99	0.74	0.80	6.50	4.19
LR	0.99	0.97	0.43	6.13	3.56
SON	0.99	0.97	0.87	6.20	3.56
SONR	0.99	0.50	0.87	6.12	4.70
TON	0.99	0.87	0.32	6.76	2.71
FOTN	0.99	0.79	0.89	6.50	-5.18
FOTNR	0.99	0.98	-22.2	$4.48496 * 10^7$	$-2.01089 * 10^{13}$
SOTN	0.99	0.79	0.89	6.45	-3.44
SOTNR	0.99	0.97	0.85	13.40	$-5.0818 * 10^{11}$
FOLN	0.99	0.75	0.81	6.50	4.17
FOLNR	0.99	0.96	0.32	6.12	3.58
SOLN	0.99	0.79	0.89	6.46	4.09
SOLNR	0.99	0.86	0.42	$5.58908 * 10^{10}$	3.87
H	0.99	0.95	0.93	11.63	-8.80

In *Table 4*, the model of SON is taken as the objective function, and the results are listed for three different optimization scenarios. This table uses MDE, MSA, MRS, and MNM algorithms for each scenario, and the results were compared. According to all algorithms for the first scenario, the maximum input values were calculated, and that gave us four different alternative input parameter triplets to achieve the weld beam area. The problem definition is the same in the second scenario, but the input parameters are forced to be integers. In this case, the input values have changed but still were close to numbers from scenario 1. In terms of reliability, achieving the very close results for the four direct search methods used in scenarios 1 and 2 increases the possibility that obtained values will be the global optimum. When we look at the results of the third scenario, we can say that we have reached the optimum parameter values similar to scenario 2. However, the best solution proposal of each algorithm is quite different from each other. This shows that it is essential to use more than one different phenomenological-based algorithm when there is a need to produce alternative optimum solutions for this problem and similar studies.

Conclusion

This study examines the impact of welding process factors WA using electron beam welding of Inconel 825. The findings of thirty welding experiments on four weld variables were derived from Ref [1]. First, non-linear multiple regression analysis is used to create predictive modeling for WA utilizing the popular ANN method's philosophy, and its efficacy is examined. After that, the results were examined to see whether the chosen models were also confined inside the specified parameter ranges. Lastly, the optimization procedure included modified versions of four direct search techniques: Nelder-Mead, Random Search, Simulated Annealing, and Differential Evolution. Some of the important findings from this inquiry are listed below. To ensure that the testing and validation values are as accurate as possible, the program should be trained using as many training values as feasible. However, only having a lot of data in the training phase is insufficient; the input values of the chosen data must also contain the maximum and minimum input values since the software struggles to estimate a value that is not in the range. The highly varied outputs also have an impact on the consistency of the projected values; the model may provide outcomes that are closer to one another. Estimates are employed throughout the model selection process since it is impossible to predict which model would provide better results; instead, alternative outcomes are discovered by trial and error, and the model that produces more accurate results is perpetuated. The specific Nelder-Mead options—ReflectRatio, Tolerance, ShrinkageRatio, Randomseed, and more—could be used if the direct search techniques produced poor results.

References

[1] B. Choudhury and M. Chandrasekaran, "Electron beam welding of aerospace alloy (inconel 825): a comparative study of RSM and ANN modeling to predict weld bead area," Optik, International Journal for Light and Electron Optics, Elsevier GmbH, vol. 219, 2020 [2] J. W. Sowards and J. Caron, "Weldability of nickel-base alloys," Comprehensive Materials Processing, Elsevier, Oxford, vol. 1, no. 6, pp. 151-179, 2014.
[3] B. Choudhury and M. Chandrasekaran, "Investigation on welding characteristics of aerospace materials –a review," Selection and Peer-review, Committee Members of the International Conference on Advancements in Aeromechanical Materials for Manufacturing, Elsevier, vol. 4, pp. 7519–7526, 2017. [4] "Application of soft computing techniques in machining performance prediction and optimization: a literature review," M.

Chandrasekaran, M. Muralidhar, C. M. Krishna, and U. S. Dixit, Int J Adv Manuf Technol, Springer-Verlag London Limited, vol. 46, pp. 445–464, 2009.
[5] F. Khademi, S. M. Jamal, N. Deshpande, and S. Londhe, "Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro fuzzy inference system and multiple linear regression," International Journal of Sustainable Built Environment, Elsevier BV, vol. 5, no. 2, pp. 355-369, 2016.
[6] "Application of an artificial neural network model to predict the ultimate tensile strength of friction welded titanium tubes," R. Palanivel, I. Dinaharan, and R. F. Laubscher, J. Braz. Soc. Mech. Sci. Eng., Springer, vol. 41, no. 111, 2019.
[7] M. F. A. Zaharuddin, D. Kim, and S. Rhee, "An ANFIS based approach for predicting the weld strength of resistance spot welding in artificial intelligence development," J. Mech. Sci. Technol., Springer, vol. 31, no. 11, pp. 5467–5476, 2017. [8] Acta Metall. Sin. (Engl. Lett.), Springer, vol. 28, no. 7, pp. 892–902, 2015 K. Anand, R. Shrivastava, K. Tamilmannan, and P. Sathiya, "A comparative study of artificial neural network and response surface methodology for optimization of friction welding of incoloy 800 H." [9] E. A. Gyasi, P. Kah, H. Wu, and M. A. Kesse, "Modeling of an artificial intelligence system to predict structural integrity in robotic GMAW of UHSS fillet welded joints," International Journal of Advanced Manufacturing Technology, Springer, vol. 93, pp. 1139–1155, 2017.
[10] M. P. Satpathya, S. B. Mishraa, and S. K. Sahoob, "Ultrasonic spot welding of aluminum-copper dissimilar metals: a study on joint strength by experimentation and machine learning techniques," J. Manuf. Process., Elsevier, vol. 33, pp. 96–110, 2018.[11] H. K. Narang, U. P. Singh, M. M. Mahapatra, and P. K. Jha, "TIG arc welding weld pool geometry prediction using fuzzy logic controller," Int. J. Eng. Sci. Technol., MultiCraft, vol. 3, no. 9, pp. 77–85, 2011. [12] N. Sivagurumanikandan, S. Saravanan, G. S. Kumar, S. Raju, and K. Raghukandan, "Prediction and optimization of process parameters to enhance the tensile strength of Nd: YAG laser welded super duplex stainless steel," Optik, Elsevier Gmbh., vol. 157, pp. 833–840, 2018. [13] M. Akbari, S. Saedodin, A. Panjehpour, M. Hassani, M. Afrand, and M. J. Torkamany, "Numerical simulation and designing artificial neural network for estimating melt pool geometry and temperature distribution in laser Ti6Al4Valloy,"Opt.-Int. J. Light Electron. Opt., 2016. [14] "Artificial neural network modeling studies to predict the friction welding process parameters of incoloy 800H joints," Eng. Sci. Technol. Int. J., Elsevier BV, vol. 18, pp. 394–407, 2015. Anand, B. K. Barik, Tamilmannan, and Sathiya.
[15] K. Sankaranarayanasamy, G. Buvanashekaran, and K. R. Balasubramanian, "Modeling of laser beam welding of stainless steel sheet butt joint using neural networks," CIRP J. Manuf. Sci. Technol., Elsevier, vol. 3, pp. 80–84, 2010.
[16] I. Polatoglu and L. Aydin, "A new design strategy with stochastic optimization on the preparation of magnetite cross-linked tyrosinase aggregates (MCLTA)," Process Biochemistry, vol. 99, pp. 131–138, 2020.
[17] I. Polatoglu, L. Aydin, B. Ç. Nevruz, and S. Ozer, "A novel approach for the optimal design of a biosensor," Anal. Lett., pp. 1–18, 2020. doi.org/10.1080/00032719.2019.1709075. [18] A. B. Ceylan, L. Aydin, H. Mamur, İ. Polatoğlu, and H. Sözen. "A new hybrid approach in choosing the best place to establish the biogas energy production plant," Biomass Conv. Bioref, 2021. https://doi.org/10.1007/s13399-021-01532-8