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Optimization of ZE41 hybrid composite density through an integrated hybrid ANN-GA and RSM models

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Highlights

- An integrated RSM–ANN–GA framework was developed to optimize the theoretical density of ZE41 hybrid composites reinforced with Ti₃SiC₂, NiTi, and GO.
- NiTi exhibited the most significant effect on density, followed by Ti₃SiC₂, while GO showed a negligible contribution.
- RSM identified the optimum composition of 2.5% Ti₃SiC₂ / 2.5% NiTi / 1.0% GO with a predicted density of 1.9054 g/cm³.
- ANN-GA identified the optimum composition of 2.5% Ti₃SiC₂ / 2.5% NiTi / 2.0% GO with a predicted density of 1.90864 g/cm³
- Experimental validation confirmed the reliability of the developed models with errors ranging from 3.00% to 4.44%.

Abstract

The density of magnesium-based hybrid composites has a direct impact on weight efficiency and suitability for lightweight structural applications. However, by stir casting, it is difficult to obtain the desired density due to the complicated interaction among the multiple reinforcement phases, particle distribution, interfacial interaction, and casting-related defects. In this study, an integrated

Response Surface Methodology (RSM), Artificial Neural Network (ANN), and Genetic Algorithm (GA) approach is proposed for optimization of the density of ZE41 hybrid composites incorporated with Ti_3SiC_2 , NiTi, and graphene oxide (GO). The effect of reinforcement weight percentage (wt.%) on the theoretical density was studied based on a Box–Behnken design. RSM was employed to determine the relation between the input variables and theoretical density, and ANN was designed to model nonlinear relationships. The predictive models were then combined with GA to determine the optimal parameter combination. The results showed that NiTi had the most important effect on density ($F = 23,012,890.00$), followed by Ti_3SiC_2 ($F = 15,737,702.50$), while GO had a minimal contribution. The ANN model showed a good predictive performance with $R = 0.97033$ and as low as an MSE of 1.0×10^{-15} . The GA predicted the optimum composition to be 2.5 wt.% Ti_3SiC_2 , 2.5 wt.% NiTi, and 2.0 wt.% GO with a minimum density of 1.9086 g/cm^3 . The experimental verification of the chosen compositions has shown errors from 3.00% to 4.44%, which has confirmed the developed models. The integrated RSM–ANN–GA framework presents an effective methodology for density optimization of ZE41 hybrid composites and provides a systematic replacement of traditional trial-and-error approaches for lightweight structural applications.

Keywords: ZE41 magnesium alloy; hybrid composite; theoretical density; RSM; ANN; GA.

1. Introduction

The increasing demand for lightweight structural materials in automotive, aerospace, transportation, and other engineering applications has led to increased research on magnesium-based alloys and their composites. Magnesium alloys have a low density, which makes them promising substitutes for weight-sensitive applications [1]. The ZE41 magnesium alloy is considered one of the most promising materials due to its relatively good castability, mechanical performance, and structural application potential. However, the performance of monolithic magnesium alloys may not meet the requirements in many engineering [2]. The addition of reinforcement particles can improve this alloy, which is an efficient way to satisfy the necessary application area. The concurrent integration of various reinforcement phases can offer complementary strengthening mechanisms, thus making hybrid metal matrix composites very attractive [3-5]. The reinforcement contents and other processing variables can affect the particle

distribution, density, the wettability, porosity, and final physical properties of the composite [6]. The density of a hybrid composite depends on the relative densities and weight/volume fractions of the reinforcement and matrix phases [7]. For a perfect composite without flaws, the density can be estimated from the rule of mixtures. But the density measured experimentally may differ from the theoretical one because of porosity, agglomeration of particles, incomplete incorporation of the reinforcement, and other effects related to the processing [8].

The hybrid reinforcement can have a profound change on the density of ZE41 magnesium-based hybrid composites due to the different densities of constituent reinforcements [9]. Simultaneous addition of Ti_3SiC_2 , NiTi, and GO as reinforcements may result in a complex change in the composite density, which cannot be explained by the density of the single components [10]. Ti_3SiC_2 and NiTi have higher density than ZE41; hence, the density of the hybrid composite can be increased owing to the addition of their weight fraction [11]. In contrast, graphene oxide (GO) has a very low density and can influence the total density in different ways depending on the amount and distribution of the GO in the matrix. Also, the experimental measurement of density may differ from the theoretical density value due to the influence of reinforcement addition on particle dispersion, wettability, interfacial bonding, agglomeration, and porosity formation during stir casting. In particular, excess reinforcement content can lead to particle clustering and increase the probability of casting defects, which affects the effective density of the composite [12]. Therefore, understanding and optimization of reinforcement fractions and associated processing conditions are important to control the density of ZE41 hybrid composites and to achieve the desired lightweight properties for structural applications, as studied by Dandekar, et al. [13].

The casting fabrication methods have a significant effect on the final density of the ZE41 hybrid composites, as the processing conditions directly affect the dispersion of the reinforcement, the growth of porosity, and the interaction b/n the matrix and reinforcement [14]. The melting temperature, stirring speed, stirring time, reinforcement preheating temperature, and pouring conditions can influence the addition and distribution of reinforcement phases in the molten base materials [15]. According to the study of Menachery, et al. [16], good mixing reveals a homogeneous distribution of the reinforcement particles, enhances the interaction, and improves wetting between the reinforcement. Poor stirring can lead to agglomeration of the particles and uneven distribution of the reinforcements [17]. However, over-stirring could cause increased melt turbulence and gas entrapment and could cause increased porosity and possibly decreased

experimentally measured density [18]. Moreover, wrong melt temperature or lack of preheating of reinforcement can lead to poor wettability and generation of voids around reinforcement particles [19, 20]. Density optimization of ZE41 hybrid composites is important for the practical use of the composites for lightweight structural applications because density directly determines the mass of a component for a given volume and therefore its weight efficiency and specific performance [9]. Reducing the mass of components in automotive, aerospace, transportation, and portable engineering systems can reduce energy consumption and improve fuel economy, increase payload capacity, and reduce material consumption [21]. However, a reduction of the density alone is not necessarily desirable, since too much reduction of the density may be associated with an excess of porosity, a poor incorporation of the reinforcement, or a deterioration of the mechanical and tribological performance [22].

The goal is therefore to achieve a controlled and optimized density while preserving the structural integrity and functional performance of the composite. Achieving such a target by trial-and-error experiments can be costly and time-consuming in industrial production, especially when multiple reinforcement fractions and stir-casting parameters interact with each other. The challenge can be overcome using RSM–ANN–GA optimization methods to identify the most influential parameters, predict the density accurately, and determine the optimum processing conditions efficiently with fewer experimental trials [23, 24]. Hence, density optimization can be a feasible approach to produce lightweight, uniform, and defect-minimized ZE41 hybrid composite parts for industrial-scale production. The use of RSM, ANN, and GA offers a complete and efficient framework for optimization of density of ZE41 hybrid composites [24]. RSM provides a statistically valid approach to experimental design, identification of significant main and interaction effects, development of interpretable mathematical models, and determination of the effect of processing and reinforcement parameters on density using a minimum number of experiments. However, the polynomial nature of RSM may not be able to capture highly non-linear relationships [25, 26]. ANN can overcome this limitation by learning the complex and nonlinear r/s b/n input parameters and density directly from experimental data and providing accurate predictive capability without a pre-defined mathematical relationship. ANN is mainly utilized for prediction purposes and does not provide an efficient way to find the global optimum of process variables [27, 28]. The GA complements the ANN by searching the parameter space globally and finding the combination of reinforcement and processing parameters that meets the specified density objective [29]. So, the

integrated approach combines the statistical RSM model, the nonlinear predictive capability of ANN, and the global optimization ability of GA to present a more reliable and efficient strategy for density optimization than any single technique alone. The combined approach is especially applicable for industrial applications where reduced experimental trials, improved process repeatability, and achievement of optimized material properties are essential for cost-effective and scalable composite manufacturing [30].

Earlier studies have concentrated mainly on the effect of the addition of reinforcement or individual processing parameters on density and other material properties. Limited research has been given to the effect of the combined effect of reinforcement wt.% on experimentally measured density, particularly when theoretical density based on the rule of mixtures and processing-induced effects such as porosity and particle distribution are considered simultaneously. The single use of RSM, ANN, and GAs cannot fully utilize the complementary advantages of statistical analysis, non-linear prediction, and global optimization. The novelty of this study is an integrated RSM–ANN-GA framework for density optimization for fabricating ZE41 hybrid composites using stir casting. The optimized condition is further validated experimentally, resulting in an end-to-end process from experimental design and mechanism-informed analysis to prescriptive modeling and practical process optimization. This integrated approach offers an innovative and effective way for density control and reduction of experimental effort and can be applied to the development of lightweight, consistent, and industrially manufacturable magnesium hybrid composite components.

2. Materials and Methods

2.1 Materials

The ZE41 magnesium alloy was selected as the matrix, while titanium silicon carbide (Ti_3SiC_2), nickel-titanium (NiTi), and GO were used as the reinforcement materials to fabricate the hybrid composites. The materials were selected for their potential to improve the properties of the ZE41 magnesium alloy. The physical properties of the materials are presented in Table 1.

Table 1 Properties of investigated materials

Material	ZE41	Ti_3SiC_2	NiTi	GO
Density	1.84 g/cm ³	4.5 g/cm ³	6.45 g/cm ³	2.2 g/cm ³
Particle size	Ingot	80–120 μm	50–100 μm	0.5–5 μm

The matrix was chosen to be ZE41 owing to its low density, and the selected reinforcements were added to improve the properties of the composite. The images of the matrix and reinforcement materials are shown in Figure 1.



Figure 1 Materials used in the fabrication of ZE41 hybrid composites.

The surface morphology of the materials was analyzed by SEM. SEM images show the particle morphology, surface features, and approximate particle size of selected reinforcement materials. Figure 2 shows the micrographs of the ZE41 matrix and the reinforcements Ti_3SiC_2 , NiTi, and GO.

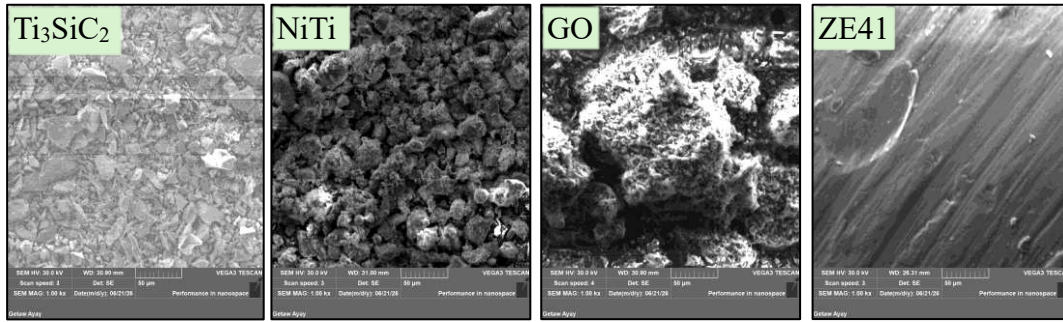


Figure 2 SEM micrographs of the investigated materials.

2.2 Experimental Design

2.2.1 RSM-Based Box–Behnken Design

Input factors and their experimental values were selected based on preliminary experiments and related literature. The chosen factors were the weight fractions of Ti_3SiC_2 , NiTi, and GO, while the remaining fraction was the ZE41 matrix. The levels of each factor used in the Box–Behnken design are presented in Table 2.

Table 2 Input factors and their experimental ranges.

Factor	Lower level	Upper level	Unit
Ti_3SiC_2	2.5	7.5	%
NiTi	2.5	7.5	%
GO	1	3	%
ZE41	82	94	%

The Box–Behnken Design (BBD) is an experimental design based on RSM help to evaluate the main and interaction effects of input factors on a response, and BBD is shown in Table 3.

Table 3 BBD of input factors

No.	Reinforcements			Matrix
	Ti ₃ SiC ₂ (%)	NiTi (%)	GO (%)	ZE41 (%)
1.	7.5	2.5	2	88
2.	2.5	5.0	1	91.5
3.	5.0	5.0	2	88
4.	5.0	5.0	2	88
5.	7.5	5.0	3	84.5
6.	5.0	2.5	3	89.5
7.	5.0	7.5	1	86.5
8.	7.5	7.5	2	83
9.	7.5	5.0	1	86.5
10.	2.5	7.5	2	88
11.	5.0	5.0	2	88
12.	5.0	2.5	1	91.5
13.	5.0	7.5	3	84.5
14.	2.5	5.0	3	89.5
15.	2.5	2.5	2	93

2.2.2 Theoretical Density of composite material

The theoretical density of the ZE41 hybrid composites was determined using the Rule of Mixtures (ROM). Since the reinforcement contents were expressed in weight percentages, the weight fractions were converted into volume fractions based on the density of each constituent material. The volume fraction of each constituent was determined as:

$$V_i = \frac{W_i/\rho_i}{\sum_{j=1}^n W_j/\rho_j} \quad (1)$$

where V_i is the volume fraction, W_i is the weight fraction, and ρ_i is the density of i^{th} constituent.

For the investigated ZE41 hybrid composite, the individual volume fractions were calculated as:

$$V_{ZE41} = \frac{W_{ZE41}/\rho_{ZE41}}{W_{ZE41}/\rho_{ZE41} + W_{Ti_3SiC_2}/\rho_{Ti_3SiC_2} + W_{NiTi}/\rho_{NiTi} + W_{GO}/\rho_{GO}} \quad (2)$$

$$V_{Ti_3SiC_2} = \frac{W_{Ti_3SiC_2}/\rho_{Ti_3SiC_2}}{W_{ZE41}/\rho_{ZE41} + W_{Ti_3SiC_2}/\rho_{Ti_3SiC_2} + W_{NiTi}/\rho_{NiTi} + W_{GO}/\rho_{GO}} \quad (3)$$

$$V_{NiTi} = \frac{W_{NiTi}/\rho_{NiTi}}{W_{ZE41}/\rho_{ZE41} + W_{Ti_3SiC_2}/\rho_{Ti_3SiC_2} + W_{NiTi}/\rho_{NiTi} + W_{GO}/\rho_{GO}} \quad (4)$$

$$V_{GO} = \frac{W_{GO}/\rho_{GO}}{W_{ZE41}/\rho_{ZE41} + W_{Ti_3SiC_2}/\rho_{Ti_3SiC_2} + W_{NiTi}/\rho_{NiTi} + W_{GO}/\rho_{GO}} \quad (5)$$

The calculated volume fractions satisfy:

$$V_{ZE41} + V_{Ti_3SiC_2} + V_{NiTi} + V_{GO} = 1 \quad (6)$$

The theoretical density of the hybrid composite was then found using:

$$\rho_{th} = V_{ZE41}\rho_{ZE41} + V_{Ti_3SiC_2}\rho_{Ti_3SiC_2} + V_{NiTi}\rho_{NiTi} + V_{GO}\rho_{GO} \quad (7)$$

where ρ_{th} represents the theoretical composite density.

2.2.3 Experimental Density Measurement

The density of ZE41 hybrid composites was experimentally determined by using the Archimedes principle as shown in Figure 3. The test specimen was measured in air, then immersed in water, and the apparent weight in water was measured. To improve the reliability of the measurement, the experimental density was measured three times for each specimen, and the mean value was used for the analysis.

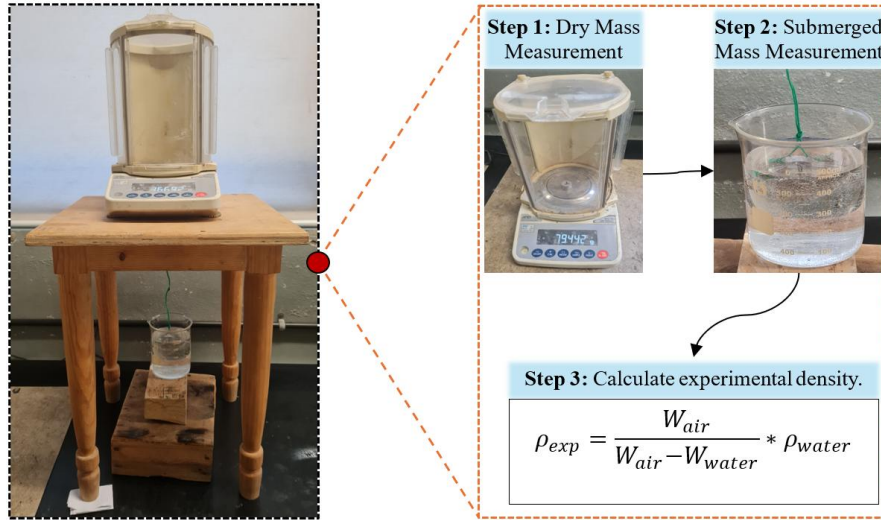


Figure 3 Experimental density measurement setup.

The experimental density was calculated using:

$$\rho_{exp} = \frac{W_{air}}{W_{air} - W_{water}} * \rho_{water} \quad (8)$$

Where ρ_{exp} is the experimental density of the composite, W_{air} is the specimen weight in air, W_{water} is the apparent specimen weight in water, and ρ_{water} is the density of water.

The experimental density obtained was compared with the theoretical density calculated using the Rule of Mixtures to assess the density variation and estimate the porosity of the produced composites. The porosity was determined as in Eq. (10):

$$P(\%) = (1 - \frac{\rho_{exp}}{\rho_{th}}) * 100 \quad (9)$$

where P represents the porosity, ρ_{exp} is the experimentally measured density, and ρ_{th} is the theoretical density calculated using the Rule of Mixtures.

2.3 Optimization Methodology

The density of the hybrid composite was predicted and optimized using a combined RSM, ANN, and GA framework. The experimental matrix was first designed by RSM; BBD experimental runs were generated using a Box-Behnken Design (BBD) in the specified parameter ranges, and a second-order polynomial model was developed. Then, the importance of the model, individual factors, quadratic terms, and interactions was checked using analysis of variance (ANOVA) [31]. Then, an ANN model was built to perform nonlinear prediction of composite density based on the experimental data generated from the RSM design. The input layer is formed by the selected material/process parameters, and the output layer has one neuron representing the density. The data set was divided into training, validation, and testing sets. The input and output data were normalized before training. Different network architectures were tested, and the one with the best predictive performance based on the root mean square error and mean absolute error was selected [32, 33]. The results of RSM and ANN models were compared based on the same statistical indicators, and the model with better predictive accuracy was selected for further optimization. Finally, GA was used to obtain the best combination of the input parameters within the experimental limits established by the RSM design. The chosen predictive model was used as the fitness-function evaluator. Selection, crossover, and mutation operators were applied iteratively in an effort to generate improved candidate solutions until the termination criterion was met [24, 34]. The optimum solution achieved by GA was compared with the RSM optimization solution. Then, a confirmation experiment was performed with the optimized parameters obtained by the GA, and the experimentally measured density was compared with the predicted value for the verification

of the reliability of optimization methods. Therefore, the proposed methodology combines the statistical interpretability of RSM, the nonlinear prediction ability of ANN, and the global optimization ability of GA for efficient density optimization of ZE41 hybrid composites. Figure 4 presents the integrated optimization methods.

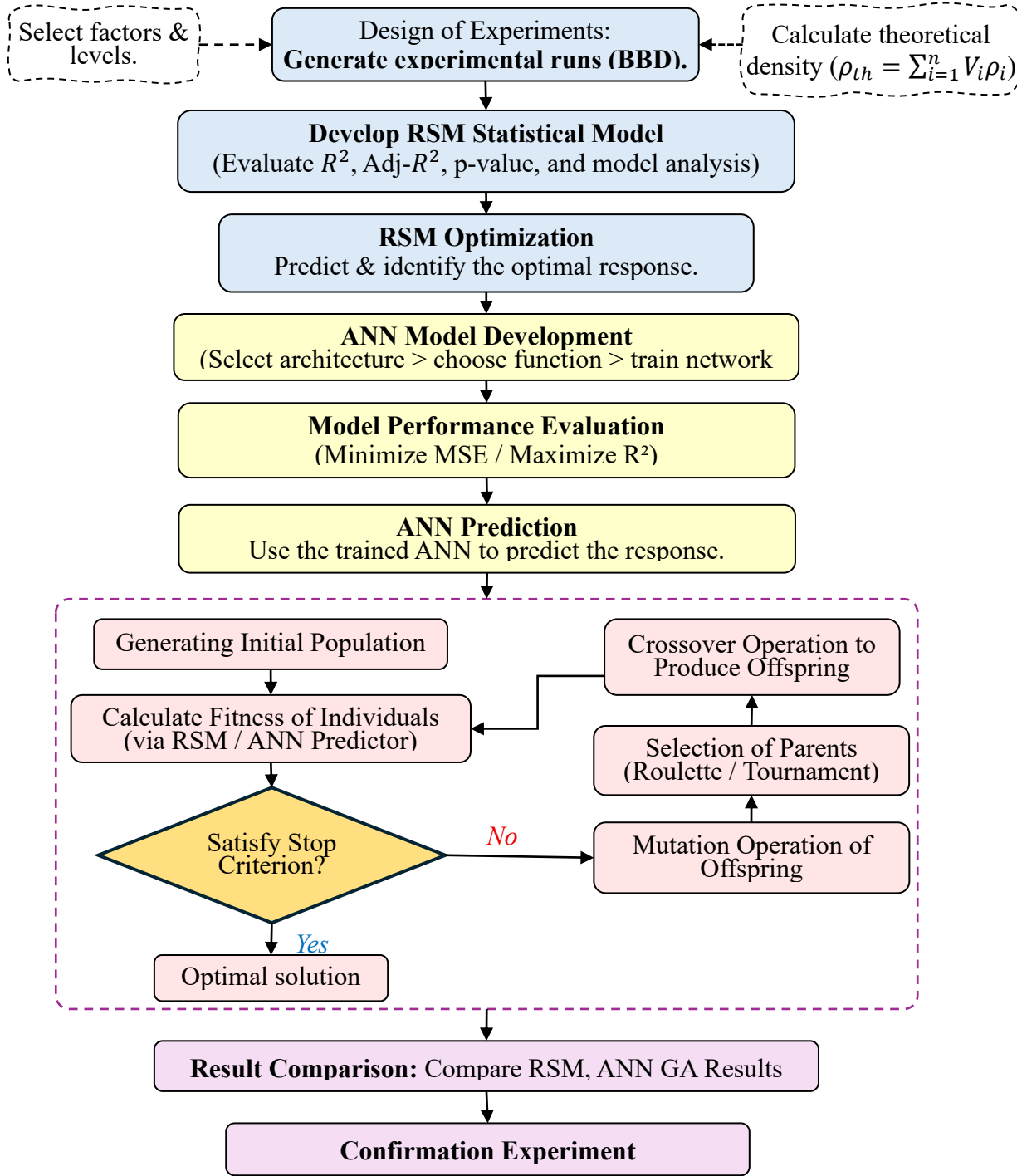


Figure 4 Flowchart of the integrated RSM–ANN–GA optimization method.

3. Results and Discussion

3.1 Experimental Results and Descriptive Analysis

The theoretical densities of the hybrid composites were calculated using the rule of mixtures based on the weight fractions of the constituents. The calculated theoretical densities range from 1.9086 to 2.0472 g/cm³, as shown in Table 4 and Figure 5. Compositional variations are mainly due to differences in the content of the reinforcing phases. The higher content of the denser Ti₃SiC₂ and NiTi particles results in a higher total density. The dominant factor controlling the composite density is the ZE41 magnesium matrix.

Table 4 Experimental design matrix and measured density.

No.	Materials				Theoretical density (g/cm ³)
	Ti ₃ SiC ₂ (%)	NiTi (%)	GO (%)	ZE41 (%)	
1	7.5	2.5	2	88.0	1.9689
2	2.5	5.0	1	91.5	1.9412
3	5.0	5.0	2	88.0	1.9754
4	5.0	5.0	2	88.0	1.9754
5	7.5	5.0	3	84.5	2.0109
6	5.0	2.5	3	89.5	1.9416
7	5.0	7.5	1	86.5	2.0105
8	7.5	7.5	2	83.0	2.0472
9	7.5	5.0	1	86.5	2.0037
10	2.5	7.5	2	88.0	1.9820
11	5.0	5.0	2	88.0	1.9754
12	5.0	2.5	1	91.5	1.9349
13	5.0	7.5	3	84.5	2.0177
14	2.5	5.0	3	89.5	1.9480
15	2.5	2.5	2	93.0	1.9086

The incorporated Ti₃SiC₂ and NiTi reinforcements had the largest effect on increasing the composite density, with samples with a higher combined fraction of these two reinforcements consistently exhibiting the highest density values above 2.0 g/cm³. Conversely, graphene oxide (GO) had a negligible effect because of its very low weight fraction and relatively low intrinsic

density. The density variations are mainly controlled by the Ti_3SiC_2 and NiTi content, while the ZE41 matrix mainly controls the baseline density. The content of reinforcement has a significant effect on the density of hybrid composite, and a higher volume fraction of high-entropy alloy particles can increase the density and hardness, while too much content of reinforcement reduce mechanical properties of composites, as reported by da Silveira, et al. [35].

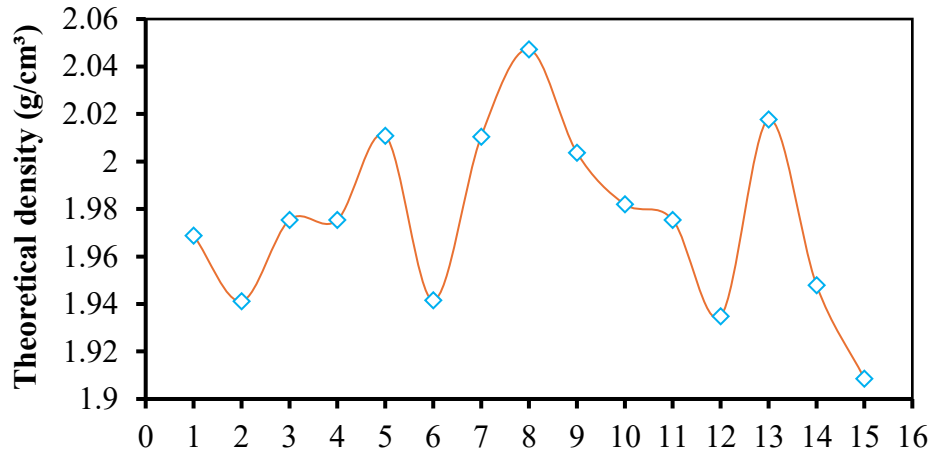


Figure 5 Theoretical density of hybrid composites.

3.2 RSM Model Development and Analysis

3.2.1 ANOVA Analysis

The results of ANOVA of the theoretical density of the hybrid composites are shown in Table 5. The model was found to be highly significant ($F = 4,329,245.96$, $p < 0.001$) with a very good coefficient of determination ($R^2 = 99.9\%$), showing that the model reveals the variability of experimental data well. Among the linear terms, NiTi showed the most substantial effect on density ($F = 23,012,890.00$), followed by Ti_3SiC_2 ($F = 15,737,702.50$) and GO ($F = 194,602.50$), which showed a relatively small but statistically significant effect. The quadratic terms for Ti_3SiC_2 and NiTi were also significant ($p < 0.001$), indicating nonlinear effects on the density. The quadratic term for GO was insignificant ($p = 0.084$), confirming the negligible role of GO in the density variation. $\text{Ti}_3\text{SiC}_2 \times \text{NiTi}$ interaction term had the most significant synergistic effect ($p < 0.001$), and the interaction effects of $\text{NiTi} \times \text{GO}$ and $\text{Ti}_3\text{SiC}_2 \times \text{GO}$ were also significant. The high predicted R^2 (99.9%) and the absence of significant lack-of-fit also confirm the reliability and the predictive ability of the developed model. ANOVA is a statistical method that is utilized to analyze the effect of different input factors on the response. Essentially, an ANOVA helps identify which variables are significant and ranks their importance in influencing the final results [36].

Table 5 ANOVA for theoretical density

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	0.019481607	0.002164623	4,329,245.96	<0.001
Linear	3	0.019472610	0.006490870	12,981,731.67	<0.001
Ti ₃ SiC ₂	1	0.007868851	0.007868851	15,737,702.50	<0.001
NiTi	1	0.011506445	0.011506445	23,012,890.00	<0.001
GO	1	0.000097301	0.000097301	194,602.50	<0.001
Square	3	0.000003	0.000001	1,936.22	<0.001
Ti ₃ SiC ₂ ²	1	0.000001018	0.000001018	2,035.38	<0.001
NiTi ²	1	0.000002077	0.000002077	4,153.85	<0.001
GO ²	1	0.00000000231	0.00000000231	4.62	0.084
2-Way Interaction	3	0.000006105	0.000002035	4,070.00	<0.001
Ti ₃ SiC ₂ × NiTi	1	0.000006003	0.000006003	12,005.00	<0.001
Ti ₃ SiC ₂ × GO	1	0.000000040	0.000000040	80.00	<0.001
NiTi × GO	1	0.000000063	0.000000063	125.00	<0.001
Error	5	0.0000000025	0.0000000005	—	—
Lack-of-Fit	3	0.0000000025	0.000000000833	—	—
Pure Error	2	0	0	—	—
Total	14	0.019481609	—	—	—
		R² = 99.9%	R²_{adj} = 99.9%	R²_{pred} = 99.9%	

3.2.2 Regression Model

The empirical relationship between the theoretical density and the reinforcement contents was established using multiple regression analysis. The equation demonstrates how the independent variables change the dependent variable [36]. Eq (10) shows how wt. % of reinforcement changes affect the theoretical density.

$$\begin{aligned}
 \text{Theoretical density (g/cm}^3\text{)} = & 1.84085 + 0.010645x_1 + 0.012890x_2 + 0.002938x_3 \\
 & + 0.000084x_1^2 + 0.000120x_2^2 + 0.000025x_3^2 + \\
 & 0.000196x_1x_2 + 0.000040x_1x_3 + 0.000050x_2x_3
 \end{aligned} \quad (10)$$

where x_1 , x_2 , and x_3 represent the weight fractions of Ti₃SiC₂, NiTi, and GO, respectively.

The high coefficient of determination ($R^2 = 99.9\%$) indicated that the model corresponds well with the experimental data. NiTi (x_2) had the highest positive coefficient (0.012890) for linear terms, followed by Ti_3SiC_2 ($x_1 = 0.010645$), showing that both significantly increased the composite density. Conversely, the GO linear coefficient ($x_3 = 0.002938$) was considerably smaller, indicating its negligible contribution to the variation of density. The positive quadratic coefficients of x_1 (0.000084) and x_2 (0.000120) indicated that density increased non-linearly at higher reinforcement loadings. In addition, the interaction terms demonstrated synergistic effects between the reinforcements, with the x_1x_2 interaction (0.000196) having the most positive contribution, followed by x_2x_3 (0.000050) and x_1x_3 (0.000040). The high predicted R^2 (99.9%) and non-significant lack-of-fit also confirm the reliability and predictive ability of the model to optimize the wt.% composition.

3.2.3 Standardized Effects

The standardized effects of the individual and interaction terms on the theoretical density were calculated in an effort to evaluate the relative importance of each factor. Figure 6 presents the Pareto chart of standardized effects, indicating that NiTi (B) has the most significant influence on theoretical density, followed by Ti_3SiC_2 (A) and GO (C). The BB ($NiTi^2$) and AA ($Ti_3SiC_2^2$) terms showed significant effects for the quadratic terms, indicating a non-linear density behavior at higher reinforcement loadings, whereas the CC (GO^2) term was insignificant. Among the interaction terms, AB ($Ti_3SiC_2 \times NiTi$) exhibited the strongest synergistic effect, followed by BC ($NiTi \times GO$) and AC ($Ti_3SiC_2 \times GO$). Monu, et al. [37] reported that the addition of NiTi to composites tends to increase the overall density, which is attributed to the inherently higher density of NiTi compared to the matrix material. Similarly, Bykova, et al. [11] demonstrated that Ti_3SiC_2 reinforcement significantly increases composite density, particularly when synthesized under optimized conditions, with Ti_3SiC_2 dominating the structure despite the presence of minor TiC and SiC phases. These findings are consistent with the present study, where increasing the wt. % of both NiTi and Ti_3SiC_2 in the ZE41 hybrid composites resulted in a progressive increase in theoretical density, confirming the dominant role of these reinforcements in tailoring composite density.

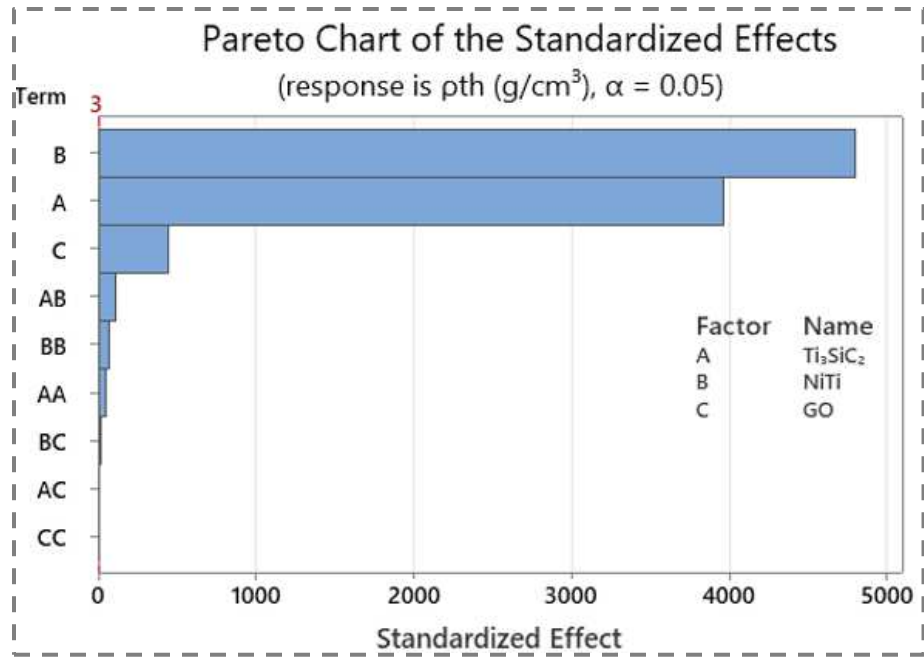


Figure 6 Pareto Chart of Standardized Effects.

3.2.4 Plot Analysis

3.2.4.1 Contour Plots

The contour plots in Figure 7 show the combined effects of reinforcement wt. % on the theoretical density of ZE41 hybrid composites. Figure 7a (Ti_3SiC_2 vs. NiTi) displays a large density gradient, with values ranging from below 1.92 g/cm^3 at low reinforcement levels to above 2.04 g/cm^3 at higher contents, with the steepest slope along the diagonal. The synergistic effect is attributed to the fact that both Ti_3SiC_2 (4.5 g/cm^3) and NiTi (6.45 g/cm^3) are much denser than the ZE41 matrix (1.84 g/cm^3). Figure 7b (Ti_3SiC_2 vs. GO) goes from below 1.95 to above 2.01 g/cm^3 and Figure 7c (NiTi vs. GO) goes from below 1.94 to above 2.00 g/cm^3 . This shows the secondary role of GO (2.2 g/cm^3) because of its lower density and narrow 1- 3 wt.% % range. These results are in agreement with the literature, where the reinforcement selection is an important factor in the composite density [38]. It has been shown that for ZE41 composites, the theoretical densities calculated by the rule of mixtures are always higher than the experimental values because of the porosity introduced during casting. The differences were attributed to improper mixing, particle agglomeration, and poor wettability at the matrix-reinforcement interface. It has been reported that the variation between theoretical and experimental density is greater for composites with higher reinforcement content due to increased cavity formation [39, 40].

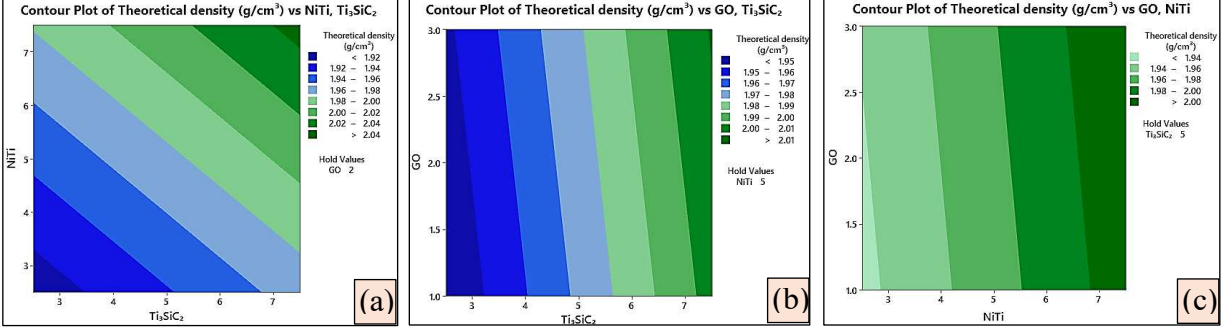


Figure 7 Counterplot of theoretical density

3.2.4.2 Residual Plot

The adequacy of the fitted quadratic response-surface model was verified by residual diagnostic plots as shown in Figure 8. The normal probability plot presents that the residuals are distributed roughly along the reference line. There is no substantial deviation or extreme outlier. This suggests an approximately normal residual pattern. The residuals versus fitted values plot shows that the residuals are randomly scattered about zero with no obvious systematic trend. The histogram of the residuals shows an approximately symmetric distribution about zero. Similarly, the residuals versus observation order plot reveals no evident systematic pattern and no obvious trend with order in the model errors. The residual magnitudes are very small, in agreement with the near-perfect fit obtained for the calculated theoretical-density response. However, since the theoretical density was determined deterministically by the rule-of-mixtures relation, these residual diagnostics should be understood as primarily reflecting the mathematical accuracy of the fitted response surface model and not as an indication of the reproducibility of the experimental measurements. Residual plot is statistical modeling and machine learning. It is an important tool in the evaluation of the precision of a model, diagnosing violations of assumptions, and refinement [41].

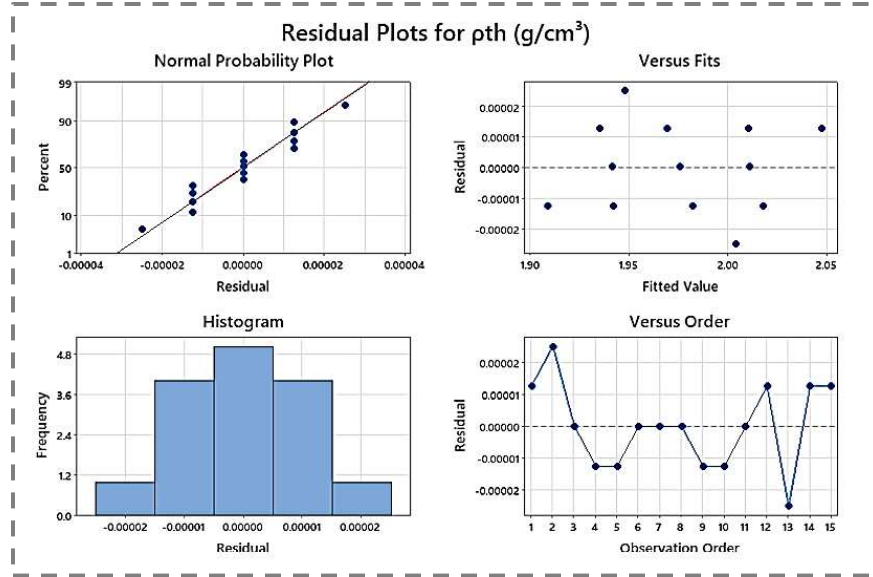


Figure 8 Residual plots for theoretical density

3.2.5 Main and Interaction Effects Analysis

Figure 9 shows the main effects for the effect of Ti_3SiC_2 , NiTi , and GO contents on the calculated theoretical density of the ZE41 hybrid composite. The main effects plot reveals a clear rise in the theoretical density with the increase of Ti_3SiC_2 and NiTi contents, with the NiTi factor having the steepest slope and the strongest main effect, followed by Ti_3SiC_2 . In contrast, the theoretical density varies little in the investigated range for the GO content. These trends are consistent with the ANOVA and Pareto analyzes that identified NiTi and Ti_3SiC_2 as the dominant linear factors.

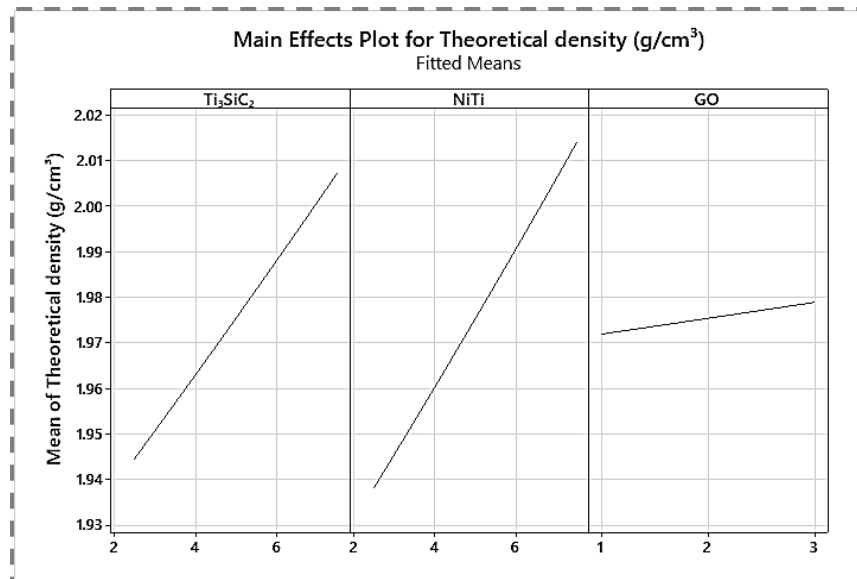


Figure 9 Main effects plot for theoretical density

Figure 10 shows the interaction plots; these plots indicate that the combined variation of Ti_3SiC_2 and NiTi causes a greater change in theoretical density than the other factor combinations, which is in agreement with the statistically significant $\text{Ti}_3\text{SiC}_2 \times \text{NiTi}$ interaction found by ANOVA. The comparatively weaker changes observed for the $\text{Ti}_3\text{SiC}_2 \times \text{GO}$ and $\text{NiTi} \times \text{GO}$ combinations suggest smaller interaction effects; nonetheless, these terms remained statistically significant in the fitted model. As investigated by Yang, et al. [42], combining B_4C and h-BN reinforcements results in an increase in the composite density, as the heavier B_4C compensates for the lighter h-BN. Moreover, the synergy of the two reinforcements reduces the porosity and improves the particle distribution, resulting in density values closer to the theoretical ones and a better structural reliability compared to the mono-reinforced composites.

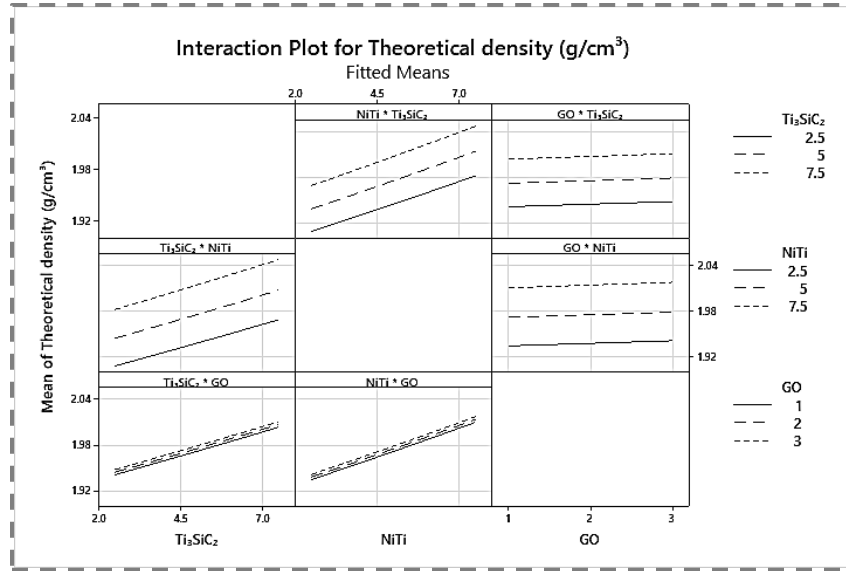


Figure 10 Interaction plot for theoretical density

The theoretical density of ZE41-based hybrid composites was optimized by the desirability function approach for the best content of reinforcements (Ti_3SiC_2 , NiTi, and GO). The optimum composition was found to be 2.5 wt% Ti_3SiC_2 + 2.5 wt% NiTi + 1.0 wt% GO with the minimum predicted theoretical density of 1.9054 g/cm³ and a desirability value of 1.000, as shown in Figure 11. The higher desirability value confirms the reliability of the predicted optimum conditions and the effectiveness of the RSM approach to optimize the composition of ZE41-based hybrid composites. RSM has many advantages compared to traditional optimization methods: it decreases the number of experiments required, it can handle multiple variables and their interactions effectively, and it can provide mathematical models that can be used to predict and optimize a

process. Unlike Taguchi or one-factor-at-a-time methods, RSM produces response surfaces and contour plots to visualize factor effects and accurately identify optimal conditions at minimum cost and effort [43].

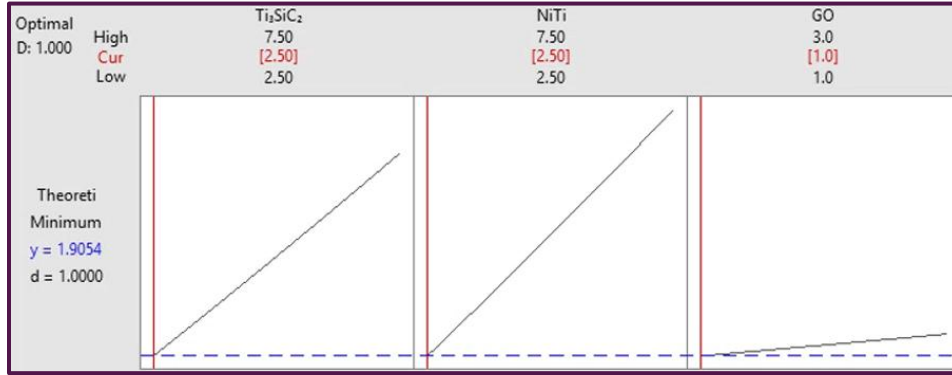


Figure 11 Optimized wt. % and theoretical density

3.3 ANN Model Development and Prediction

ANN in the 3-10-1 architecture was developed for the prediction of the theoretical density of the ZE41-based hybrid composites based on the weight fractions of Ti₃SiC₂ (x_1), NiTi (x_2), and GO (x_3). As shown in Figure 12, the network consisted of an input layer of three neurons, a hidden layer of ten neurons, and an output layer of one neuron corresponding to the theoretical density (ρ_{th}). This architecture was chosen to be able to capture the complex nonlinear relations between the reinforcement contents and the composite density. The model was trained on experimental data to optimize the network weights and biases for correct prediction of the theoretical density in the studied composition range [44].

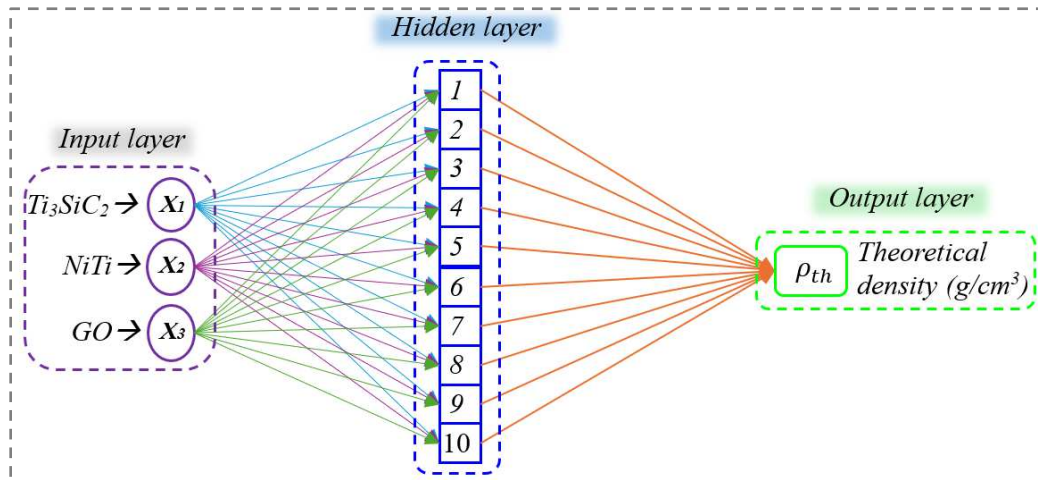


Figure 12 Architecture of the developed ANN model.

3.3.1 ANN Model Development and Prediction

The regression analysis of the training, validation, testing, and overall datasets was performed to evaluate the predictive performance of the developed ANN model [45] and is shown in Figure 13. The training dataset had a correlation coefficient of $R = 0.96361$, and the validation and test datasets achieved $R = 1.0$, indicating an excellent correlation between the predicted and experimental values. The overall correlation coefficient of all datasets was $R = 0.97033$, which confirmed the strong predictive capability of the model. The closeness of the data points to the ideal fit line in all data sets indicates the validity of the ANN model in accurately capturing the non-linear relationships between the reinforcement contents and the theoretical density of the ZE41-based hybrid composites [46, 47].

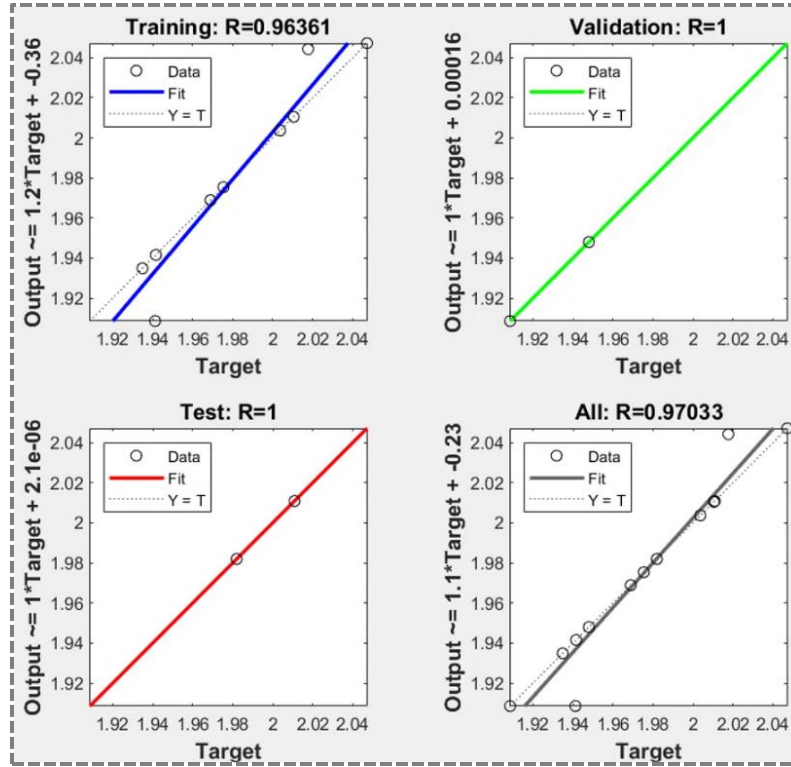


Figure 13 Regression plots of the ANN model

Figure 14 shows the convergence behavior of the ANN model during training, reporting the MSE values for the training, validation, and test datasets for five epochs. The MSE values for all datasets decreased consistently from the first epoch (2.0×10^{-5} for training, 1.0×10^{-5} for validation and test) to the last epoch (1.0×10^{-15} for all datasets). The reduction of MSE is consistent, and the curves of training and validation are in good agreement, which indicates efficient learning and

good generalization ability of the model [48], confirming the reliability of the model for the prediction of the theoretical density of ZE41-based hybrid composites.

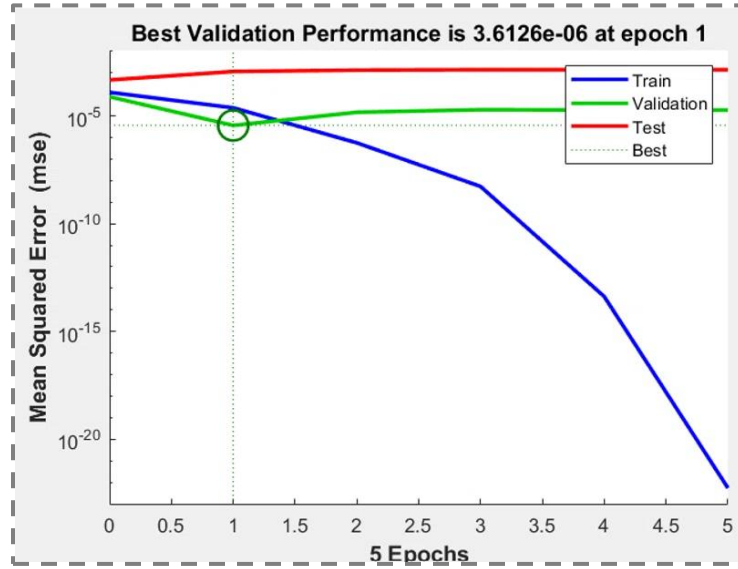


Figure 14 Mean squared error (MSE) convergence of the ANN model

3.4 GA Optimization

The ANN model along with a genetic algorithm (GA) was employed to optimize the composition of the ZE41-based hybrid composites to achieve the desired theoretical density. The GA parameters were selected to allow an efficient exploration of the design space and convergence to the optimal solution. The population size, selection operator, crossover fraction, and mutation function were set to balance the optimization process between exploration and exploitation [49]. The specific GA parameters and their selected values are presented in Table 6.

Table 6 GA parameters and their values

No	Parameters	Values
1	Size of population	100
2	Type	Double vector
3	Function	Constraints dependent
4	Scaling	Rank
5	Selection operator	Roulette wheel
6	Elite count	Default (0.05*PS)
7	Cross over	0.8
8	Mutation function	Constraint dependent

9	Number of generations	100
10	Direction	Forward

The convergence behavior of the GA is illustrated in Figure 15 (a), which shows the best and mean fitness values of the GA during the optimization process over 150 generations. The best fitness value gradually improved from 1.890 at Generation 0 to 1.90861 at Generation 150, which means a continuous improvement in the solution quality was made during the optimization process. Conversely, the average fitness values stayed relatively stable at around 1.905 throughout all generations, indicating that the population maintained similar average performance while the best individual kept improving. This trend shows that the GA was able to explore the design space effectively and to progressively improve the optimal solution, without degrading the overall population quality. The current best individual obtained from the GA is shown in Figure 15 (b). The composition is $x_1 = 2.5$ wt.% (Ti_3SiC_2), $x_2 = 2.5$ wt.% (NiTi) and $x_3 = 2.0$ wt.% (GO). The optimized composition corresponds to the best fitness value of 1.90861, which is the minimum theoretical density that can be obtained in the composition range studied. The continuous improvement of the best fitness values and uniformity of the mean fitness value confirms the robustness and efficiency of the genetic algorithm for determining the optimal wt. % [46].

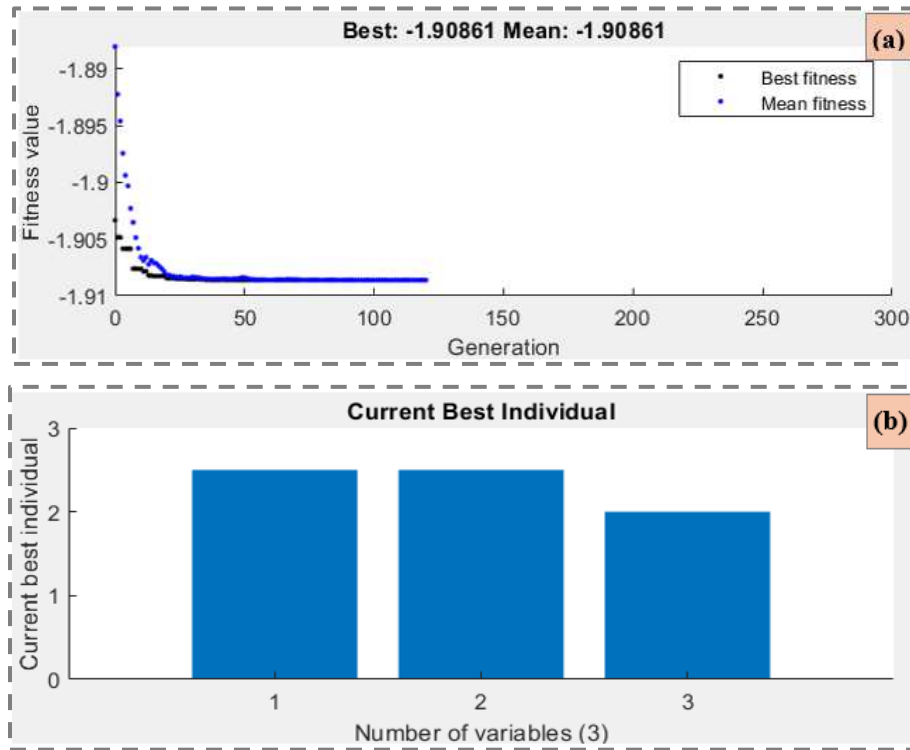


Figure 15 Convergence plot of the genetic algorithm showing best and mean fitness values.

3.5 Comparison of Optimization Approaches

Table 7 shows the predicted optimal compositions and theoretical densities for RSM and hybrid ANN-GA. The RSM model predicted the optimal composition of 2.5 wt.% Ti_3SiC_2 , 2.5 wt.% NiTi, 1 wt.% GO with a density of 1.9054 g/cm^3 , while the ANN-GA predicted the optimal composition of 2.5 wt.% Ti_3SiC_2 , 2.5 wt.% NiTi, and 2 wt.% GO, with a density of 1.90864 g/cm^3 which was slightly higher than the RSM model. Both methods led to similar optimal contents of Ti_3SiC_2 and NiTi, but the ANN-GA method was slightly better in terms of predictive performance for predicting the optimal contents of Ti_3SiC_2 and NiTi, because of its better ability to model non-linear relationships and perform global optimization. These results confirm both optimization techniques and highlight the hybrid ANN-GA approach's higher accuracy in optimizing the composition of ZE41-based hybrid composites. The hybrid ANN-GA method has demonstrated excellent predictive and optimization capabilities in many manufacturing and materials engineering applications. El Ghadoui, et al. [50] found that an integrated ANN-GA scheme for injection molding yielded a successful combination of ANN and GA that improved lens shape accuracy and emphasized that the ANN-GA hybrid is vital to achieve global optimization. Similarly, Liu, et al. [51] independently validated both techniques for the design optimization of composite laminates, where the ANN had the best R^2 of the compared models and the following GA optimizations, confirming that each technique does well independently and in the hybrid coupling. Overall, the results indicate the reliability and effectiveness of the ANN-GA hybrid approach for complex engineering optimization problems.

Table 7 Predicted theoretical densities obtained from RSM and hybrid ANN-GA approaches.

Methods	Optimal (wt.%)			Predicted theoretical density (g/cm^3)
	Ti_3SiC_2	NiTi	GO	
RSM	2.5	2.5	1	1.9054
Hybrid ANN-GA	2.5	2.5	2	1.90864

3.6 Experimental Validation

Table 8 shows the predictive accuracy of the developed regression model validated on five further experiments. The experimental densities varied from 1.861 to 1.975 g/cm^3 , and the predicted values varied from 1.9168 to 2.0501 g/cm^3 . The difference between the predicted and experimental densities varied from 3.00% to 4.44%. The lowest error (3.00%) was obtained for the composition

with 2.5 wt.% Ti_3SiC_2 , 2.5 wt.% NiTi, 2 wt.% GO, and the highest error (4.44%) was obtained for the composition with 2.5 wt.% Ti_3SiC_2 , 7.5 wt.% NiTi and 2 wt.% GO. The acceptable error range confirms the reliability and predictive ability of the regression model for the estimation of the theoretical density of the ZE41-based hybrid composites in the studied composition range. The difference between the experimentally determined density and the value predicted by the regression equation was found to be less than 5%. The acceptable range of errors confirms the reliability and predictive ability of the regression model for the estimation of the theoretical density of the ZE41-based hybrid composites in the studied composition range. These results are in line with the previous work of Thanikodi [52], who used regression-based models for predicting properties of ZE41 composites, and Huang, et al. [53], who studied magnesium matrix composites in general. The theoretical density of such systems is generally estimated by the rule of mixtures and compared with the measured values to determine porosity and the accuracy of the model, as reported by Pandiyaraj, et al. [54].

Table 8 Experimental validation of the regression model

Exp	Composition (wt.%)			Theoretical density (g/cm^3)		Error
	Ti_3SiC_2	NiTi	GO	Regression	Experimental	
1.	2.5	2.5	2	1.9168	1.861	3.00%
2.	5	5	2	1.9786	1.910	3.59%
3.	7.5	7.5	2	2.0501	1.975	3.80%
4.	7.5	2.5	2	1.9927	1.9150	4.06%
5.	2.5	7.5	2	2.0116	1.9260	4.44%

4. Conclusion

The present study successfully developed an integrated RSM–ANN–GA framework for optimization of the density of stir-cast ZE41 hybrid composites incorporated with Ti_3SiC_2 , NiTi, and GO. From the experimental and analytical results, the conclusions are as follows:

- Theoretical densities of the hybrid composites calculated using the rule of mixtures were in the range of 1.9086 – 2.0472 g/cm^3 . The density variations were mainly governed by the weight fraction of Ti_3SiC_2 and NiTi, where the higher reinforcement contents resulted in an increase in composite density, while GO had a negligible effect due to its low weight fraction (1–3%) and relatively low intrinsic density.

- The ANOVA results demonstrated that the developed RSM model was highly significant ($F = 4,329,245.96$, $p < 0.001$) with an excellent coefficient of determination ($R^2 = 99.9\%$). Among the linear terms, NiTi had the greatest effect on density ($F = 23,012,890.00$), followed by Ti_3SiC_2 ($F = 15,737,702.50$), while GO had a smaller but statistically significant effect ($F = 194,602.50$). The quadratic terms of Ti_3SiC_2 and NiTi were significant ($p < 0.001$), suggesting non-linear density behavior at higher reinforcement loadings. The quadratic term of GO was insignificant ($p = 0.084$), confirming its negligible role.
- The 3-10-1 architecture of the ANN model was shown to have excellent predictive performance with $R=0.96361$ for training and $R= 0.97033$ for all data sets and MSE values as low as 1.0×10^{-15} . The predicted values were in good agreement with the experimental values and validated the approach's capability of capturing complex nonlinear relationships between reinforcement contents and composite density.
- The GA optimization suggested the optimum composition of 2.5 wt.% Ti_3SiC_2 , 2.5 wt.% NiTi, and 2.0 wt.% GO. The ANN-GA hybrid approach showed slightly better predictive performance compared to RSM, with predicted density of 1.90864 g/cm^3 compared to 1.9054 g/cm^3 for RSM.
- Experimental validation of selected compositions showed that the errors between the predicted and measured densities ranged from 3.00% to 4.44%, confirming the reliability and practical utility of the developed regression model to estimate the theoretical density of ZE41-based hybrid composites.

The integrated RSM-ANN-GA framework efficiently merges the statistical interpretability of RSM, the nonlinear predictive capability of ANN, and the global optimization power of GA, presenting a thorough and dependable methodology for density optimization. This methodology significantly reduces experimental trials and provides a systematic alternative to the conventional trial-and-error approach for the development of lightweight, defect-free ZE41 hybrid composite components for automotive, aerospace, and other structural applications.

CRedit author statement.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Availability of Data and Materials

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