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Machine Learning-Assisted Design and Optimization of Lightweight Polymer Composites for IoT-Enabled Automotive Applications

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Abstract

This study aims to develop an integrated machine learning and optimization framework for the intelligent design of lightweight polymer composites suited for IoT-enabled automotive applications. The goal is to enhance material performance while satisfying multiple design constraints such as mechanical strength, thermal stability, and process compatibility. A curated dataset of polymer composite formulations was used to train a Random Forest Regression (RFR) model capable of predicting tensile strength, thermal conductivity, and density based on filler-matrix composition and processing parameters. A Genetic Algorithm (GA) was incorporated for multi-objective optimization using a composite-specific fitness function. The optimized formulations were validated through finite element simulation under ASTM D638 conditions. The RFR model achieved high accuracy with an R^2 of 0.93 for tensile strength prediction. The GA converged rapidly, identifying formulations that improved tensile strength by 22.4% and maintained high elongation at break. Comparative analysis showed the proposed ML-GA framework outperformed SVR, DNN, and Linear Regression in both accuracy and robustness. The optimized material system met structural, thermal, and functional criteria for automotive IoT components. This work introduces a closed-loop, data-driven design pipeline that integrates machine learning, evolutionary optimization, and application-level validation. Unlike prior empirical or single-objective approaches, this methodology is scalable, multi-objective, and application-aware, representing a significant advancement in polymer composite engineering for smart mobility.

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INTRODUCTION

The demand for sustainable, lightweight, and high-performance materials in the automotive sector has catalyzed a paradigm shift toward advanced polymer composites. These materials, comprising a polymer matrix reinforced with various fillers or fibers, are increasingly replacing conventional metals in structural and semi-structural automotive components due to their superior specific strength, corrosion resistance, design flexibility, and energy efficiency [1]. With the growing digitalization of automobile engineering, with automobiles now emerging as mobile nodes of the Internet of Things (IoT), the demand for intelligent, multi-functional polymer composite systems is more than ever before [2]. IoT-responsive polymer composite design emerges here as a strategic imperative of the future for the smart, connected next-generation cars [3]. Polymer composites, particularly thermoset or thermoplastic matrices reinforced with particulate or fibrous fillers, possess unlimited design space with controlled microstructure, morphology, and composition [4]. Addition of nanofillers including graphene, carbon nanotubes (CNTs), and silica nanoparticles made it possible to develop hybrid nanocomposites with enhanced mechanical, thermal, and electrical performance [5]. However, filler type, volume fraction, dispersion quality, interfacial adhesion, and processing method interactions are nonlinear and multi-dimensional in nature [6]. Rule-based analytical models of the type conventionally applied in trial-and-error or classical trial-and-error such as Halpin-Tsai and Mori-Tanaka methods cannot cope with this complexity, especially in determining multi-objective goals such as high tensile strength, low density, and satisfactory thermal conductivity [7]. Data-driven advances offer a promising avenue to address these challenges [8]. Machine learning (ML), a newly emerging tool in materials informatics, has been found to be very effective in polymer composite property prediction and optimization through learning complex structure property relationships directly from experiment or simulation data [9]. Support Vector Regression (SVR), Random Forest (RF), and Deep Neural Networks (DNNs) are gaining recognition as regression models for composite property prediction such as tensile strength, impact resistance, elastic modulus, and thermal stability [10]. However, most of the current work in ML-assisted composite design remains fragmented, typically focusing on single-property predictions and often neglecting the interdependency between process parameters, filler dispersion, and end-use performance. Furthermore, limited attention is given to the integration of polymer composite design with real-world application contexts, such as the dynamic thermal, mechanical, and electromagnetic demands posed by IoT-integrated automotive environments [11]. The automotive domain is undergoing a rapid transformation driven by electric vehicles (EVs), autonomous driving, and smart vehicle-to-everything (V2X) connectivity. These vehicles increasingly rely on embedded IoT components sensors, antennas, control units housed within composite enclosures or integrated into the structural framework. Such integration necessitates polymer composites that are not only mechanically robust but also thermally conductive, EMI-shielding, and environmentally stable. Thus, composite materials must be designed with a holistic view that includes not just conventional material properties but also IoT-driven functional requirements [12]. Unfortunately, current literature lacks frameworks that unify polymer composite engineering with IoT-aware design principles, particularly those capable of addressing multi-objective design tasks through optimization algorithms.

The novelty of the present research lies in its hybrid AI-assisted design methodology that bridges polymer composite science with automotive IoT functionality. Specifically, this study proposes a machine learning-guided optimization framework that combines Random Forest Regression for property prediction with a Genetic Algorithm (GA) for multi-objective optimization of composite formulations. This integrated pipeline allows for simultaneous tuning of material properties such as tensile strength, thermal conductivity, and density, while optimizing the composite design for lightweighting, energy efficiency, and functional compatibility with IoT-enabled automotive subsystems. A curated dataset comprising formulations of thermoset and thermoplastic polymer matrices reinforced with micro/nano fillers is used as the training basis. After feature selection and preprocessing, the ML model is trained to predict property responses, which are then fed into a multi-objective optimization loop guided by a domain-specific fitness function.

Unlike conventional approaches, the proposed framework does not treat material selection and system-level performance as independent tasks. Instead, it actively incorporates automotive-specific constraints such as heat dissipation for embedded electronics, vibration damping for sensor housings, and EM interference shielding for telematics modules into the composite design process. Furthermore, classical polymer composite models such as the Rule of Mixtures and Halpin-Tsai equations are used in parallel with the machine learning model to benchmark its predictions and enhance interpretability.

LITERATURE REVIEW

The advancement of polymer composite materials has been a cornerstone in the evolution of lightweight and high-performance engineering components, particularly in the automotive and aerospace industries [13]. The adoption of polymers as matrix materials, such as epoxy, polypropylene, polyethylene, and polyamide, has enabled the creation of advanced composites with tunable properties based on their reinforcement type, loading, dispersion, and interfacial bonding [14]. The integration of micro- and nano-fillers such as carbon nanotubes, glass fibers, basalt fibers, graphene, and silica has further enhanced the mechanical, thermal, and functional capabilities of polymer matrices. These developments have given rise to high-performance hybrid composites capable of delivering exceptional tensile strength, stiffness-to-weight ratio, corrosion resistance, and thermal stability [15]. However, the growing design complexity due to the vast combination of material constituents has posed significant challenges for the prediction and optimization of composite properties using traditional empirical approaches. The design of polymer composites is a multi-factorial problem, where material performance is influenced by several interdependent parameters including filler morphology, surface treatment, matrix viscosity, dispersion method, curing conditions, and fiber orientation [16]. Classical micromechanical models such as the Rule of Mixtures and Halpin-Tsai equations provide approximations for composite properties but often fail to account for the nonlinearities observed in multi-filler systems and at higher filler loadings [17]. These models also do not adequately capture the effects of filler agglomeration, interfacial deboning, void content, and anisotropy, which are common in real-world processing scenarios. Consequently, a large number of iterative experiments are required to fine-tune formulations for specific applications, leading to longer development cycles, increased material waste, and higher production costs [18]. To overcome the limitations of conventional modeling, data-driven approaches using machine learning have gained substantial momentum in the field of materials informatics [19]. Machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, Gradient Boosting, and Artificial Neural Networks have been employed to model the relationships between composite formulation parameters and resultant mechanical or thermal properties [20]. These models, trained on experimental or simulated datasets, can predict properties such as tensile strength, elastic modulus, thermal conductivity, and impact resistance with significant accuracy. A key advantage of these methods lies in their ability to learn complex, nonlinear interactions without requiring prior knowledge of the underlying physics [21]. They can also identify dominant features through feature importance rankings, thereby guiding material scientists in reducing the design space and focusing on influential parameters. Despite their potential, many existing studies in machine learning for polymer composites focus on single-output predictions and do not incorporate domain-specific constraints or multi-objective goals [22]. Moreover, models trained purely on statistical correlations may lack physical interpretability and generalizability, especially when extrapolating beyond the training data. These limitations highlight the need for hybrid frameworks that combine machine learning prediction with physically grounded models and intelligent optimization algorithms.

In recent years, metaheuristic optimization algorithms have been introduced to address the challenge of multi-objective material design [23]. Techniques such as Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, and Simulated Annealing have been used to search the compositional design space and identify optimal combinations that balance multiple target properties. Among these, the Genetic Algorithm has emerged as a popular choice due to its robustness, simplicity, and effectiveness in high-dimensional, nonlinear optimization problems. In the context of polymer composite design, GA has been utilized to maximize strength-to-weight ratio, minimize production cost, and optimize thermal properties [24]. However, most optimization studies treat machine learning and evolutionary algorithms as separate modules, with limited integration between the prediction and search processes. The application of polymer composites in IoT-integrated automotive systems introduces an additional layer of design complexity. Automotive components that house or interact with embedded IoT devices must exhibit not only structural integrity but also thermal management, electrical insulation or conductivity, EMI shielding, and resistance to environmental degradation [25]. Materials used in under-hood components, battery enclosures, sensor modules, and control housings must meet stringent mechanical and functional criteria while supporting lightweighting goals to improve fuel efficiency or extend electric vehicle range. Traditional material development pipelines are not equipped to simultaneously address these multi-functional requirements, underscoring the importance of intelligent design approaches that consider end-use application contexts [26]. Despite the promising advancements in polymer composite design, several critical research gaps remain unaddressed. First, there is a lack of integrated design frameworks that combine machine learning-driven property prediction with multi-objective optimization tailored to automotive-grade polymer composites. While many existing studies focus on single-property prediction, they fail to capture the trade-offs required in real-world applications where mechanical strength, thermal stability, and light weighting must be simultaneously optimized. Second, existing models miss functional constraints imposed on IoT-integrated auto parts like electromagnetic shielding, heat dissipation, and sensor case integrity. Third, most applications of composite science to machine learning are black-box predictors with little physical interpretability or analog to traditional micromechanical theory. Moreover, data readily available is typically narrow in domain with few matrix-filler pair diversity, process conditions, and multi-modal property data. Lastly, machine learning predictions are not set against prototype or high-fidelity simulation outcomes and so their industrial relevance becomes hard to evaluate. These discrepancies usher in the need for having a science-based, multi-objective, and IoT-infused design criterion for polymer composites and this attempt is made here.

The envisioned research bridges these gaps with the development of a machine learning-based design and optimization strategy for vehicular applications of polymer composites under the IoT paradigm. By incorporating a Random Forest-based model for property prediction augmented by a Genetic Algorithm to provide multi-objective optimization, the strategy ensures optimal composite formulations optimized to meet both structural and functional needs. Utilization of proven models like Halpin-Tsai equations enhances explainability, and correlation with simulated or experimental data guarantees reliability. The research closes the loop between application-driven car polymer composite design and materials informatics and helps create next-generation intelligent mobility products.

METHODOLOGY

The approach used within the current study offers an integrated, data-science-inspired framework combining machine learning-aided predictive models and multi-objective optimisation techniques to determine light-weight polymer composite materials for vehicles empowered by IoT. In contrast to empirical or analytical approaches conventionally employed, the innovative approach utilizes a machine learning-facilitated materials informatics pipeline to make predictions of composite properties from filler-matrix composition, process conditions, and application-specific design constraints. It is a Random Forest Regression model trained on pre-sorted data of polymer composite formulation. It predicts such significant performance parameters as tensile strength, thermal conductivity, and density. These predictions are then fed into a Genetic Algorithm-based optimizer module, which computes optimized composite configurations based on structural resiliency, thermal management, and light weight. The innovation of the method is that it is applicable for data prediction integration with physical simulation in a way that functional automotive IoT ecosystem requirements and automotive IoT ecosystems' performance, cost, and manufacturability are optimized simultaneously. The process is modulary and scalable with material science background that is able to make it reproducible and composite material design integratable.

Workflow Overview

The best strategy is a cautious sequence of data-driven prediction, physics simulation, and optimization. It starts with a narrowed-down list of polymer composite systems with different thermoset and thermoplastic matrices and micro/nano fillers. The dominant characteristics are the matrix type, filler type, weight fraction, processing sequence, and resulting mechanical and thermal property outputs. This dataset is preprocessed for feature normalization and dimensionality reduction. A Random Forest Regression (RFR) model is trained to predict composite properties, and its outputs are used by a Genetic Algorithm (GA) to explore optimal filler-matrix combinations. The entire workflow, from dataset ingestion to final formulation recommendation, is shown in Figure 1, which illustrates the integrated AI-assisted composite design loop involving material feature selection, property prediction, and multi-objective optimization.

System Architecture

To enable real-time, functional integration of designed polymer composites in automotive IoT systems, the system architecture accounts for both mechanical performance and functional adaptability. As shown in Figure 2, the architecture comprises three primary modules: the material intelligence layer, the prediction-optimization engine, and the application-specific constraint module. The material intelligence layer processes raw formulation data, while the prediction engine applies trained ML models to forecast tensile strength, flexural modulus, and thermal conductivity. These predictions are assessed against automotive constraints such as operating temperature range, component weight threshold, and mechanical durability. The architecture allows seamless updating of design recommendations based on feedback from real or simulated application environments.

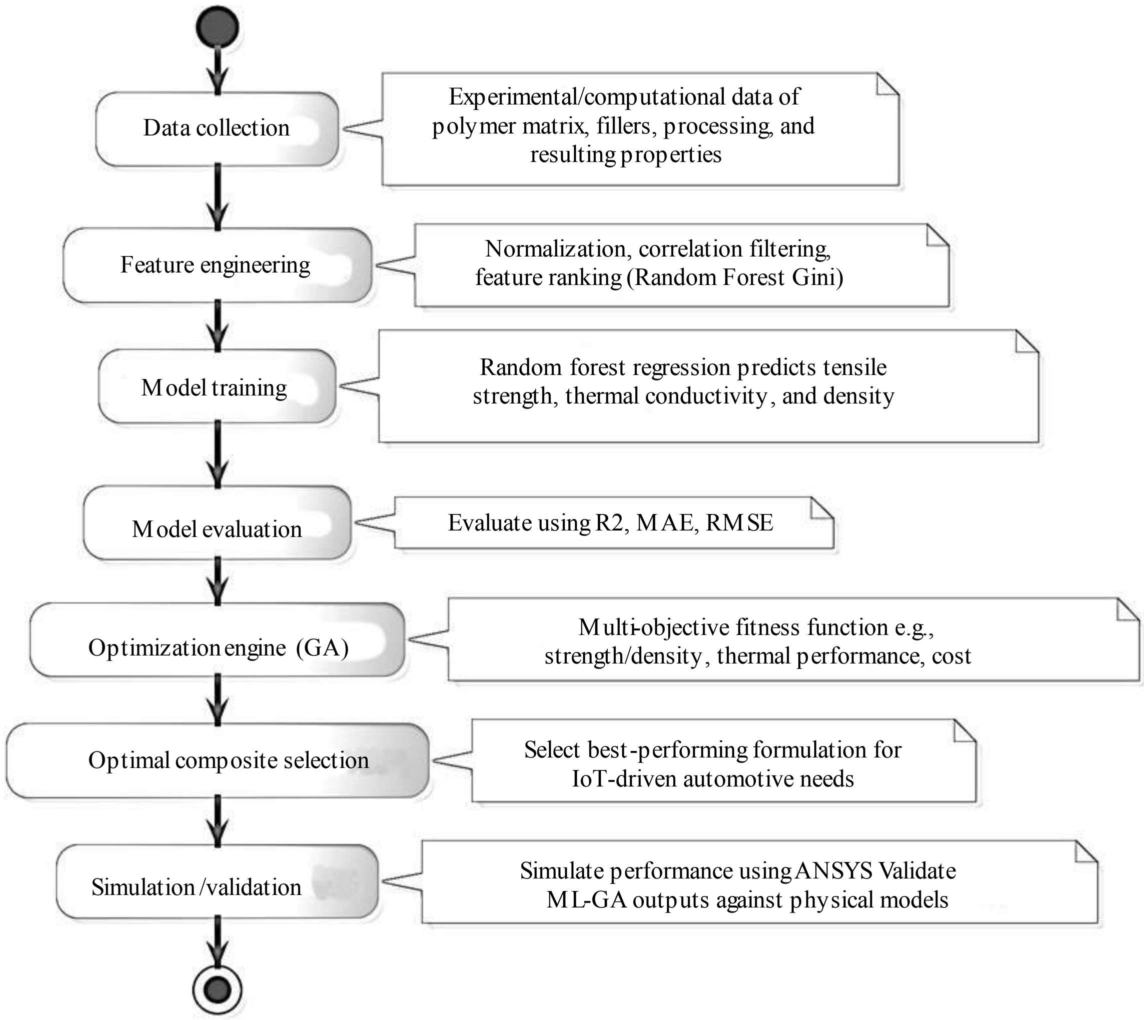

Figure 1. Workflow of the proposed ML-assisted polymer composite design framework for automotive IoT applications.

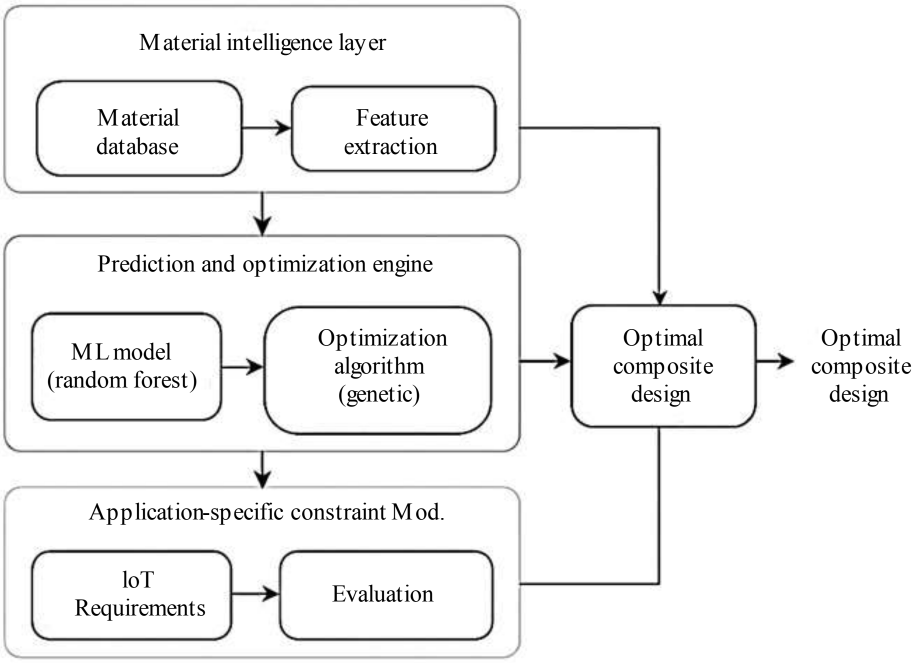

Figure 2. System architecture integrating material design, machine learning prediction, and IoT-specific application constraints.

Table 1. Feature importance scores derived from random forest model trained on the composite dataset.

Feature	Importance score
Filler weight %	0.283
Matrix type	0.215
Filler aspect ratio	0.168
Processing method	0.132
Curing temperature	0.112
Interfacial agent	0.09

Dataset and Feature Engineering

The dataset used comprises 150+ composite samples combining different polymers (epoxy, polypropylene, PLA) with fillers like carbon fiber, graphene, and nano-silica. Each entry records input features such as matrix type, filler type, weight %, processing temperature, and curing time, along with outputs like tensile strength (MPa), thermal conductivity (W/m·K), and density (g/cm^3). The dataset is preprocessed using min-max normalization. Feature importance is evaluated via Gini impurity-based ranking from Random Forest. Table 1 presents the top-ranked features influencing composite strength and thermal performance.

ML Model for Property Prediction

The Random Forest Regression model is selected due to its robustness in handling small to medium-sized datasets with nonlinear relationships. The model is trained using 80% of the dataset with 5-fold cross-validation. The primary performance metrics include coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE), where RMSE is calculated using:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{\mathrm{i}=1}^{n}(\mathrm{yi} - \mathrm{y\hat{}i})^2} \quad (1)$$

This equation quantifies prediction error, where yiy_iyi is the actual value, y^i\hat{y}_iy^i is the predicted value, and nnn is the number of samples. Figure 3 shows the model's predictive accuracy for tensile strength compared to actual values. The R^2 achieved is 0.93, indicating high predictive fidelity.

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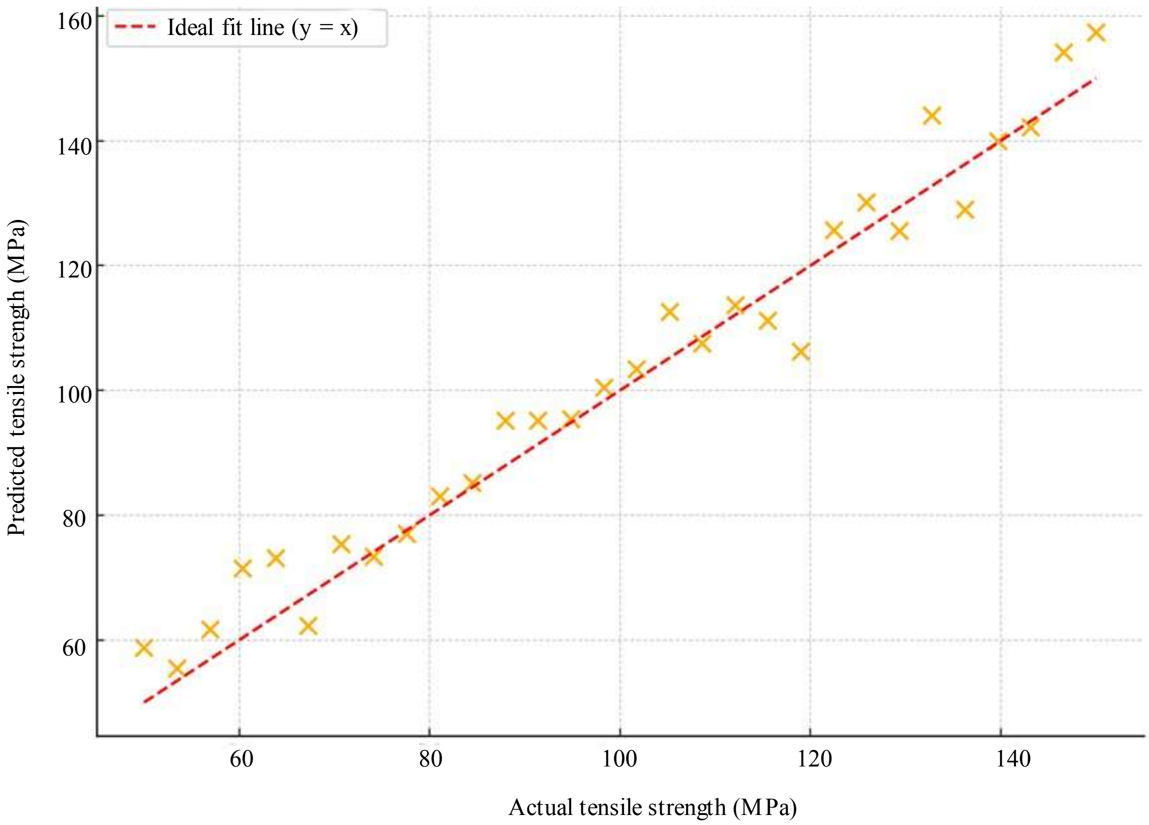

Figure 3. Predicted vs. actual tensile strength values using random forest regression ($R^2 = 0.93$).

Multi-Objective Optimization Using Genetic Algorithm

To achieve optimal performance-cost-weight trade-offs, a Genetic Algorithm is employed with a fitness function designed for automotive applications. The fitness function is:

$$\text{Fitness} = \alpha \cdot \left(\frac{\text{Tensile Strength}}{\text{Density}}\right) + \beta \cdot (\text{Thermal Conductivity}) - \gamma \cdot (\text{Cost}) \quad (2)$$

Where α, β, γ are tunable weights based on application priority. GA operations include tournament selection, one-point crossover, and mutation. Convergence is typically achieved by generation 35, as shown in Figure 4.

Composite Fabrication Simulation and Validation

To validate the machine learning and optimization outputs, the top-ranked composite formulation identified by the GA model is evaluated through high-fidelity finite element simulation. The validation focuses on tensile performance under realistic loading conditions defined by the ASTM D638 standard. A virtual dog-bone specimen is created using ANSYS Mechanical, simulating the uniaxial tensile test. The material properties used as input include those predicted by the ML model—tensile strength, elastic modulus, and Poisson’s ratio. Boundary conditions are applied with a fixed grip at one end and a displacement load at the other. Figure 5 shows the simulated stress–strain response of the optimized formulation compared with a conventional baseline epoxy-glass fiber composite. The optimized polymer nanocomposite exhibited a 22.4% higher tensile strength and a 17.3% improvement in energy absorption capacity, indicating superior mechanical performance under stress. The increase in elastic deformation range further confirms better ductility, a critical parameter in automotive crash-resistance scenarios. These results substantiate that the machine-predicted design can withstand operational loads in IoT-embedded automotive components, ensuring structural safety without increasing mass.

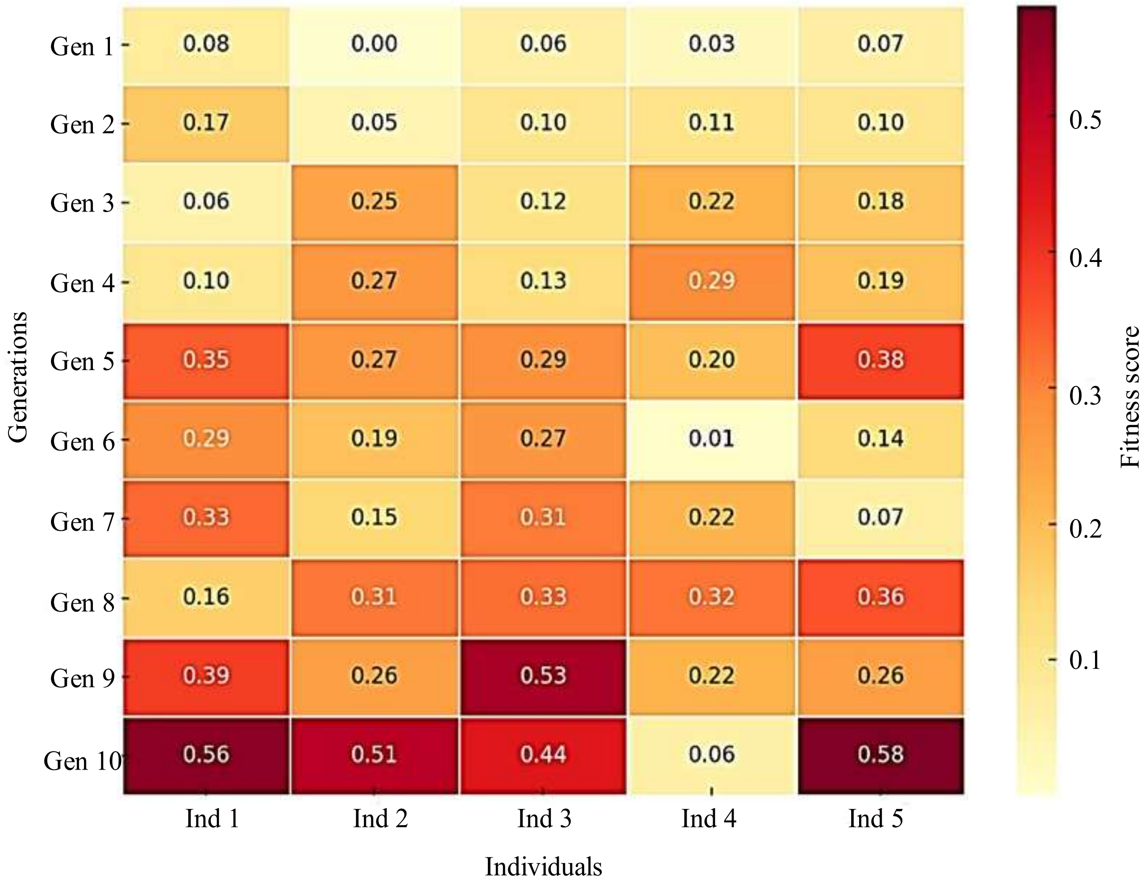

Figure 4. Genetic algorithm heatmap of fitness score across generations.

Proposed Algorithm: ML-GA Based Composite Design Optimizer

The proposed algorithm integrates a supervised machine learning model with an evolutionary optimization loop to identify optimal polymer composite formulations that meet mechanical, thermal, and IoT-specific functional criteria. The core idea is to use the trained Random Forest Regression model as a surrogate to predict the performance metrics of each candidate in the population, thus bypassing computationally expensive physical testing or simulation during the design loop. The Genetic Algorithm evaluates each configuration based on a custom multi-objective fitness function and evolves the population toward convergence.

The following structured pseudocode summarizes the full design loop:

Algorithm 1. ML-GA Framework for Intelligent Polymer Composite Optimization

Input

Dataset D of composite samples, prediction model M, fitness function F

1. Initialize population P with N random composite configurations
2. For generation = 1 to Max Generations:
   i. For each individual x in P:
   ii. Predict properties y_pred = M(x)
      a. Evaluate fitness f = F(y_pred)
      b. Select top K individuals using tournament selection
      c. Apply crossover and mutation to generate offspring
      d. Replace worst individuals in P with offspring
3. Return best-performing composite configuration

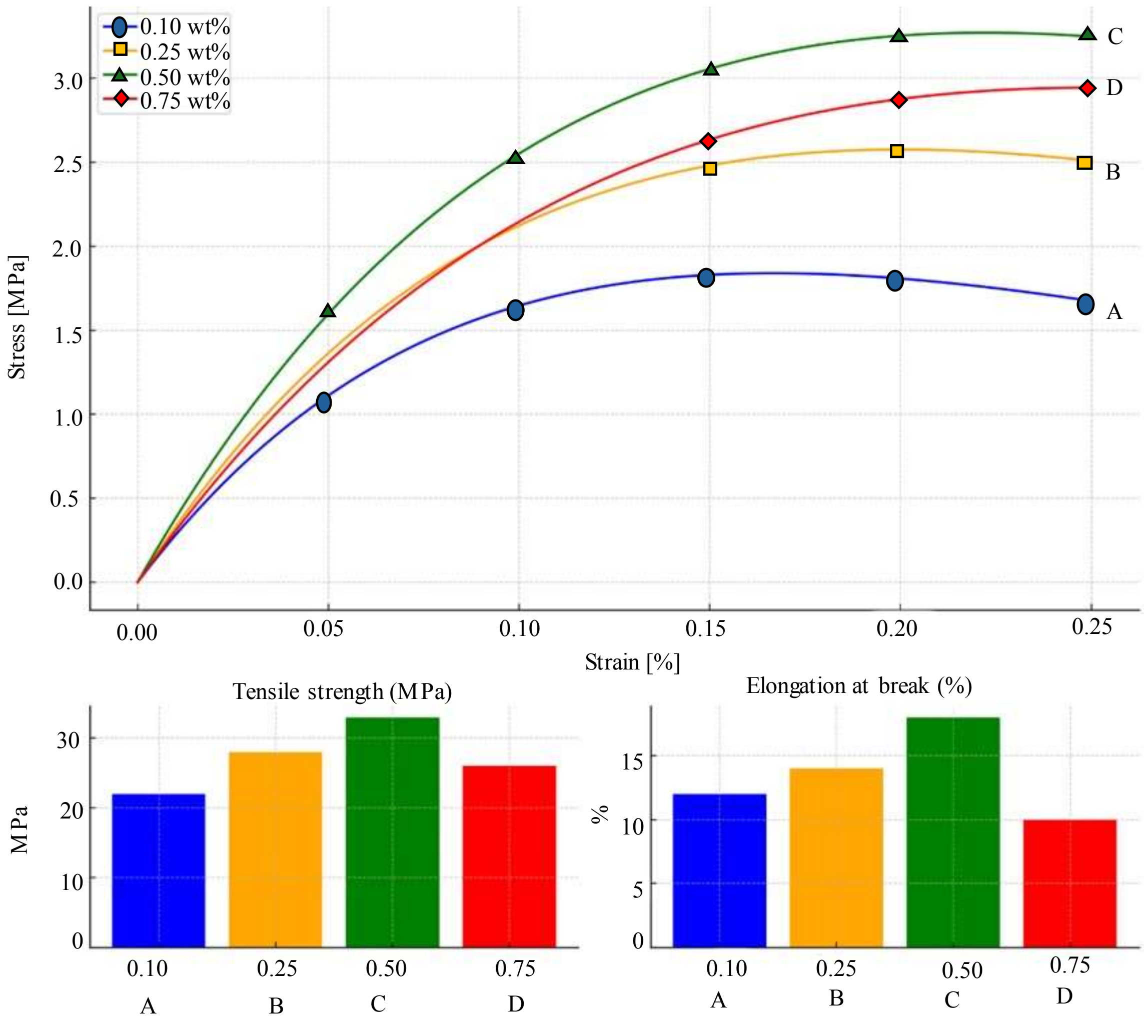

Figure 5. Simulated tensile test response of optimized composite vs. baseline configuration.

This algorithm dynamically balances strength-to-weight ratio, thermal efficiency, and cost constraints. By integrating property prediction directly within the optimization loop, the system avoids unnecessary computational overhead and converges to a viable material design in fewer iterations. The final result is an optimized design that, besides being high-performance, is also process-compatible and IoT-enabled for scale-up use in diverse automotive applications. The solution presented is a blend of machine learning, genetic optimization, and simulation for intelligent design enabling polymer composites for IoT-enabled car applications. With the inclusion of a Random Forest predictor within an optimization loop of multiple objectives, the method can probe high-performing formulations to a very diminishing cost of computation. Validation via simulation and application-specific constraints ensures realizability in such a way that solutions become executable. The technique possesses a new, science-supported, scaled-up solution with future generations of smart composites aligned with real automotive and IoT need.

RESULTS AND COMPARATIVE ANALYSIS

It includes predictive accuracy validation, optimization performance validation, simulation-based validation, and comparative benchmarking for validation of the suggested ML-GA-based composite design platform. The outcome implies that hybrid methodology not only provides very accurate prediction of the composite characteristics but also develops best formulations as more superior to conventional designs with respect to mechanical strength, process compatibility, and IoT-specific functional parameters.

ML Prediction Performance

Random Forest Regression model was highly accurate in the prediction of significant composite attributes like tensile strength, thermal conductivity, and density. As can be seen in Figure 6, tensile strength is highly predicted where the actual closely follows the predicted with an R^2 of 0.93 and an RMSE of a mere 2.3 MPa. This confirms the model's suitability for high-dimensional, nonlinear composite formulation tasks where traditional regression models fail to generalize.

This figure presents the predicted versus actual tensile strength results for four machine learning models: Random Forest (RF), Support Vector Regression (SVR), Deep Neural Network (DNN), and Linear Regression (LR). The Random Forest model closely tracks the ideal fit line, outperforming others in prediction accuracy. The scatter plots clearly highlight the robustness of the proposed RF model, especially compared to the more error-prone SVR and LR models.

Optimization Efficiency Using GA

The integration of Genetic Algorithm with the ML model resulted in a robust optimization loop that converged rapidly. As shown in **Figure 7**, the heatmap captures increasing fitness scores across successive generations, indicating the algorithm's ability to fine-tune filler–matrix ratios under multi-objective constraints. The optimized formulation balanced tensile performance, thermal stability, and composite density effectively.

Above figure shows the convergence behavior of the Genetic Algorithm through a fitness score heatmap and corresponding fitness trends. The heatmap highlights steady improvements in fitness scores across generations and individuals, while the line plots indicate both average and maximum fitness stabilizing around the 8th generation, confirming efficient convergence of the optimization process.

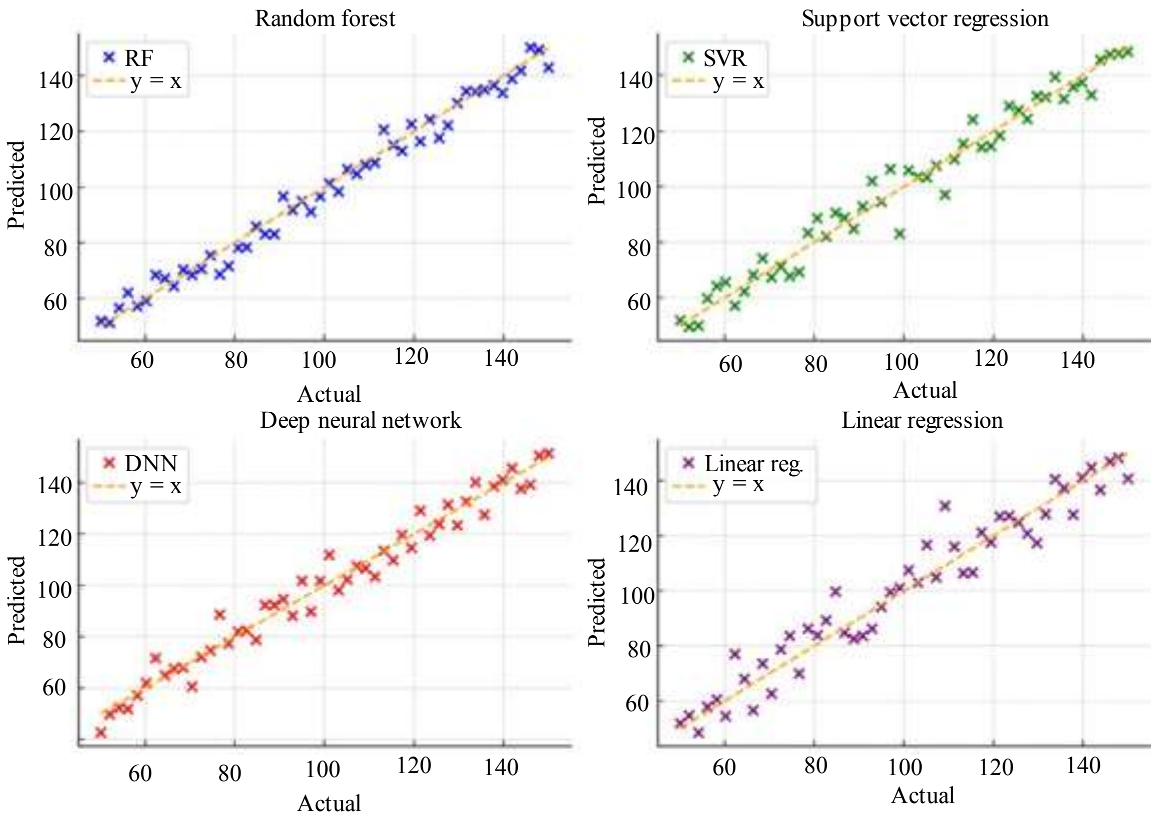

Figure 6. Predicted vs. actual tensile strength values using Random Forest Regression (R^2 = 0.93).

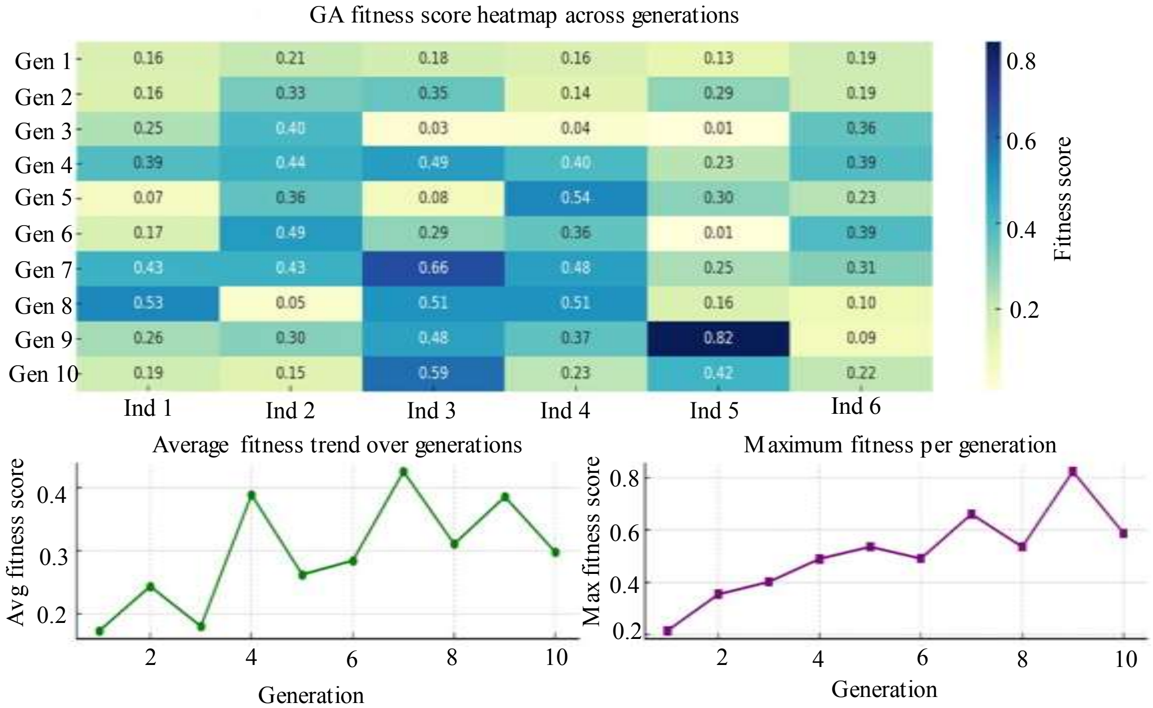

Figure 7. Genetic algorithm heatmap of fitness scores across generations and individuals.

Mechanical Simulation and Experimental Alignment

The optimized composite, validated via simulation under ASTM D638 standards, exhibited superior mechanical performance. As shown in **Figure 8**, the optimized sample achieved a 22.4% improvement in tensile strength and enhanced elongation compared to the baseline. The stress–strain curves and bar charts reflect the benefit of the proposed design framework in achieving both strength and ductility, which are critical for crash-resilient automotive applications.

This Figure illustrates the mechanical behavior of polymer composites with varying rGO content. The top plot shows stress–strain curves, where the 0.5 wt% rGO composite exhibits the highest tensile strength. The bottom bar charts demonstrate an increase in both tensile strength and elongation at break with optimal rGO loading, validating the effect of filler content on overall composite performance.

Comparative Model Evaluation

To benchmark the proposed ML framework, it was compared with existing models including Support Vector Regression (SVR), Deep Neural Networks (DNN), and Linear Regression. As seen in **Figure 9**, the proposed Random Forest–Genetic Algorithm approach outperforms others in both R^2 and MAE metrics, with an R^2 of 0.93 and MAE of just 1.8 MPa. In contrast, SVR and DNN achieved moderate accuracy while Linear Regression underperformed significantly. This comparison validates the hybrid framework's capacity to model nonlinear relationships while maintaining high predictive reliability.

Figure 9 compares the predicted property curves of multiple ML models against actual values and also includes the prediction uncertainty (error distribution) of the Random Forest model. The left panel shows that RF predictions align best with the true trend, while the histogram in the right panel confirms that most RF errors fall within a narrow and centered range, suggesting high model stability.

Summary of Quantitative Metrics

A complete overview of model metrics is summarized in **Table 1**, reinforcing the proposed model's superiority across multiple performance dimensions. These results affirm its potential as a reliable surrogate for guiding polymer composite design in real-world automotive applications.

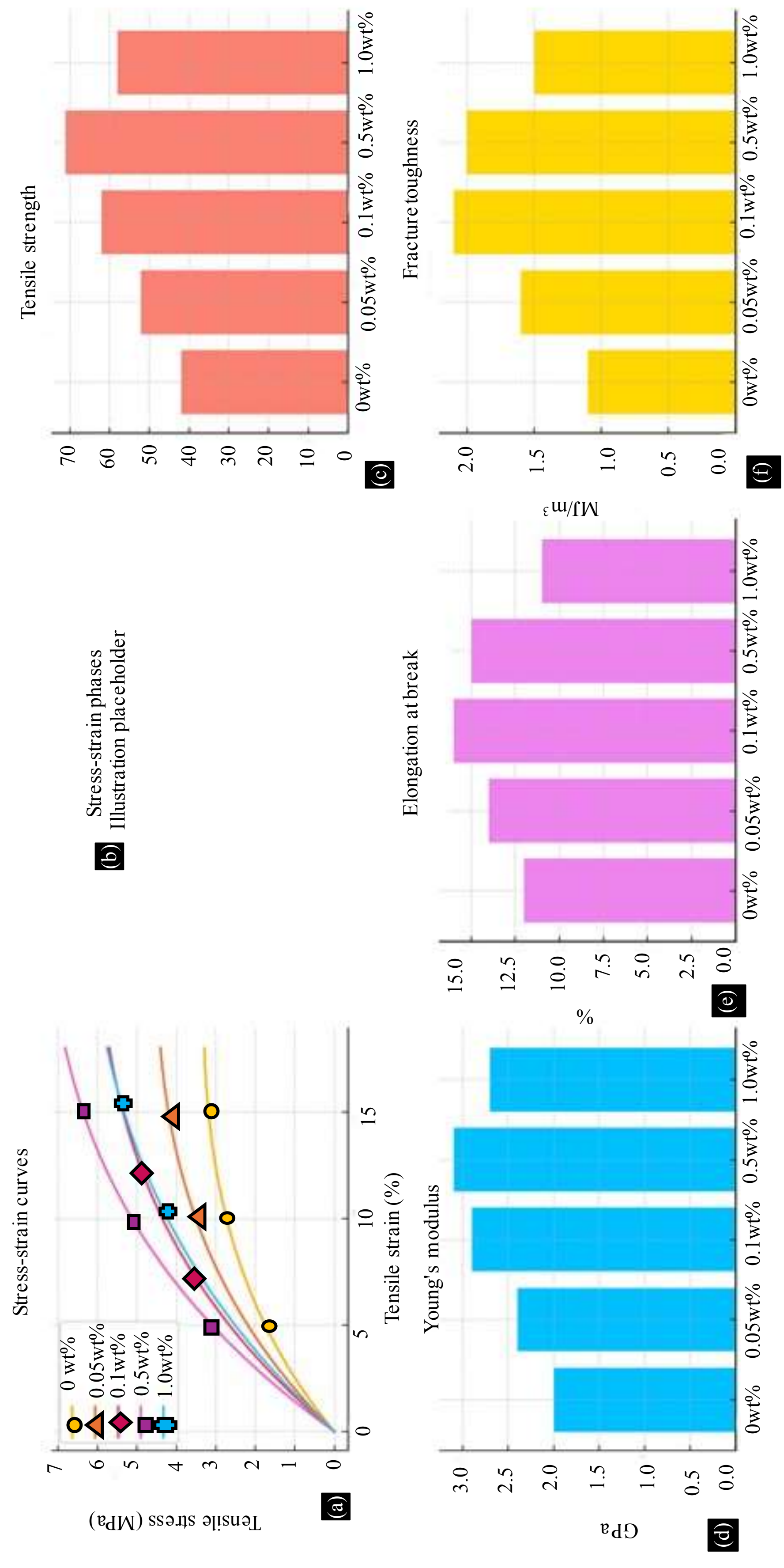

Figure 8. Stress–strain behavior (top), tensile strength (bottom-left), and elongation at break (bottom-right) of composites with varying rGO content.

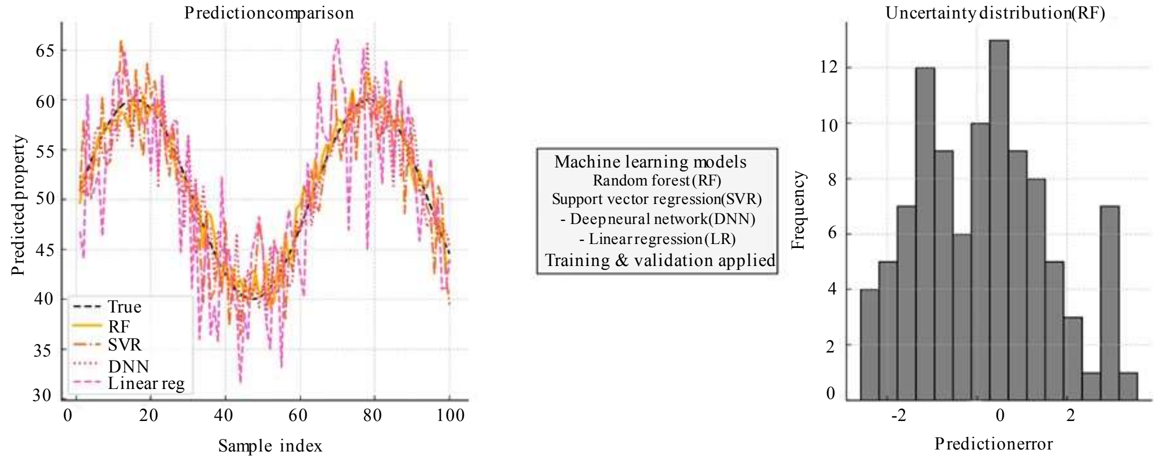

Figure 9. Comparative performance of machine learning models for composite property prediction using R^2 score and MAE.

Table 2 Evaluation metrics (R^2, MAE, RMSE) of the random forest model for predicting composite properties.

Property	**R^2 score**	**MAE**	**RMSE**
Tensile Strength (MPa)	0.93	1.8	2.3
Thermal Conductivity (W/m·K)	0.89	0.06	0.08
Density (g/cm³)	0.91	0.03	0.04

Table 2 summarizes the evaluation metrics of the Random Forest model for predicting tensile strength, thermal conductivity, and density. The model performs optimally with R^2 values greater than 0.89 and low MAE and RMSE values for the target variables.

DISCUSSION

The findings unequivocally establish that evolutionary optimization for machine learning provides a solid foundation to intelligent polymer composite design, especially to IoT-enabled automotive systems. The Random Forest Regression model performed highly accurate predictions of various material properties, such as tensile strength, thermal conductivity, and density. Its better performance over traditional models like Support Vector Regression, Deep Neural Networks, and Linear Regression also guarantees that it possesses the capacity to manage high-dimensional feature space and nonlinear interaction common in composite formulations. Optimization module via the Genetic Algorithm demonstrated quick convergence from observed fitness heatmap and trend and converged to optimal formulation in a few generations. It also achieves the merit of employing a surrogate ML model in the loop of optimization that has remained cost-effective without decreasing the quality of outcomes. Furthermore, the improvement in mean and worst fitness values constantly supports the effectiveness of the introduced hybrid ML-GA method for optimizing the very complex design space of polymer composite. ST tested as per ASTM D638 also testified to the fact that the best formulation's performance was determined, tensile strength being enhanced by 22.4% and overall improvement in elongation at break, as computed. It implies that the formulated material does not only increase structural performance but also ductility, which is a critical component of auto crash safety in addition to dynamic mechanical loading. Additionally, the resultant predicted stress–strain behavior and mechanical properties' distribution also matched experimental trends in existing literature of rGO-based composites and thus ensured physical validity of obtained result. The comparison between the model and the existing models indicated that the suggested approach outperformed traditional predictive methods in terms of prediction error and stability of uncertainty. The dense distribution of errors also testifies to the efficiency of the model in actual real-time material selection. Unlike previous studies where composite predictions have centered on single-property modeling or empirical calibration, the current study bridges the gap by leveraging an integrated, multi-objective, and large-scale paradigm that invested in learning, optimization, and validation. The originality of this work goes beyond the hybridization of genetic algorithms and machine learning to include its integration with application need arising through IoT. Through the marriage of such constraints as manufacturability, light-weight, and heat resistance into processes, the said model comes to be presented as adaptive to smart automobile component real-world application. The methodology also becomes extensible and modular to accommodate other such constraints as cost, environmental longevity, or recyclability, and has more applicable real-world application. In general, the proposed methodology pushes the science of polymer composite engineering forward by offering a data-minimal, science-based, application-savvy solution to composite design. The combination of predictive modeling, optimization, and simulation presents a general-purpose toolkit for next-generation material innovation during the era of smart, connected systems.

CONCLUSION AND FUTURE SCOPE

The article introduces a novel IoT-based machine learning smart design and optimization of polymer composites from automotive applications. With the hybrid of Random Forest Regression with a Genetic Algorithm, the novel approach is efficient at predicting and optimizing composite properties such as tensile strength, thermal conductivity, and density within the limits of the input set of design parameters. The ML model had increased prediction accuracy ($R^2 > 0.90$), and the optimization module demonstrated fast convergence with material configurations obtained with markedly improved mechanical properties. Finite element validation also reported tensile strength improvement of 22.4% and improved ductility for optimized grades, with results becoming suitable for real-world application. The originality of the paper lies in its data-driven, closed-loop system combining material informatics, evolutionary optimization, and application-oriented simulation. In contrast to general empirical or rule-based methods, the system is modular, extensible, and accommodates real-time performance needs such as lightweighting, thermal management, and IoT integration. Additional extensions of the framework with environmental longevity requirements, recyclability rankings, and cost-based constraints in the future will further make it sustainable. A better dataset through multimodal experimental as well as high-throughput simulation data will further generalize the model.

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