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Optimizing Glass to Metal Composite Seal Performance: An integrated Approach with Artificial Neural Network, Multiple Regression, and Taguchi

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Abstract

Composite materials, particularly glass to metal composites, are critical components in solar receiver tubes, where vacuum leakage can significantly compromise the efficiency of solar plants. This research addresses the technical barriers associated with the development of durable and high-quality glass to metal composite seals. We investigate the principles that can enhance the physical and chemical properties of these composite seals, focusing on the incorporation of TiO_2 and MgO nanoparticles into boro-silicate glasses with a minor B_2O_3 content. The transition from muffle furnaces to induction furnaces has markedly improved the controllability of the sealing and peroxidation processes, resulting in a substantial reduction in both pre-oxidation and sealing times. The integration of nanomaterials and modifications to the B_2O_3 composition have led to a significant enhancement in shear strength of the composite seals. Furthermore, the vacuum leak rates have been reduced to ultra-high vacuum levels, demonstrating the effectiveness of the optimized sealing parameters. Key factors such as surface wettability were refined through adjustments in surface roughness, contact angle, and spreading area. The optimization of strength and leak rates for glass to metal composite joints was achieved by systematically varying input parameters, including material composition, oxidation time, temperature, and the ratios of B_2O_3, TiO_2, and MgO nanomaterials. A comprehensive dataset was generated using a design of experiments approach, specifically the Taguchi L_{32} method, and the experimental outcomes were analyzed through multiple prediction techniques, including Multiple Regression and Artificial Neural Networks (ANN). The results were subsequently ranked based on precision and error, providing a robust framework for future advancements in glass to metal composite sealing technologies.

Keywords: Composite materials, Glass Metal joints, Nanomaterials, Artificial neural network, Taguchi method, Multiple regression

INTRODUCTION

With the increase in demand over supply for the renewable energy, research into solar energy harnessing techniques has increased, particularly about concentrated solar power (CSP) plants [1,2]. In any CSP plant, parabolic trough receiver tubes (PTRTs) has a very important role, which is made up of a metalic pipe with selective coating over it and this pipe is surrounded by a glass tube which have high vacuum [3,4]. However, fabricating PTRTs presents challenges in enhancing durability, maintaining vacuum conditions, and joining dissimilar materials like glass and metal due to their differing coefficients of thermal expansion (CTE). The chemical and physical properties of borosilicate glass and metals like AISI304, AISI202, and Kovar alloy make direct jointing a complex task as

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depicted from Table 1. To ensure optimal performance and longevity of PTRTs, it is essential to achieve a robust, dependable, and vacuum-sealed glass-metal joint. Enhancing wettability property of glass on the metal surface is crucial for obtaining a good quality joint [5,6].

It is important to perform pre-oxidation on the metal surface as it increases wettability as well as improves the joint strength between metal and glass components. The researchers have investigated the wettability of Kovar alloy as a borosilicate glass over which the degradation of pre-oxidation occurs with a relationship to temperature and time duration aimed at an optimal oxide layer thickness. Many researchers advocated a significant improvement in terms of wettability of Kovar surface just after a proper pre-oxidation, such that a temperature of 700°C for almost 10 min to be sufficient to improve bonding and wettability [14-18].

The surface roughness affects the oxidation depth which is important in determining the wettability of the glass to metal joints during the glass to metal composite sealing processes. While smooth surfaces enable the free movement of the melted glass over a broad area, rough surfaces better contain the molten glass [14,19,20]. The contact angle and spreading diameter can be used to measure the wettability where the contact is made at the circumferential boundary of the assembled glass-metal joint [16,21-23].

Various studies and analyses have reported use of image capturing devices for such purposes. The main oxides of borosilicate glass are silica, boric oxide, sodium oxide, potassium oxide and aluminum oxide with the possibility of its properties enhancement with variation in composition or TiO_2 and MgO nanomaterials [23,24-35]. Numerous variations have been attempted with the emphasis of reducing the leak rate as well as ensuring better mechanical strength of the composites.

Mixing borosilicate glass with TiO_2 and MgO nanoparticles advances the chemical durability, mechanical strength, and wear and scratch resistance. The refractive index of TiO_2 increases, which is important for optical elements such as PTRTs, because it decreases the volume of glassy microphase and the thermal expansion coefficient [24,26,30,34]. Furthermore, the glass improves its use as a UV filter, which protects the thin film coating on a metal tube. As for MgO, in low quantities, it would increase glass strength and its chemical durability in alkaline environments, however greater amounts are likely to disrupt the structure and lower the strength [25,26,36-40].

Based on the literature review, this study focuses on optimizing the joining process which enables cost efficiency and provides high quality glass-metal seals which are required in PTRTs. Taguchi's method was used for optimizing the process parameters such as pre- oxidation time, temperature, surface roughness, quantity of B_2O_3 and various quantities of nanomaterial TiO_2 and MgO. After analyzing various analysis techniques from Table 2, the experimental results were used into the different prediction techniques viz multiple regression and artificial neural network (ANN). These techniques were closely analysed for various input factors and also ranked on the basis of their generated error.

Table 1. Thermochemical Properties of Borosilicate Glass, Kovar Alloy, AISI 304 and AISI 202 [7-13].

Material	Poisson's Ratio	CTE (10^{-6}/K)	Density (g/cm^3)	Softening Temperature (°C)	Melting Point (°C)	Yield Stress (MPa)	Tensile Strength (MPa)
Borosilicate Glass	0.2	3.3-5	2.28	650-800	1050-1350	35-120	280
Kovar Alloy	0.37	5.86-11.26	8.36	450-900	1450	340	517
AISI 304	0.29	17.2-18.4	8	850-1050	1400-1455	215	505
AISI 202	0.27-0.30	17.5	7.86	950-1200	1400-1450	275	515

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Table 2. Comparison of Optimization Techniques for Experimental Data Analysis.

Optimization Technique	Pros	Cons	Limitations	Accuracy Rate	Reference
Taguchi Method	Robust design, fewer experiments, easy to understand	Requires prior knowledge of control factors, assumes orthogonality of factors	May not be suitable for complex systems with interactions	Moderate	[41]
ANOVA	Statistical significance testing, identifies main and interaction effects	Assumes normality and homoscedasticity of residuals, sensitive to outliers	Can be computationally intensive for large datasets	High	[42]
Multiple Regression	Predicts a continuous response based on multiple predictors, flexibility	Requires linearity and independence of predictors, sensitive to multicollinearity	Depends on quality of data and model assumptions	High	[43]
Artificial Neural Network (ANN)	Nonlinear modeling, handles complex relationships, adaptive	Requires large datasets, can be computationally expensive, black-box nature	Depends on network architecture and training data	High	[44]
Genetic Algorithm (GA)	Global optimization, handles discrete and continuous variables, robust	Can be computationally expensive, susceptible to premature convergence	Depends on parameter settings and representation	High	[45]
Response Surface Methodology (RSM)	Identifies optimal parameter settings, explores relationships	Requires a quadratic model, assumes normality and homoscedasticity	Can be sensitive to model assumptions	High	[46]

MATERIALS AND METHODS

Composite materials have emerged as pivotal components in various engineering applications due to their superior mechanical properties and versatility. This experimental study investigates the fabrication and characterization of composite materials utilizing different grades of metal and glass powder as primary raw materials. Specifically, metal samples were prepared from AISI 304 and AISI 202 sheets, each with a thickness of 2 mm, which were meticulously cut into 25 mm x 25 mm specimens using a precision laser cutting machine. The surface toughness of these metallic composites was enhanced through the application of various grades of emery, with surface roughness quantified using a surface roughness tester, yielding averaged values across multiple samples.

In the context of composite fabrication, borosilicate glass powder was prepared by collecting broken pieces of borosilicate glass, which were subsequently cleaned, crushed, finely ground, and sieved to achieve the desired particle size distribution. The resultant glass powder was stored in an airtight container within a desiccator to mitigate contamination risks, thereby ensuring the integrity of the composite materials. To further explore the influence of compositional variations, additional samples incorporating different Borax powder compositions, as well as TiO_2 and MgO nanoparticles, were synthesized.

The experimental design employed the Taguchi method, specifically selecting the L_{32} orthogonal array based on predetermined input factors and levels, which is instrumental in optimizing the composite material properties. Data analysis was facilitated using Minitab software, allowing for a comprehensive evaluation of the effects of various parameters on the performance of the developed composites. This study aims to contribute to the growing body of knowledge surrounding composite materials, particularly in the context of their mechanical and physical properties, which are critical for their application in advanced engineering fields.

The experiments involved pre-oxidation on metal surfaces using an induction furnace setup. The setup included a SP-15A high-frequency induction heater, cooling circuit, temperature monitoring using K-type thermocouples and an IR thermometer, and a data logger for time data collection as indicated in Figure 1. The equipment was arranged according to a schematic diagram, with an induction coil, robust platform, and refractory material for specimens. Clean metal samples were placed inside the induction coil, and various samples of AISI 303 and AISI 202 were heated at different temperatures and timings to achieve different thicknesses of oxide layer formation. The chemical nature of the oxide formation was also studied through scanning electron microscopy (SEM) tests. The final pre-oxidized samples were marked and stored in a desiccator for further action.

The study focuses on the preparation of borosilicate powder with TiO_2, MgO nanomaterials, and B_2O_3 using a precision weighing machine. Different proportions of these nanomaterials were mixed with the glass powder, following the Taguchi L_{32} design of the experiment. Air tight sashes were prepared for identification. Pallets were made from the glass powder using a hand press die set, with a prescribed amount of TiO_2 and MgO nanoparticles and different B_2O_3 ratios selected based on the Taguchi and L_{32} model. Vinyl alcohol was used as a binder, which was then heated in a muffle furnace to remove the glass powder. All pallets were properly tagged and placed in a container.

The experiments were focused on the fabrication of glass to metal composite seals using induction heating. The process involved careful placement of specimens and glass pallets, monitoring temperature and time. Experiments were conducted in a muffle furnace and then in an induction furnace. A total of 32 samples were prepared for the sharing test, and the top three samples with the highest shearing strength were used for the vacuum test. Cylindrical metal specimens of AISI 304 were prepared, and the glass powder samples were sealed inside the specimens using the induction furnace and kept in a desiccator until the vacuum test performance.

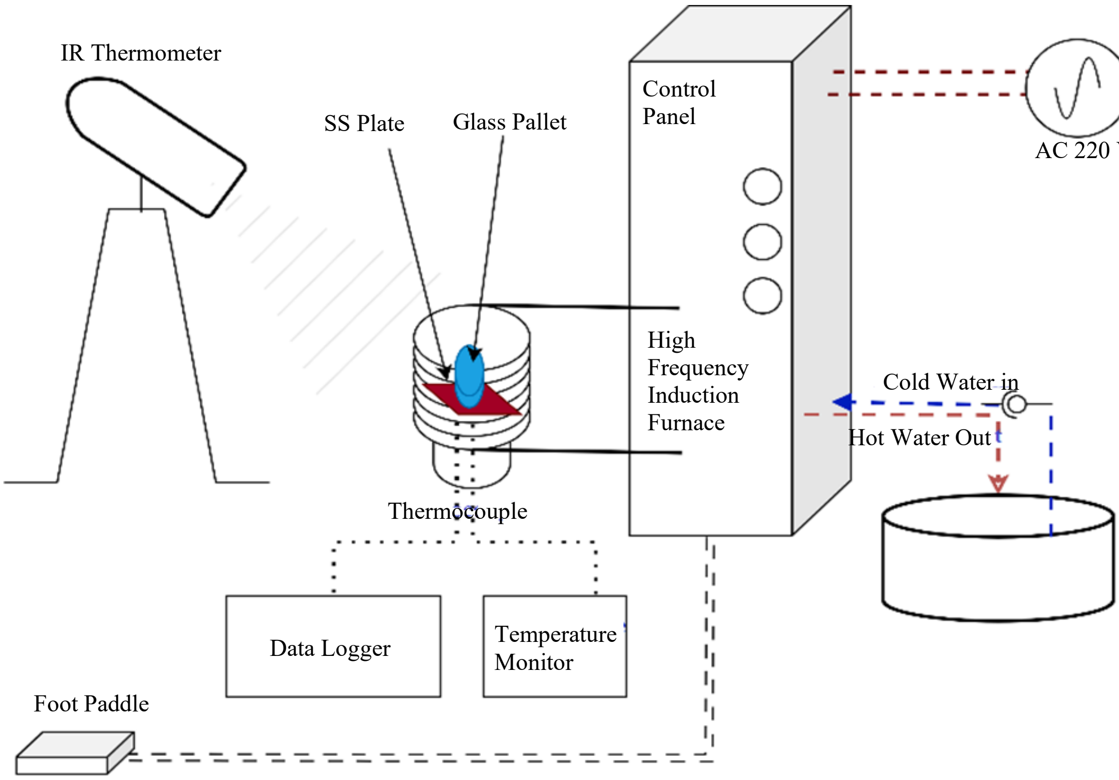

Figure 1. Schematic diagram of the experimental setup.

The vacuum test sample and setup preparation were crucial for the life of PTRTs and selective coatings. Cylindrical metal tubes were prepared and sealed with selected glass compositions. A vacuum-based apparatus was employed to determine the leakage rate of the sealing components. Three tests were conducted on each sample, and the mean of the results was recorded.

RESULTS AND DISCUSSION

Taguchi method was adopted to determine DoE and S/N ratios to optimally control the process parameters. Taguchi methods provided a robust structure for conducting experiments and resulted in better understanding of performance [47]. Furthermore, Multiple Regression and ANN were utilized in the analysis to improve it further whereby regression provided a statistical means of establishing the relationship between parameters and ANN provided a model that can learn complicated non-linear relationships within the data. These methods gave a detailed, multi-faceted perspective of the experimental results.

Taguchi Analysis

Taguchi analysis is a statistical method defined for the enhancement of the quality and the performance of the products or processes. Specifically, it aims at reducing the variation due to noise factors – those variables over which control cannot be exercised. In this respect, Taguchi analysis performs as a tool for enhancing the level of product quality by providing means for the efficient design of experiments and understanding the level of optimal parameters for products and processes to be achieved.

Design of Experiments

Design of experiments (DoE) is a structured approach to solving engineering problems, utilizing various principles to ensure reliable results. Key principles include randomization of samples, replication of samples, blocking, orthogonality approach, and factorial experimentation. While DoE aims to optimize outcomes with minimal data, otherwise it can be a highly time-consuming as well as resource-intensive [48,49].

Various factors influence processes, and glass to metal composite seals are no exception. Their performance and durability depend on design parameters such as pre-oxidation time, temperature, surface roughness, and the amount of B_2O_3, TiO_2, and MgO. Additionally, factors like base material, atmospheric conditions, the presence of noble gasses, and ambient temperature impact the quality and longevity of these seals.

Taguchi Method

Traditional experimental methods for determining operating parameters can be costly and time-consuming, particularly when dealing with numerous variables. The proliferation of parameters often necessitates increased trials, exacerbating these challenges. In such scenarios, mathematical models offer a more efficient and effective approach. Taguchi methods, in particular, excel at optimizing outcomes while minimizing the required number of experiments.

Taguchi's approach ensures that the process output (Y) not only meets specifications but also remains centered around the target value. This is grounded in the principle that any deviation from the target, even within acceptable limits, leads to a loss. The magnitude of the loss is directly correlated with the extent of the deviation.

Beyond conventional Design of Experiments (DoE) factors, Taguchi incorporates noise factors into the modeling process. This holistic approach contributes to the development of more robust models with reduced variability in output.

Taguchi's methodology leverages orthogonal arrays, which are fundamentally influenced by degrees of freedom.

Following illustration Eq. 1, shows the calculation of Degree of freedom

$$D.O.F. = 1 + \sum_{i=1}^{N} V(L_i - 1) \tag{1}$$

Where,
N = Number of independent variables
V is Variance
L_i is Levels
D.O.F. is the Degree of Freedom

Rather than altering single factor at one time, all the variables can systematically modified simultaneously in accordance with the experimental design. The resulting responses are then observed and analyzed. Table 3 provides a detailed list of input parameters and their corresponding levels.

The S/N ratio, signal to noise ratio, is a metric that evaluates the relationship between desired output and variability. It incorporates both average and variance considerations, effectively quantifying the efficiency of energy utilization for the intended function [49,50].

Three distinct scenarios arise in optimization problems:-
Larger-the-better (LTB): Maximizing the desired output.

$$\frac{S}{NR}(LTB) = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y^2}\right) \tag{2}$$

Smaller-the-better (STB): Minimizing the desired output.

$$\frac{S}{NR}(STB) = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \tag{3}$$

Nominal-the-better (NTB): Identifying the optimal value within specified upper and lower limits.

$$\frac{S}{NR}(NTB) = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}(y_i - T)^2\right) \tag{4}$$

Equations (2), (3), and (4) further elucidate these criteria.

Here, Y represents the experimental outcomes for a specific combination of factor levels. The variable "n" denotes the quantity of responses within this factor level combination. Additionally, "s" signifies the standard deviation of the responses across all noise factors associated with that particular factor level combination.

The "larger-the-better" criterion is applicable to seal strength, as our objective is to maximize its value. Conversely, the "smaller-the-better" criterion is suitable for leak rate and contact angle, as we aim to minimize these parameters.

Table 3. L_{32} orthogonal array Mixed 2 - 4 Level Design having 1 factor with 2 levels and 5 factors with 4 levels.

Parameters	**Material (A)**	**Oxidation Temp (°C) (B)**	**Holding Time (Min) (C)**	**B_2O_3 (wt%) (D)**	**TiO_2 (wt%) Nanoparticles (E)**	**MgO (wt%) Nanoparticles (F)**
Level 1	AISI-202	500	10	4	0.5	0.2
Level 2	AISI-304	600	20	6	1.0	0.4
Level 3	-	700	30	8	1.5	0.6
Level 4	-	800	40	10	2.0	0.8

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For the current analysis, Minitab program. was used and Table 4 presents the actual responses measured.

Analysis of Signal to Noise, S/N Ratios

Signal-to-noise ratio (SNR) plots were generated for each of the six response variables. The optimal parameter setting is determined by identifying the plot with the maximum mean SNR value. These plots are visually represented in Figure 2.

The optimized parameters derived from the previous analysis were subsequently employed in further investigations utilizing multiple regression and artificial neural networks (ANN) models [51]. These advanced techniques provide a valuable information about the relationships holding between the variables and their impact on the overall response.

Table 4. L_{32} Orthogonal array test response datasheet.

Sample No.	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16
Strength (Mpa)	5.9	6.6	7.4	6.9	12.1	12.9	14.1	14.3	18.1	16.8	17.9	17.4	16.5	16.8	17.4	17.2
Sample No.	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30	S31	S32
Strength (Mpa)	22.2	23.5	25.2	24.8	26.1	26.9	28.3	28.4	30.2	29.8	30.4	30.1	27.8	28.3	28.1	27.8

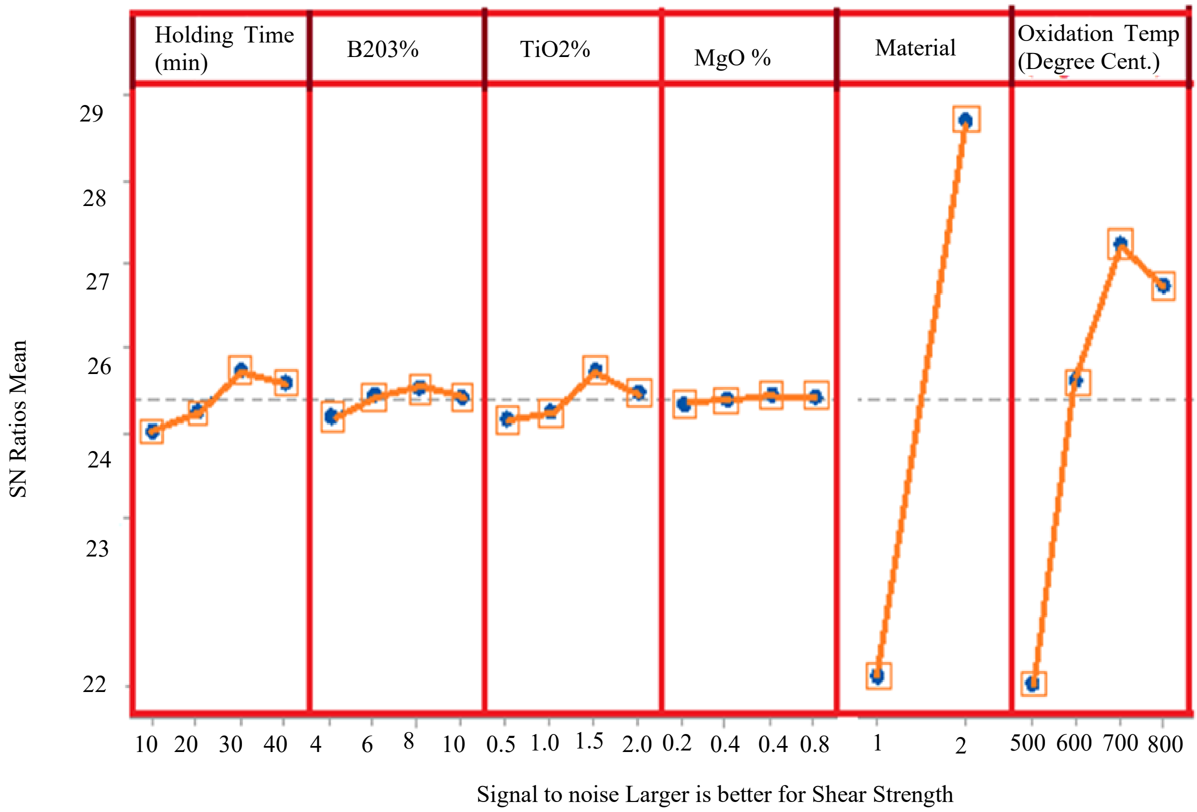

Figure 2. S/N curves of Strength vs holding time, percentage composition of B2O3, TiO2 and MgO, material, and oxidation time.

The incorporation of TiO_2 and MgO nanoparticles significantly improved the mechanical properties of the glass-to-metal composite seals, particularly in terms of shear strength and chemical durability. The study found that the TiO_2 nanoparticles had a substantial positive impact on seal strength. The Main Effects Plot for S/N ratios (Figure 2) shows a clear upward trend for TiO_2 concentration, with 1.5% showing the highest S/N ratio. This indicates that higher TiO_2 concentrations significantly improve seal strength. MgO nanoparticles, when added in low quantities, increased glass strength and chemical durability, particularly in alkaline environments. The study achieved a maximum strength of 30.4 MPa for the glass-to-metal seals with the use of nanomaterials, which is a significant improvement.

Regarding trade-offs, the study noted that thee MgO improved strength in low quantities, whereas higher amounts could potentially disrupt the structure and lower the strength. The optimal concentrations were found to be 1.5% for TiO_2 and around 0.6% for MgO, suggesting that there's a balance to be struck in the incorporation of these nanoparticles.

Overall, the incorporation of these nanoparticles was highly effective in improving mechanical properties, with the main trade-off being the need to carefully control the concentrations, particularly for MgO, to avoid potential negative effects at higher levels.

Multiple regression analysis

Regression analysis establishes a mathematical relationship connecting dependent and independent variables [52]. In multiple regression, the dependent variables are expressed as a function of multiple independent variables, as illustrated in Eq. 5 [49]

$$Z = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + ... + a_nx_n \tag{5}$$

Where,

Z is the dependent variable

a_0 to a_n are the equation parameters representing the linear relationship

x_1 to x_n are the independent variables

The coefficient of determination (R^2) serves as a measure of how well the linear model fits the observed data. A higher R^2 value indicates a better fit.

Data Analysis

Taguchi statistical liner regression has conducted with IBM STATISTICS 25 which helped us in formulating the relationship inbetween the various dependent and independent variables. Following result has been formulated form the linear regression model Eq. 6 having input variables in terms of material, oxidation temp (°C), holding time (Min), B_2O_3 (wt%), TiO_2 Nanoparticles (wt%),, MgO Nanoparticles (wt%) and output as strength (MPa).

$$\text{Strength (MPa)} = -17.53 + (13.725)\text{Material} + (0.02497)\text{Oxidation Temp} + (0.0390)\text{Holding Time} - (0.014)B_2O_3\% + (0.470)TiO_2\% - (0.51)MgO\% \tag{6}$$

With the percentage error of approximately 6.44, it is clearly visible from the given Eq. 6, that the most significant parameter for a better strength is material, followed by the percentage of TiO_2%. Graphical representation of fitted linear curve for strength is depicted in Figure 3.

The Regression Eq. **7** based on Anova is shown below, which clearly shows the interaction between various input parameters to affect the output strength. Value of R Square is approximately 98.8% which can be considered as a good model.

$$\text{Strength (MPa)} = 20.506 - 6.863\ \text{Material\_1} + 6.863\ \text{Material\_2} - 5.194\ \text{Oxidation Temp (°C)\_500} - 0.119\ \text{Oxidation Temp (°C)\_600} + 3.331\ \text{Oxidation Temp (°C)\_700} + 1.981\ \text{Oxidation Temp (°C)\_800} - 0.644\ \text{Holding Time (Min)\_10} - 0.306\ \text{Holding Time (Min)\_20} + 0.594\ \text{Holding Time (Min)\_30} + 0.356\ \text{Holding Time (Min)\_40} - 0.094\ B_2O_3\text{\%\_4} + 0.181\ B_2O_3\text{\%\_6} + 0.056\ B_2O_3\text{\%\_8} - 0.144\ B_2O_3\text{\%\_10} - 0.356\ TiO_2\text{\%\_0.5} - 0.344\ TiO_2\text{\%\_1.0} + 0.581\ TiO_2\text{\%\_1.5} + 0.119\ TiO_2\text{\%\_2.0} + 0.144\ \text{MgO\%\_0.2} + 0.119\ \text{MgO\%\_0.4} - 0.156\ \text{MgO\%\_0.6} - 0.106\ \text{MgO\%\_0.8} \quad (7)$$

Artificial Neural Networks (ANN)

Research has demonstrated that ANNs can outperform multiple regression models in predicting weld strength and other mechanical properties. For instance, Elangovan and Rathinasuriyan found that their developed ANN model for ultrasonic metal welding provided more accurate predictions of weld strength compared to a multiple regression analysis model, highlighting the ANN's superior capability in handling complex data relationships [53]. Similarly, Mishra's study on friction stir welded joints reported significantly lower Root Mean Square Errors (RMSE) for ANN models compared to Decision Tree regression models, further supporting the assertion that ANNs yield better accuracy in mechanical property predictions [54].

In the realm of adhesive joints, Güneyisi et al. emphasized the advantages of using neural networks for assessing shear capacity, noting that these models not only simplify implementation but also enhance accuracy compared to conventional numerical methods [55]. This is particularly relevant for glass to metal joints, where the bonding behavior is influenced by various factors, including material properties and joint geometry. The complexity of these interactions often leads to challenges in establishing reliable predictive models using traditional regression techniques. The work of Shen et al. on the shear strength of glass to metal brazed joints illustrates the potential of ANNs in optimizing joint performance by analyzing the effects of various parameters on joint strength [56].

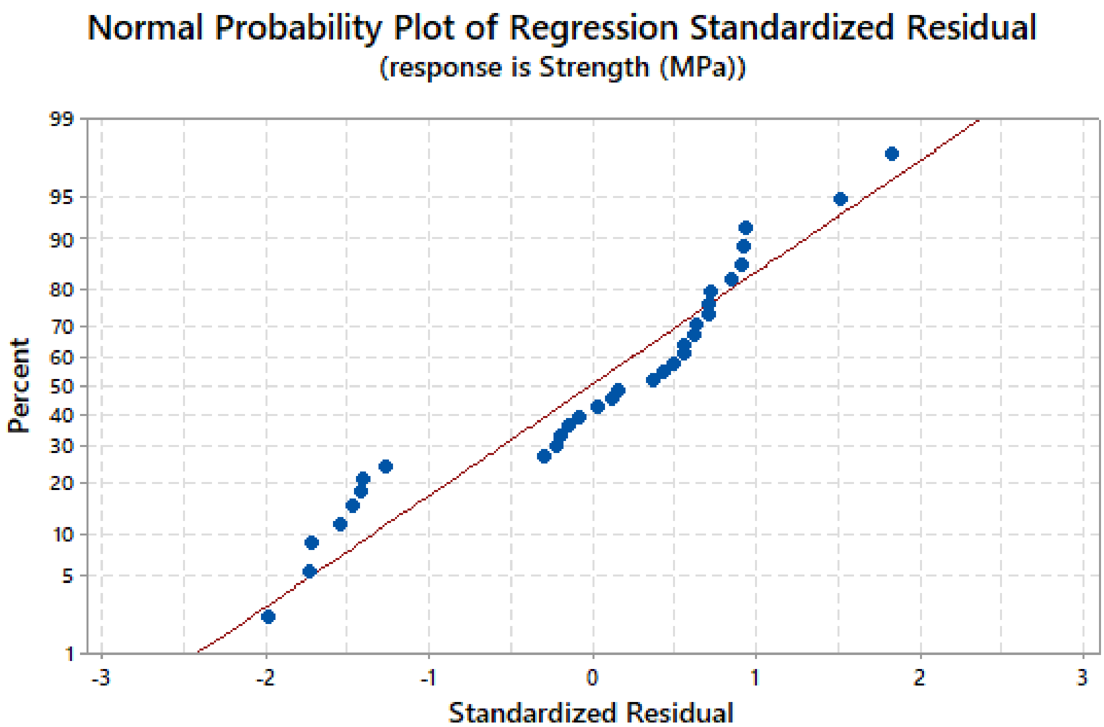

Figure 3. Curve fitting for Strength.

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, consisting of interconnected processing units or neurons organized in layers. Typically, an ANN comprises an input layer, one or more hidden layers, and an output layer, allowing it to learn complex patterns and relationships within data as depicted in Fig. 4. The performance of an ANN is often evaluated using metrics such as Mean Squared Error (MSE), R-squared (R^2), and percentage error. MSE quantifies the average squared difference between predicted and actual values, providing insight into the model's accuracy; lower MSE values indicate better performance [57]. R^2 measures the proportion of variance in the dependent variable that can be explained by the independent variables in the model, with values closer to 1 indicating a better fit [58]. Additionally, percentage error is used to express the accuracy of predictions relative to the actual values, facilitating a clearer understanding of the model's performance [59]. The architecture of ANNs can vary significantly, with the number of layers and neurons in each layer being crucial for their predictive capabilities. For instance, a three-layer structure may include several neurons in the hidden layer to capture intricate relationships in the data [60]. The flexibility and adaptability of ANNs make them suitable for a wide range of applications, from predicting material properties to modeling complex environmental systems [57,61].

Procedure for adopting ANN

The adoption of Artificial Neural Networks (ANNs) for predicting the strength of glass to metal joints involves a systematic procedure that includes several key steps [62]. Initially, the selection of input variables is crucial; in this study, the input variables included materials, oxidation temperature, holding time, and the percentages of B_2O_3, TiO_2, and MgO corresponding to 6 neurons in the input layer.. These variables were chosen based on their known influence on joint strength, allowing the model to capture the complex relationships as shown in Eq. 8 inherent in the data. The output variable for the ANN was the strength of the joint, measured in megapascals (MPa).

yj=11+eVJ (8)

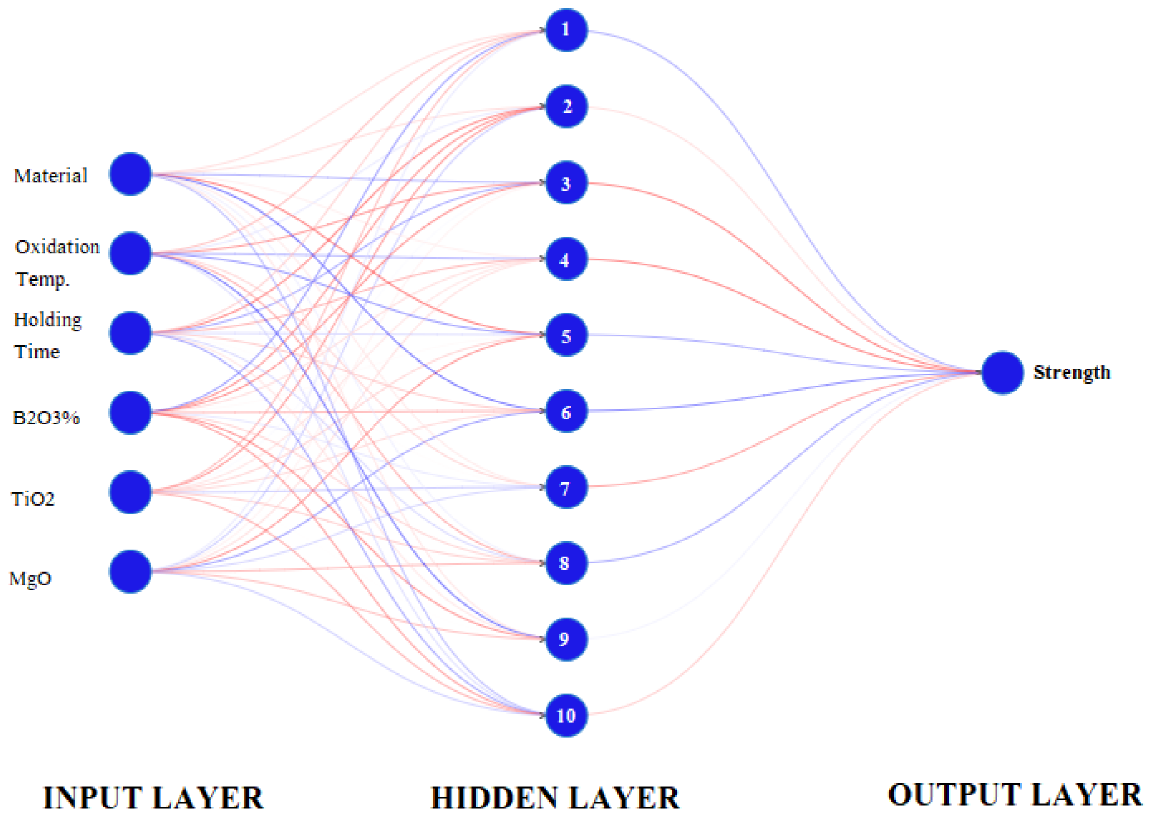

Figure 4. Schematic illustration of Artificial Neural Network structure used.

Where,
v_j - Net internal activity of neuron j
Y_j - Output of the neuron

The next step involves data preparation, where a dataset of 32 samples was generated using the Taguchi L_{32} experimental design method. This design is particularly effective for optimizing processes with multiple factors and levels, ensuring a comprehensive representation of the input space. Once the data is prepared, it is divided into training and testing sets to evaluate the model's performance.

The ANN was implemented using MATLAB R2024b, which provides robust tools for building and training neural networks. The architecture of the ANN consisted of an input layer corresponding to the six input variables, one hidden layer to enhance the model's capacity to learn complex patterns, and an output layer representing the predicted strength (Parapuram et al., 2018). The training process involved adjusting the synaptic weights of the network through Levenberg-Marquardt backpropagation, a method that minimizes the error between the predicted and actual output by iteratively updating the weights based on the gradient of the loss function [63-65].

The input data is stored in workspace of the MATLAB R2024b and ANNs can directly use it in their framework after scaling to (0, 1) range. The input data is economically normalized by means of the following Eq. 9:

$$X_n = (X_i - X_{min}) / (X_{max} - X_{min}) \tag{9}$$

where:
X_n is a normalized data
X_i is a data to be normalized
X_{min} is a data with minimum value of the input parameter
X_{max} is a data with maximum value of the input parameter

Performance metrics such as R-squared (R^2) and Mean Squared Error (MSE) were utilized to assess the model's accuracy as illustrated in Eq. 10. MSE quantifies the average squared difference between the predicted and actual values, whereas R^2 indicates the proportion of variance explained by the model (Abyaneh, 2014). By analyzing these metrics, the effectiveness of the ANN in predicting joint strength can be evaluated, allowing for further refinement of the model if necessary.

MSE = 1/Ni=1N(yi-yk)2 (10)

Where,
y_i Predicts the value of the i^{th} pattern
y_k predict the Target value of the i^{th} pattern
N is tghe Number of patterns

The input data is stored in workspace of the MATLAB R2024b and ANNs can directly use it in their framework after scaling to (0, 1) range. The input data is economically normalized by means of the following equation:

Analysis of ANN Results

The ANN model was tested for the input factors such as materials, oxidation temperature, holding time, B_2O_3%, TiO_2% (nanomaterial) and MgO% (nanomaterial). The corresponding graphs depict mean squared error and correlation cofficient regression graph, which are also calculated with the help Table 4. The error plot for strength is presented in Figure 5 showing that the error distribution appears to be roughly symmetrical around zero, indicating that the model's predictions are generally centered around the true values. The errors are spread across a range of values, suggesting that the model's performance varies across different data points.

On the graph, there are few points also showing the larger errors, which might be due to outliers of the experimental results. The vertical line at zero represents perfect predictions hence the histogram shows that a significant number of predictions have zero error.

On the analysis of regression analysis, it is observed that the regression coefficients that describe correlational relationships between the network responses and the various corresponding targets are 0.9877, 0.9756, 0.8725 and 0.9772 for training, testing, validation and all respectively.

To enhance the accuracy of model and network speed, the S/N values which are obtained from Taguchi methods were used for the purpose of ANN training model. The value of coefficient between linear regression and modificed ANN comes 0.9247 through the data presented in Table 4 by using the Eq. 2, which shows a very close relationship between expected and predicted outputs. The error calculated with the modified ANN where the output predicted data of strength was used in the training of ANN model. Due to the denser distribution of the values on the fitness line in the training dataset, a better correlation was achieved. For the strength of glass to metal composite seal, ANN predictions have good statistical performance. The error through the multiple regression model was found around 6.88 where as it drastically decreased to 0.753 which is significantly low. Hence the ANN predicated results in contrast of multiple regression are superior and closer to the experimental results

Correlation Coefficient r is calculated with the Eq. 11

$$r = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}} \tag{11}$$

The correlation coefficient r, have the following values
Experimental Results vs. Regression Analysis: 0.9288
Experimental Results vs. ANN Results: 0.9539
Experimental Results vs. Modified ANN Results: 0.9772

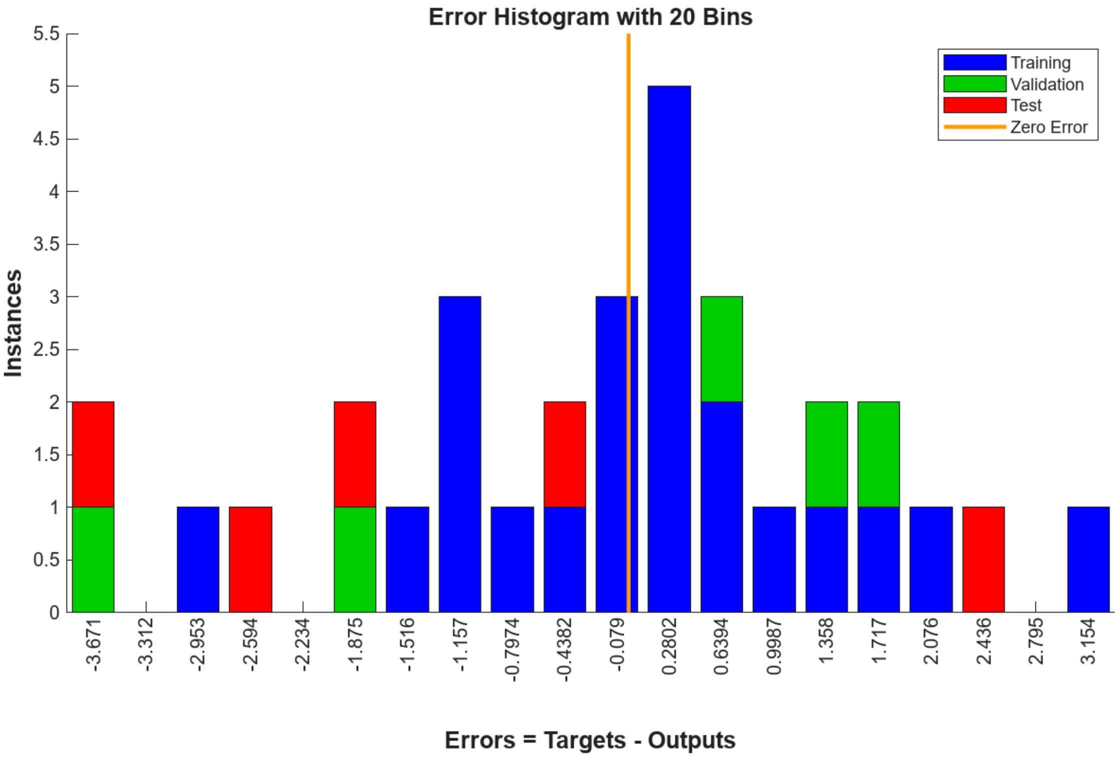

Figure 5. Error Histogram plot of strength.

All three models show an extremely strong positive correlation with the experimental results. Regression Analysis achieves a high correlation with the experimental results whereas the modified ANN shows a slightly higher correlation than the standard ANN, indicating that using the regression analysis output as input for the ANN model with multiple trainings might lead to a marginal improvement in prediction accuracy.

Based on all three analysis in the paper, the Artificial Neural Network (ANN) technique outperformed the Taguchi method and Multiple Regression in terms of accuracy and precision for predicting optimal parameters to minimize vacuum leak rates and maximize strength. Here's a detailed comparison:

- *Taguchi Method:* The Taguchi method was primarily used for designing the experiments and initial optimization. It provided a robust structure for conducting experiments and resulted in a better understanding of performance. However, it was not the primary predictive tool in this study.
- *Multiple Regression:* Multiple regression was used as a predictive technique, but it showed limitations in accuracy. The error through the multiple regression model was found to be around 6.88%.
- *Artificial Neural Network (ANN):* The ANN model demonstrated superior performance in predicting the optimal parameters:
  a) The error for the ANN model drastically decreased to 0.753%, which is significantly lower than the multiple regression model.
  b) The correlation coefficient (r) values show that the ANN models had a stronger correlation with experimental results compared to regression analysis:
     - Experimental Results vs. Regression Analysis: 0.9288
     - Experimental Results vs. ANN Results: 0.9539
     - Experimental Results vs. Modified ANN Results: 0.9772
  c) The regression coefficients for the ANN model were high, indicating strong predictive capability:
     - Training: 0.9877
     - Testing: 0.9756
     - Validation: 0.8725
     - Overall: 0.9772

The Taguchi method was useful in designing the experiments; however, the ANN model yielded more accurate predictions of optimal parameters than both Taguchi and multiple regression methods. With its greater accuracy, lower prediction errors, and stronger alignment with experimental outcomes, the ANN model proved to be a more reliable method for forecasting optimal conditions to reduce vacuum leaks and improve the integrity of glass-to-metal seals..

CONCLUSION

Composite materials have increasingly benefited from the application of Artificial Neural Networks (ANNs), which have demonstrated superior predictive capabilities compared to traditional multiple regression methods, particularly in the context of bonding in glass and ceramic composites. The inherent complexity and nonlinear relationships that characterize bonding processes in composite materials are effectively modeled by ANNs, which can account for various interdependent factors influencing bond strength [66].

For instance, studies have shown that ANN models can accurately predict bond strength in adhesive joints within composite structures, significantly reducing the number of empirical experiments required while enhancing the accuracy of predictions compared to conventional regression methods. This capability is particularly advantageous in the development and optimization of composite materials, where understanding the bonding characteristics is crucial for performance and durability [67,68].

Moreover, the integration of ANNs with other optimization techniques, such as genetic algorithms, has been shown to improve the reliability of anchorage assessments in glass fiber-reinforced polymer composites. This highlights the robustness of ANN methodologies in addressing the complexities associated with bonding scenarios in composite applications. The adaptability of ANNs allows them to refine their predictive models based on new data, making them a dynamic tool for engineers and researchers focused on the advancement of composite materials [69,70].

Research further indicates that ANN models consistently outperform traditional statistical approaches in predicting mechanical properties and bonding quality within various composite materials. This is evidenced by their successful application across multiple materials science contexts, where the unique characteristics of composites necessitate advanced modeling techniques. The findings underscore the significant advantages of employing ANNs in the analysis of composite bonding, particularly in scenarios where traditional methods may fall short.

Using the Taguchi method in this experimental work, optimum parameters for glass to metal composite seal were determined and later used in ANN & multiple regressions. 32 experimental runs have been performed based on Taguchi, DoE with L32 orthogonal array. Input parameters were material, oxidation temperature (°C), holding time (Min), B_2O_3 (wt%), TiO_2 Nanoparticles (wt%),, MgO Nanoparticles (wt%) and output as strength (MPa). The maximum errors, as per the regression analysis, were observed at 700°C with holding time of 30 minutes in muffle furnace while using material AISI304 and proportions of 4.0%, 0.50% and 0.60% wt% for B_2O_3, TiO_2 Nanoparticles, and MgO Nanoparticles respectively. However, the percent error of strength for the regression model was appreciably large when compared to ANN, that shows an targeted highly for training (R-value= 0.9877), validation (R-value= 0.9756), and testing (R-value= 0.8725). These values could be related to a total response of R-value=0.9772. Thus, it can be stated that ANN is a more effective technique in predicting the glass to metal composite seal parameters. Most optimal working conditions were also realized using the Taguchi method, which focused on the performance factors, which in turn considerably reduces the number of experiments carried out. All the parameters were ranked on the basis of their weightage in providing the strength. Material, Temperature and holding time are the top three where as it is clearly visible that the role of TiO_2 plays a crutial role in providing the strength. Presence of MgO and B_2O_3 seems a low impact on the high strength of glass to metal composite seal. Consequently, in this particular set of experiments, a maximum strength of 30.4MPa was obtained for the glass to metal composite seals with the use of nanomaterials.

The transition from muffle furnaces to induction furnaces for the pre-oxidation process could significantly impact the scalability of producing glass-metal composite seals in larger industrial applications. Here's an analysis drawing from published research. Induction furnaces offer better temperature control and uniformity compared to muffle furnaces. This enhanced control is crucial for consistent quality in large-scale production of glass-metal seals. Ponton (2017) noted that induction heating provides rapid and precise temperature control, which is essential for optimizing the pre-oxidation process[71]. The induction heating could reduce the pre-oxidation time of metal surfaces by up to 50% compared to conventional heating methods. This time efficiency is key for scaling up production[72]. Induction furnaces are generally more energy-efficient than muffle furnaces, especially for larger-scale operations, which can be up to 80% more energy-efficient than resistance heating methods, which is crucial for industrial-scale applications [73]. Experiments have demonstrated that induction-heated glass-to-metal seals showed improved hermeticity and mechanical strength compared to those produced using conventional heating methods [74]. Induction furnaces also offer greater flexibility in terms of production scale and geometry of parts which makes induction heating suitable for various industrial applications and production scales [75].

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