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Smart Polymer Composites with Multifunctional Capabilities Integrating Electroactive Polymers Conductive Nanofillers and Flexible Electronics for Advanced Sensing and Actuation Systems

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Abstract

Smart polymer composites have gained significant attention to their ability to integrate polymer matrices with conductive nanofillers, offering tunable electrical, mechanical, and electroactive properties. These composites are highly responsive to external stimuli such as electrical fields, mechanical stress, and temperature variations, making them ideal for applications in flexible electronics, soft robotics, and adaptive sensing systems. This research investigates the effect of nanofiller dispersion on the performance of polymer composites, optimizing nanofiller concentration to enhance electrical conductivity, mechanical strength, and flexibility. A one-way ANOVA was used to analyze the significance of material composition, particularly nanofiller concentration and polymer type, on composite properties. The long-term environmental stability of EAPs, such as polypyrrole (PPy) and polyvinylidene fluoride (PVDF), was examined to improve their reliability. The integration of flexible electronics through conductive inks and screen printing was explored to enhance the mechanical compliance and durability of these composites in wearable devices and robotics. ML models, including Random Forest, Support Vector Machines (SVM), and Neural Networks, are employed for multi-property optimization, predicting and improving composite performance. The study also addresses the scalability and cost-effectiveness of fabrication techniques to ensure the commercial viability of these advanced materials. The potential for incorporating biodegradable or environmentally friendly materials into smart polymer composites was explored to meet the growing demand for sustainable technologies. This research aims to advance the design, optimization, and application of smart polymer composites, paving the way for their widespread use in next-generation electronic and robotic systems.

Keywords: Smart Polymer Composites; Electroactive Polymers; Carbon Nanotubes; Graphene Nanoplatelets; Flexible Electronics; Machine Learning Optimization.

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INTRODUCTION

Smart polymer composites have become important in the field to their capability to combine polymer matrices with functional reinforcements that offer controlled electrical as well as mechanical properties and electroactive behavior [1]. The smart composites demonstrate adjustable behavioral responses to electrical fields in addition to mechanical stress as well as temperature changes so they work optimally for flexible electronics and adaptive sensing systems and soft robotic applications [2]. The stretchable features of conductive smart polymers make them suitable for use in flexible electronic sensors and wearable devices that demonstrate high reliability [3]. Softer robotic systems benefit from shape-altering capabilities which allows researchers to create artificial muscles and imitation biomimetic parts [4]. Smart polymers have earned their status as sensitive materials when utilized in sensors to track environmental together with physiological changes [5]. Modern smart composite technology development benefits from continuous advancements in their material designs and fabrication processes and material optimization strategies applied to different practical applications [6]. The actuation response of these composite materials depends on Electroactive polymers (EAPs) because their electric field-triggered deformation capability. The EAP materials PPy and PVDF demonstrate separate value-adds to electromechanical systems since PPy maintains high electrical stability and electroconductivity for devices but PVDF functions well for actuators and energy harvesting capability [7-8]. These polymers gain mechanical strength and transportation of electrical charge becomes better when combined with carbon nanotubes (CNTs) and graphene nanoplatelets (GNPs) [9]. Scientific findings indicate that polymer composites gain improved electrical properties together with mechanical reinforcement when CNTs and GNPs are added [10]. The extent of nanofiller presence and distribution directly influences composite performance characteristics [11]. CNTs enhance charge transport capabilities but GNPs reinforce mechanical strength as well as network conductivity [12]. The proper dispersal technique served as a necessary condition to stop aggregation because it creates performance limitations. Meticulous fabrication techniques exist for these composites since they need both uniform nanofiller dispersion and successful flexible electronic integration [13]. Two techniques namely ultra-sonication and high-shear mixing serve for nanofiller dispersion and solution blending along with spin-coating establish composite formation [14]. Flexible electronics receive installation through conductive inks during screen printing operations that lead to high-resolution patterning required for wearable devices and soft robotics [15]. Comparing different processing parameters leads to stable mechanical composites with reinforced multifunctional properties [16]. Electroactive composite characterization requires the testing of electrical features and mechanical properties as well as actuation capabilities according to [17]. EIS and four-point probe analysis enable researchers to evaluate charge transport and material conductivity through electrical examinations [18]. Laboratory examinations such as tensile and force-displacement assessments determine the material strength together with flexibility and resistance capabilities [19]. Testing for material actuation analyzes mechanical deformation caused by electrical stimulation since it directly affects actuator functionality [20]. Today ML functions as an advanced method that optimizes composite materials development [21]. Random Forest algorithms in addition to SVM and Neural Networks are ML tools that analyze complex processing parameter and material property relationships [22]. Such predictive models find optimal materials compositions and nanofiller amounts when used to forecast electrical conductivity and tensile strength and actuation displacement properties [23]. Thorough material discovery becomes faster through ML-driven optimization methodology which simultaneously decreases experimental testing requirements and improves polymer components for advanced uses [24].

RESEARCH GAP

Despite the promising advances in smart polymer composites, several research gaps remain that need further exploration. One significant challenge was achieving uniform dispersion of nanofillers like CNTs and GNPs, which directly impacts the composite's performance. Developing advanced dispersion techniques or hybrid methods could address this issue. The environmental stability of EAPs such as PPy and PVDF under varying conditions, like humidity and temperature fluctuations, requires further investigation to enhance their long-term reliability. Another gap lies in optimizing nanofiller concentration, as the relationship between loading percentage and composite properties was not fully explored. Further research could refine this balance for improved mechanical and electroactive performance. ML-based optimization techniques can be expanded to simultaneously predict and optimize multiple material properties, including actuation response, conductivity, and flexibility, by integrating real-time experimental data. The scalability and cost-effectiveness of fabrication methods need to be addressed to facilitate widespread commercial applications.

Research Objectives

- To explore various nanofiller dispersion techniques, such as ultrasonication and high-shear mixing, and evaluate their impact on the electrical conductivity, mechanical strength, and electroactive properties of smart polymer composites. This help optimize the distribution of conductive nanofillers like CNTs and GNPs within the polymer matrix.
- To determine the optimal concentration of conductive nanofillers in the polymer matrix that balances electrical conductivity, mechanical strength, and flexibility, thereby enhancing the multifunctional performance of the composite materials.
- To investigate the long-term stability of EAPs, such as PPy and PVDF, under varying environmental conditions, including temperature and humidity fluctuations, and develop strategies to improve their environmental durability for real-world applications.
- To assess the integration of flexible electronics, such as conductive inks and screen printing methods, into polymer composites and evaluate their impact on the mechanical compliance, durability, and overall performance of devices used in wearable electronics and soft robotics.
- To implement ML algorithms, including Random Forest, SVM, and Neural Networks, for optimizing multiple properties of smart polymer composites, such as electrical conductivity, tensile strength, flexibility, and actuation performance, using experimental data for real-time predictions and optimization.

RESEARCH METHODOLOGY

In this work, the systematic methodology was adopted, which aimed at combining materials selection, composite fabrication, and multi-level characterization to evaluate the multifunctional behavior of smart polymer composites. The methodology is a combination of experimental processing and analytical appraisals to comprehend the effects of polymer type, concentration of nanofiller, and curing conditions on electrical, mechanical, and electroactive behaviors. An optimization system of machine learning was used to find the most effective formulations. Figure 1 presents the general working process of this study in a summary, which follows a systematic flow of the work between the preparation of materials and the prediction of performance. The general workflow used in this paper, including selecting materials, fabricating, characterizing, and optimizing it through machine learning, is shown in Figure 1.

Materials Selection

The chosen materials for this development underwent selection process which focused on their combined electrical and mechanical as well as electroactive properties to achieve optimal sensing and actuation performance [25]. Positive factors that led to the selection of EAPs include their capacity of mechanical deformation which responds to electrical triggers used for creating flexible adaptive systems. PPy received selection to its exceptional electrical conductivity and stable electrochemical behavior that helps boost charge movement in the composite. The addition of PVDF brought strong piezoelectric and ferroelectric properties to the actuation performance of the system. The composites received strengthening abilities and conductivity enhancement through the addition of these electrically conductive nanofillers. The choice of CNTs in specific applications stemmed from their long structural dimensions and excellent electrical conductivity properties together with their ability to enhance mechanical performance thus enabling better charge transmission and flexible performance. The large surface area together with high thermal stability and excellent mechanical capabilities of GNPs make them suitable for reinforcing the composite structure and maintaining a

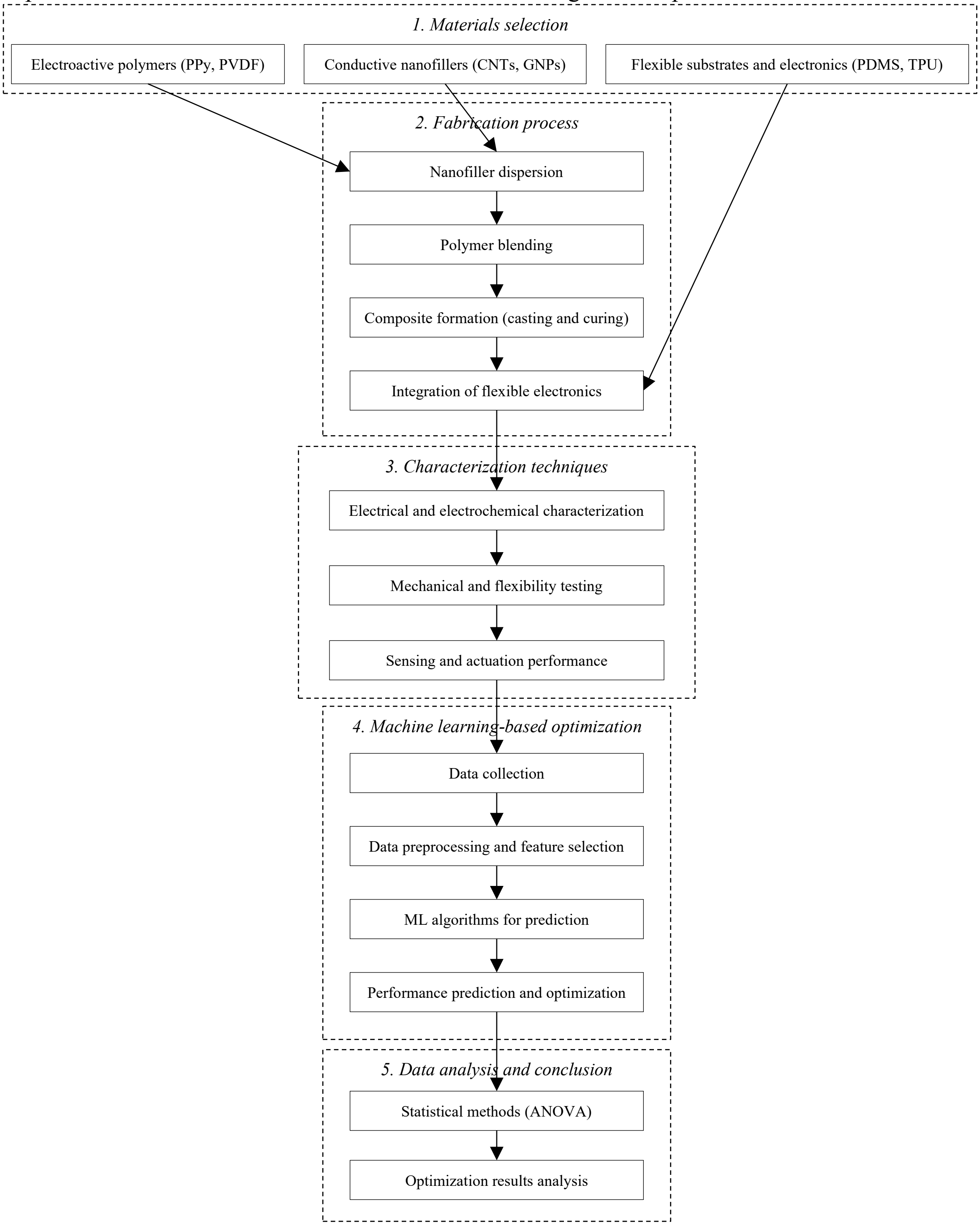

Figure 1. Methodology flow chart

lightweight and flexible material. Flexible substrates along with electronics became necessary elements for durable composites that maintain their mechanical compliance. Polydimethylsiloxane (PDMS) exhibited excellent properties for flexible substrate selection because they are stretchable and show high biocompatibility and repeated survival under mechanical stress. Efficient integration of flexible electronic circuits in wearable and soft robotic applications was made possible by the use of conductive inks particularly carbon-based inks. The composite materials improve the creation of

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advanced sensing and actuation systems through high-performance smart polymers operated by multifunctional operation.

Fabrication Process

The fabrication process was designed so that there is even distribution of nanofillers, a good polymer-filler interaction, and dependability of incorporation of flexible electronic materials. These processes were chosen according to the industry standards and prior experimental knowledge that showed that they were appropriate to generate highly conductive and mechanically strong polymer materials. The section provides the fabrication steps in a sequential manner, such as dispersion of the nanofiller, polymer blending, formation of a composite on flexible substrates, and integration of printed conductive circuitry to provide sensing and actuation functions.

Synthesis of Polymer Composites

Polymer composite synthesis was done by using a controlled series of dispersion, blending, and deposition processes to obtain uniform distribution of nanofillers and stable composite structures. As the workability of smart polymer composites is significantly influenced by the microstructural uniformity, the agglomeration of the CNTs and the GNPs was minimized, and the appropriate contact between the Ppy and PVDF matrices was taken care of. The subsection explains the step-by-step processes that were employed to disperse nanofillers, dissolve polymers, and create composite films that could be used to perform mechanical, electrical, and electroactive testing.

Nanofiller Dispersion

The procedure outlined in ASTM E2456-06 for uniform nanomaterial dispersion enabled ultrasonication of CNTs and GNPs dispersion in dimethylformamide (DMF). The researchers weighed nanofillers alongside the required weight percentage (wt.%) in relation to the polymer matrix before adding them to DMF [26]. We performed ultrasonication of nanofillers for 30–60 minutes at 500W and 20 kHz using a probe ultrasonicator to obtain uniform dispersion while maintaining a power level that stopped agglomeration. The dispersion process included periodic cooling steps in order to shield solvent degradation during the processing time.

Polymer Blending

The PPy and PVDF separately in DMF under 500 rpm stirring at room temperature for six hours according to ISO 11357-3:2018 standards to achieve complete dissolution and homogeneity. Magnetic stirring was used to add the dispersion of ultrasonicated nanofillers into the polymer solution for attainment of a homogeneous mixture. The blend consisting of polymer and nanofillers needed additional 12 to 24 hours of stirring to enable complete incorporation of nanofillers within the polymer framework. The rotational viscometer evaluated blend viscosity to confirm printing and coating uniformity.

Composite Formation

PDMS flexible substrates received the polymer-nanofiller solution through spin-coating according to ASTM D1004-13 for achieving consistent film thickness and ideal mechanical qualities. The PDMS substrates required base agent mixing with curing agent at a ratio of 10:1 prior to vacuum chamber degassing for 30 minutes to eliminate trapped air bubbles from the solution. The mixture underwent curing at 70°C for two hours after it had been transferred into molds. The application of the polymer-nanofiller solution onto the PDMS substrate took place after curing at either 2000 rpm spin-coating for 60 seconds or doctor blade casting for thicker films to reach 100–500 µm thickness. A six to twelve hour curing process at 60-80 degrees Celsius in accordance with ASTM D1004-13 allowed the substrates to stabilize their composite structure while the solvent evaporated.

Integration of Flexible Electronics

The procedure defined in IEC 62899-202:2019 was used to screen-print carbon-based conductive inks onto the composite surface when printing flexible substrates. The patterned electrodes received heat treatment at 120°C for 30 minutes to achieve secure electrical connections. An electrical connection between printed electrodes and external wiring required application of silver paste. A multimeter verified electrical continuity of the composite material before additional tests by checking its proper conductivity.

Characterization Techniques

An integrated collection of characterization methods was used to assess the performance of the developed composites in terms of electrical, mechanical, and electroactive functionality. Such techniques made it possible to correlate the material composition, processing conditions, and functional output. This was done by electrical and electrochemical measurements to determine conductivity and charge-transfer properties, and mechanical tests determined strength, elasticity, and deformation properties. Also, sensing and actuation tests were carried out in order to establish the voltage-induced displacement and dynamic responsiveness, which gave a comprehensive understanding of the multifunctional nature of the composite.

Electrical and Electrochemical Characterization

Figure 2 shows the Nyquist plot from electrochemical impedance spectroscopy (EIS), which illustrates the frequency-dependent impedance behavior and reveals charge-transfer resistance and double-layer capacitance components. Observed data from real impedance measurements and imaginary impedance provides identification of composite charge transport capabilities and conductivity values. The semicircular arc on the plot indicates that the material possesses both charge transfer resistance and double-layer capacitance components important for electrochemical behavior characterization [27]. The material demonstrates capacitive behavior when frequency grows higher because impedance values lower down. The results presented significant information for assessing the composite's suitability for energy storage devices and sensing applications because impedance function as a critical performance parameter in these systems. Measurement of the composite sheet resistance occurred through the Four-Point Probe Method at different nanofiller concentrations (Figure 3). This method decreases contact resistances that typically occur during conductivity measurements. The experimental findings show that both CNTs and GNPs nanofiller concentration increases leads to decreased sheet resistance thereby improving electrical conductivity of the composite material. The experimental results indicate that elevated nanofiller concentrations lead to improved electrical performance of the composites because wearable sensors and flexible electronics demand such capabilities.

Mechanical and Flexibility Testing

From tensile testing reveal complete mechanical properties of the composite material through its stress-strain curve (Figure 4). Elastic deformation manifests as the first linear part of the curve until plastic deformation starts from the yield point. A measurement of Young’s modulus was determined

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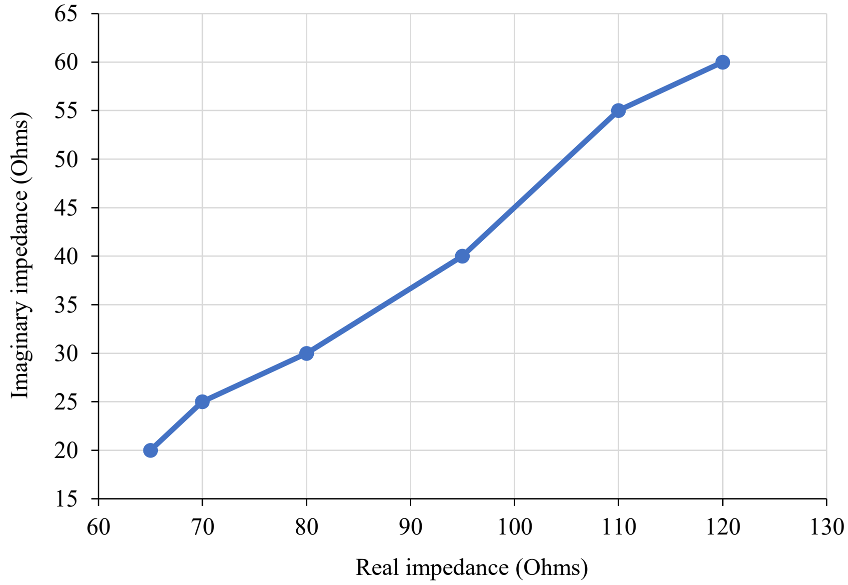

Figure 2. Nyquist Plot for EIS (Impedance and Frequency)

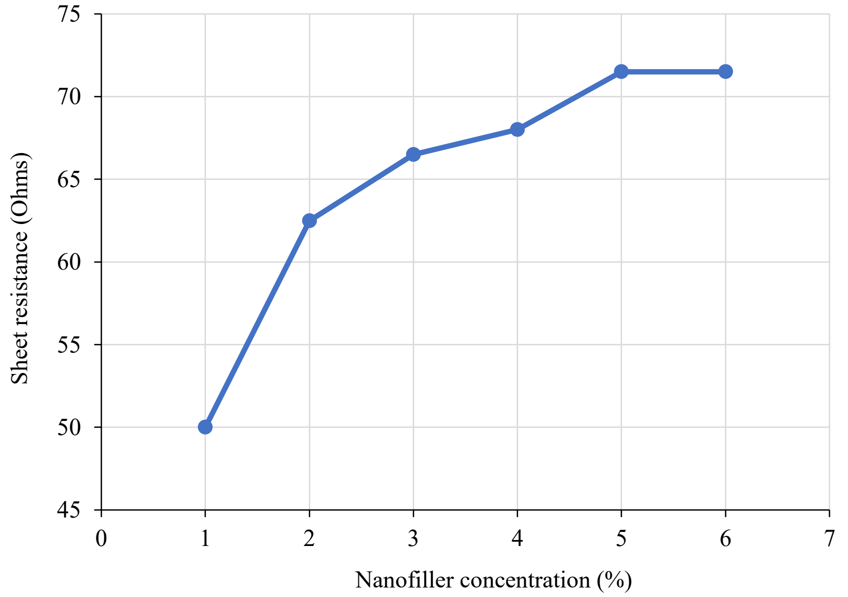

Figure 3. Sheet resistance and nanofiller concentration (four-point probe method)

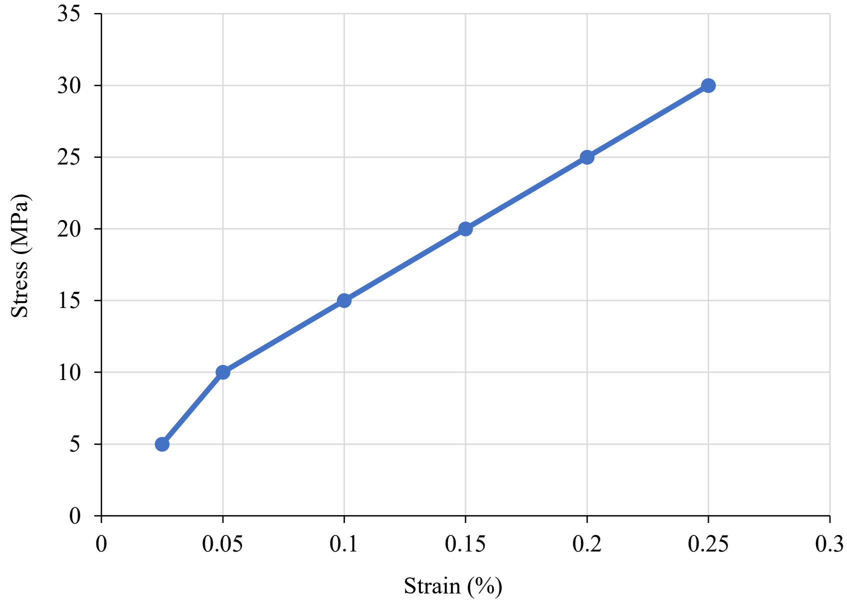

Figure 4. Stress-strain curve (tensile testing)

from the linear slope of the data. The material's strength characteristics together with its ductility potential appear in the ultimate tensile strength and elongation at break values [28]. The material demonstrated excellent mechanical capabilities by combining high strength with flexibleness making it appropriate for wearable electronics and soft robotics applications which need components to experience strain without breaking.

The force-displacement curve shown in Figure 5 displays the direct connection between applied forces and resulting material deforms of the composite. The deformability character of the material under load appears through this curve. The deformation extent of the material becomes visible through displacement measurements while the material stretches because of applied force. The ability of the composite material to deform under force determines its usefulness in applications with dynamic loads that expose it to mechanical forces.

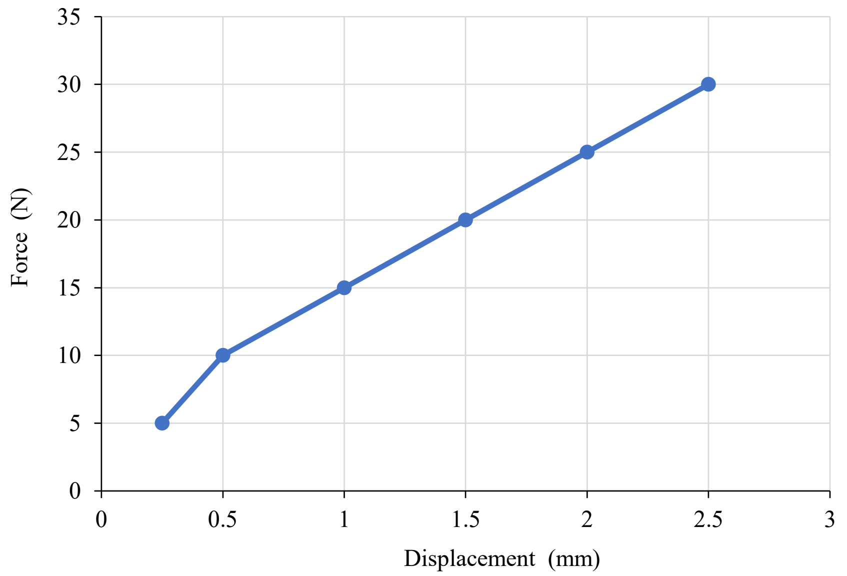

Figure 5. Force and displacement (tensile testing)

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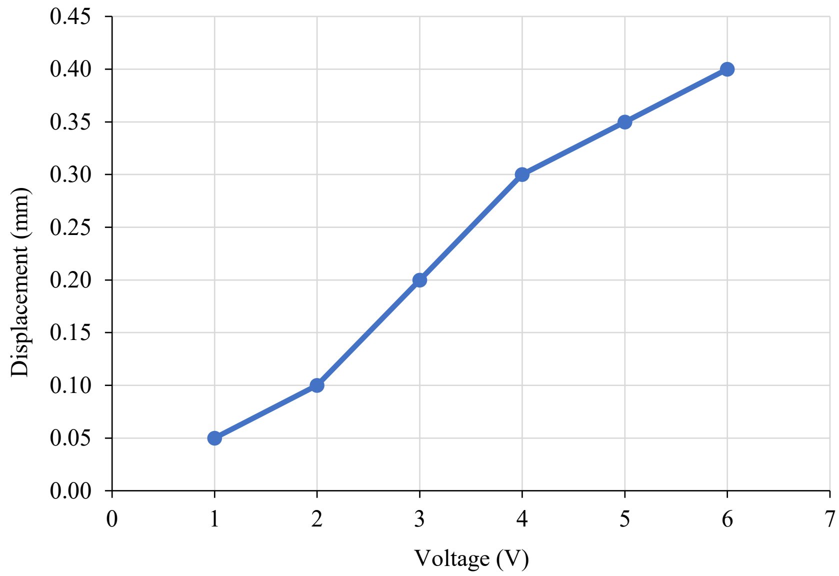


Figure 6. Displacement and voltage (electroactive response testing)

Sensing and Actuation Performance

The electroactive response testing of the composite material produced a displacement-voltage graph (Figure 6) that revealed its response to different levels of voltage through its movements. A voltage supply causes the composite material to move while measuring the displacement amount. The electrical signal activates the electroactive properties of the composite which results in a changeable shape. The analyzed data reveals that the material achieves notable displacement when supplied with minimal electrical voltage which makes it suitable for utilization in lightweight actuators utilized for soft robotics frameworks and wearable technology [29]. The sensor capabilities of the material depend on its high sensitiveness to voltage variations. The composite required evaluation for its response time through Figure 7 because it measures how quickly the material reaches its actuated state after introducing voltage. The response time of this material remained short enough to work in real-time with applications that need adaptive prosthetics and interactive devices. Multiple tests confirmed that the composite would respond rapidly while sustaining repeated changeable patterns of state in multiple cycles to serve dynamic actuation applications.

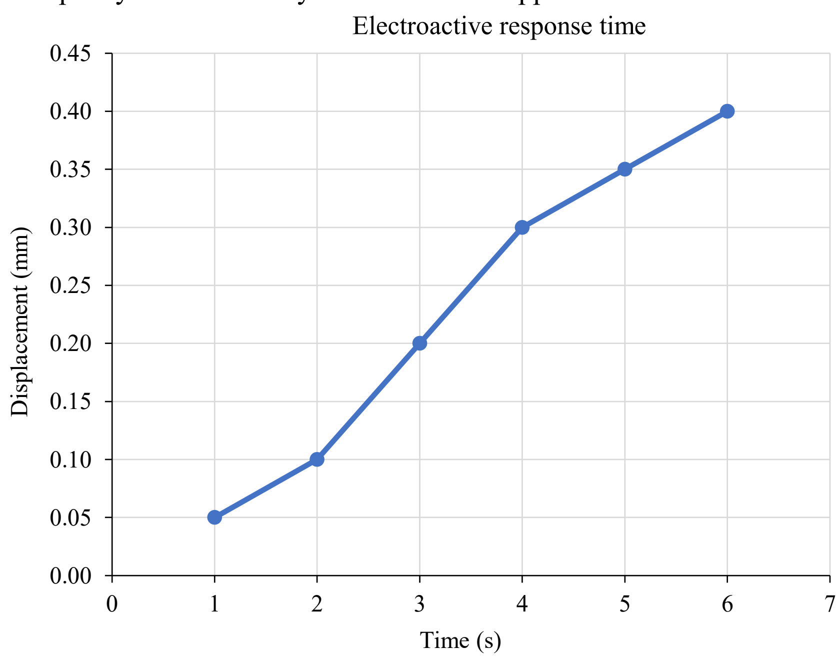


Figure 7. Response time for actuation (electroactive response)

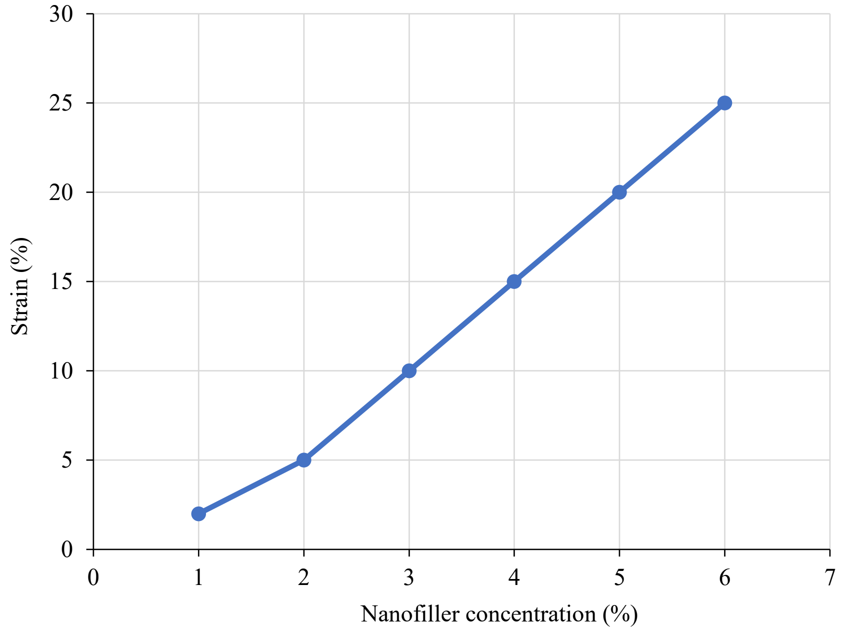


Figure 8. Strain and nanofiller concentration (tensile testing)

The analysis researched the relationship of filler content with strain (Figure 8). Strain resistance increased proportionally with nanofiller content in the composite materials until the point where the materials became mechanically stiffer. The optimal design of the material flexibility and deformability for multiple applications including wearable devices can be achieved through this discovery [30]. Electroactive response testing through the displacement-force curve (Figure 9) demonstrates the material's ability to produce force during displacement caused by supplied voltage. Force output by the composite material proved fundamental for practical actuator and soft robotic applications that needed simultaneous force production and displacement motions. The experimental results indicate that the composite material possesses both high force output potential and elastic behavior which establishes its potential role as an advanced material in actuator development.

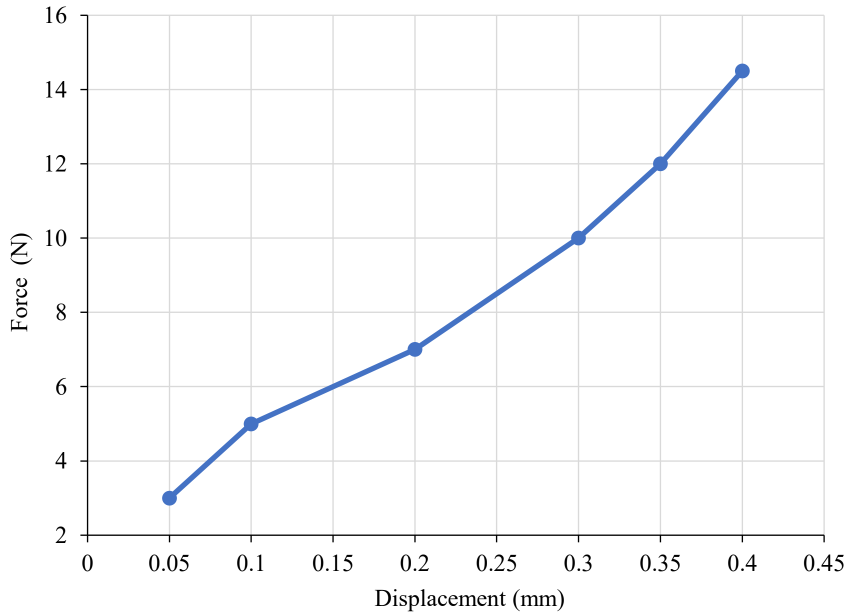


Figure 9. Displacement and force (electroactive response)

MACHINE LEARNING-BASED OPTIMIZATION

Table 1 lists the experimental dataset of control parameters (polymer type, nanofiller concentration, curing temperature/time, and applied voltage) and response variables (electrical conductivity, tensile strength, flexibility, actuation displacement) used for ML model training. The analysis involves five control parameters Polymer Type and Nanofiller Concentration (%), Curing Temperature (°C), Curing Time (hours) as well as Applied Voltage (V). These factors were chosen for their significance in determining the electrical, mechanical, and actuation characteristics of the composite material. PPy and PVDF were chosen because they exhibit different electroactive and mechanical properties. A performance evaluation of each composite formulation relied on measurements taken for response variables that consisted of Electrical Conductivity (S/m) Tensile Strength (MPa) Flexibility (%) and Actuation Displacement (mm). The electrical conductivity measurements depended heavily on polymer composition and nanofiller ratios because these components develop networks for efficient charge movement. Nanofiller reinforcement leads to enhanced tensile strength but the addition of filler content tend to decrease material flexibility except when it results in matrix stiffening. The electroactive response exhibited by the composite depended heavily on its actuation displacement which got determined by the properties of both polymer type and nanofiller distribution and applied voltage. A data dataset served as the training ground for ML algorithms Random Forest and SVM and Neural Networks to predict formula improvements for maximal multifunctional performance. Experimental testing validated the ML predictions by using the optimized model results. This data collection functions as an essential component to create computational design methods for composites which reduces experimental testing requirements to find optimal sensing and actuation formulations.

The Random Forest Model analysis demonstrated that Nanofiller Concentration (%) together with Curing Temperature (°C) remained the most crucial variables for Actuation Displacement (mm) prediction through the Feature Importance (Figure 10). Nanofiller Concentration (%) and Curing Temperature (°C) were recognized as fundamental factors before Curing Time (hours) and Voltage (V). The percentage of Nanofiller Concentration emerged as the main influential factor because it directly affects both conductivity and mechanical strength together with electroactive behavior. The actuation efficiency and mechanical properties of the polymer matrix receive impacts from Curing Temperature (°C) which determines the crosslinking level in the material. The results demonstrate that both nanofiller optimization and proper curing treatment enabled maximum actuation perfection. Using the Actual and Predicted Plot (Figure 11) the experimental measurements of actuation displacement

Table 1. Experimental dataset for machine learning-based optimization of smart polymer composites

Run	Polymer type	Nanofiller concentration (%)	Curing temperature (°C)	Curing time (h)	Voltage (V)	Electrical conductivity (S/m)	Tensile strength (MPa)	Flexibility (%)	Actuation displacement (mm)
1	PPy	3.74	70	4	2.45	0.85	56.3	72	3.63
2	PVDF	1.8	70	6	1.8	0.45	53.1	78	2.26
3	PPy	2.58	60	4	1.92	0.65	60.2	74	3.29
4	PVDF	3.04	70	2	2.98	0.78	63.4	77	3.28
5	PPy	4.82	80	4	2.23	1.05	70.1	68	4.21
6	PVDF	1.94	80	2	2.1	0.52	54.9	79	2.62
7	PPy	2.98	60	2	2.34	0.69	61.5	75	3.16
8	PVDF	4.58	70	6	2.91	1.03	69.7	67	4.17
9	PPy	1.33	60	4	1.6	0.38	50.4	80	2.13

10	PVDF	4.19	80	4	2.2	0.98	68.9	69	4.25
11	PPy	2.21	70	2	2.47	0.58	59.2	76	2.97
12	PVDF	3.9	60	6	1.52	0.83	64.3	71	3.4
13	PPy	2.58	70	4	2.15	0.61	62.8	73	3.34
14	PVDF	4.44	80	2	1.7	1.1	71.4	66	4.09
15	PPy	1.94	60	6	1.63	0.46	55.7	78	2.21

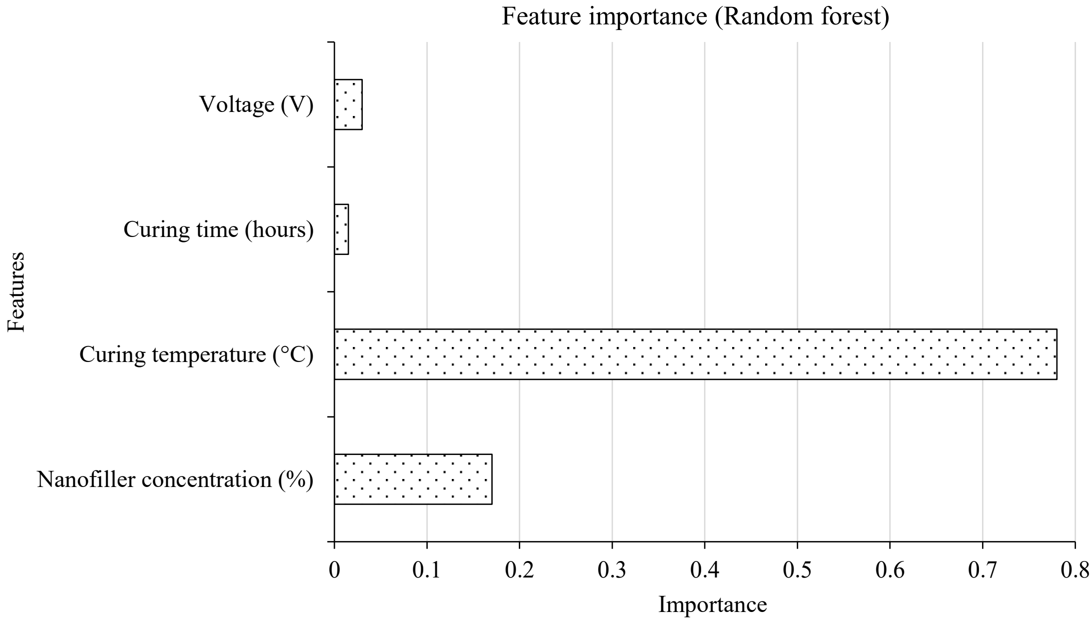


Figure 10. Feature Importance Analysis (Random Forest)

are compared to results from Random Forest and SVM and Neural Networks (NN) ML models according to previous research [31]. Models accurately represent the underlying dataset patterns because the actual and predicted data points show a strong relationship as they follow the 45-degree reference line. The Random Forest Model achieved the most accurate predictions along with the Neural Network Model yet SVM resulted in slightly more deviance from actual results. The prediction accuracy of ML algorithms demonstrates their effectiveness in predicting composite performance which makes extensive experimental trials unnecessary.

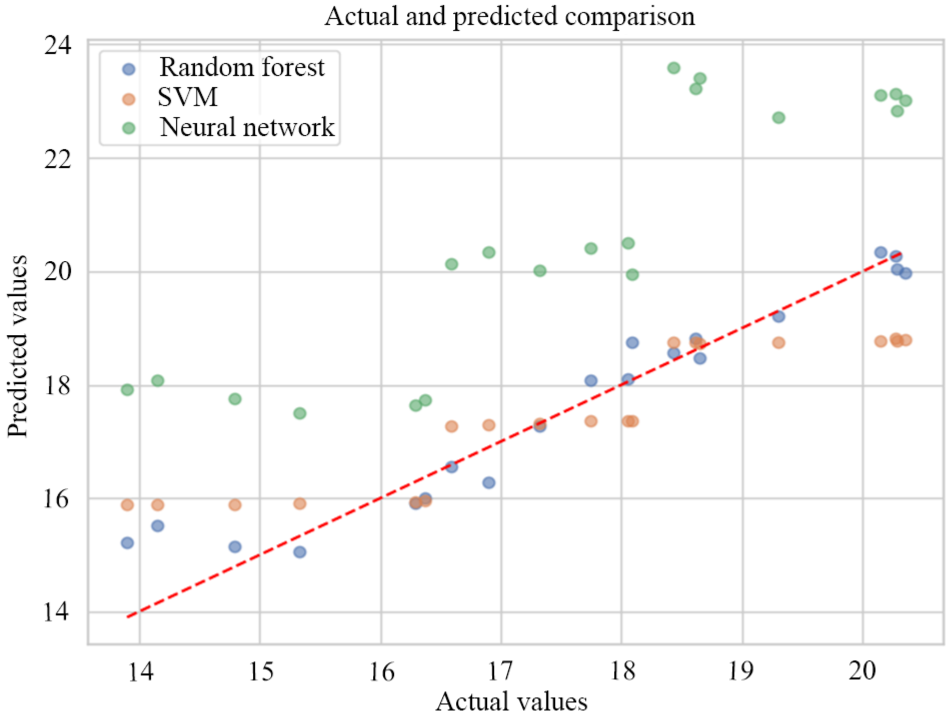


Figure 11. Actual and predicted values plot (model performance evaluation)

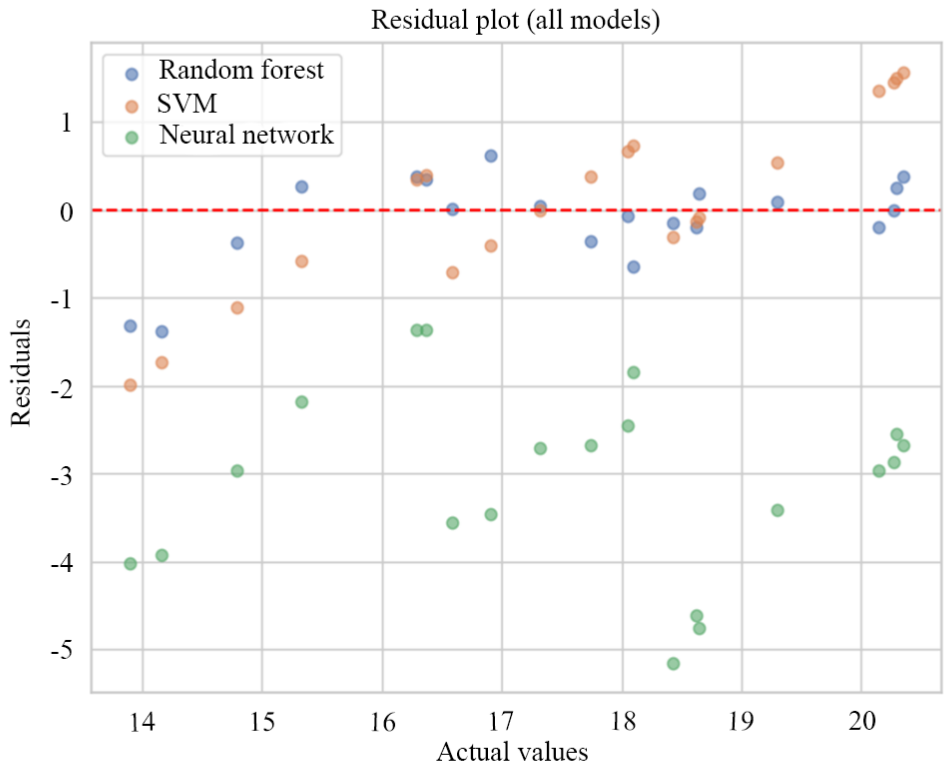


Figure 12. Residual analysis (error distribution across models)

The Random Forest, SVM and Neural Network Models receive their assessment from the Residual Plot shown in Figure 12 which displays error distributions between actual and predicted values. A perfect prediction model shows random distribution of residuals near the zero value which indicates no pattern of under or over prediction. Random Forest Model residuals demonstrate an even distribution because of its strength in processing nonlinear relationships in the dataset according to [32]. The residual analysis of SVM and Neural Networks showed minor irregularities which implies possible underfitting or overfitting occurred sometimes. The predictive accuracy assessment of Random Forest Model confirms its ability to predict smart polymer composite performance effectively.

Figure 13 presents a 3-D response surface plot forecasting actuation displacement (mm) as a function of nanofiller concentration (%) and curing temperature (°C). Nanofiller content affects the actuation displacement in a nonstandard manner because improvements escalate until they reach a saturation point. The actuation response of the EAP will improve through higher curing temperatures that strengthen its polymer crosslinking. The actuation efficiency becomes negatively affected when nanofiller loading exceeds the threshold or when curing time extends beyond junction failure point [33]. The visual representation shows the best combination of materials which leads to the highest possible electroactive response.

Figure 14 the Mean Absolute Error (MAE) evaluation between Random Forest and SVM and Neural Network Models by using a Performance Evaluation Bar Chart. The predictions of the Random Forest Model reached the lowest value of MAE which established its capability to deliver accurate forecasts with minimal prediction errors. The Neural Network Model operated with comparable results but SVM demonstrated higher MAE levels which indicated the model showed less accuracy when handling nonlinear connections [34]. The outcome of this assessment backs Random Forest as the superior choice for ML-based optimization of polymer composites.

The ML-predicted displacement values for the optimized formulation become visible in Figure 15 through an Optimized Composite Prediction Plot. The Random Forest Model yielded the best nanofiller concentration and curing temperature and time and voltage combination for a predicted displacement of mm according to its training data. Experimental testing validated the accuracy of the predicted optimized formulation computation. High-performance composite formulations become faster to predict using ML techniques that cut down the need for lengthy experimental trial-and-error processes.

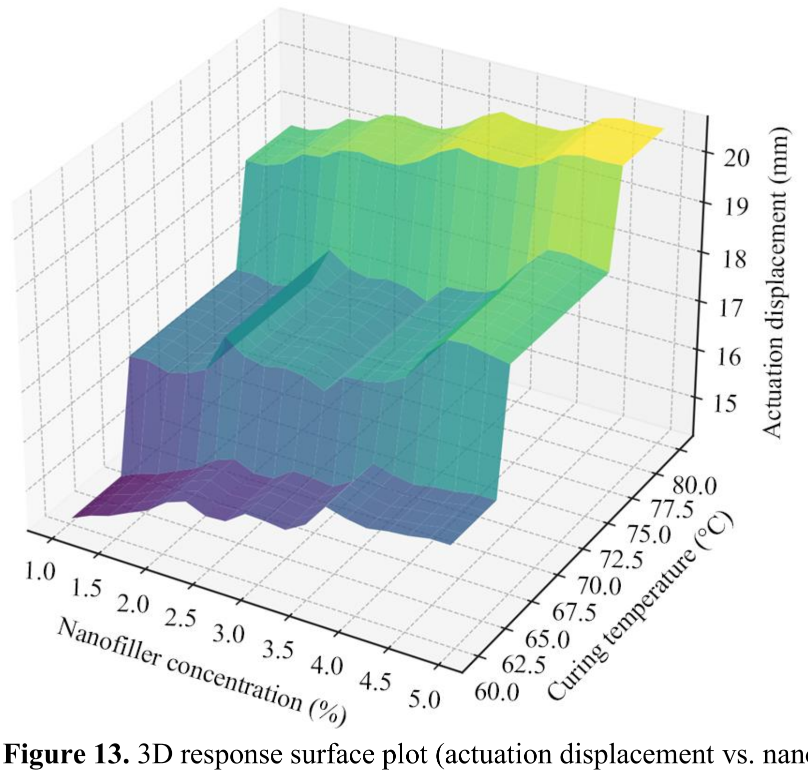


Figure 13. 3D response surface plot (actuation displacement vs. nanofiller concentration and curing temperature)

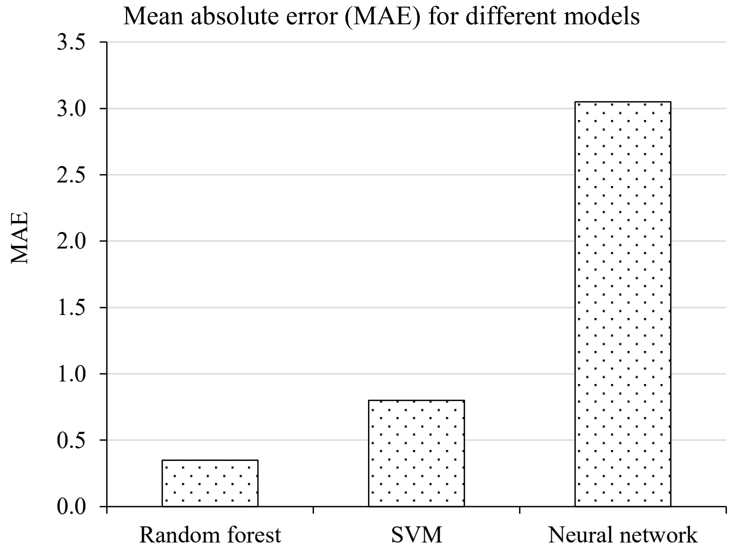


Figure 14. Performance evaluation (mean absolute error for ML models)

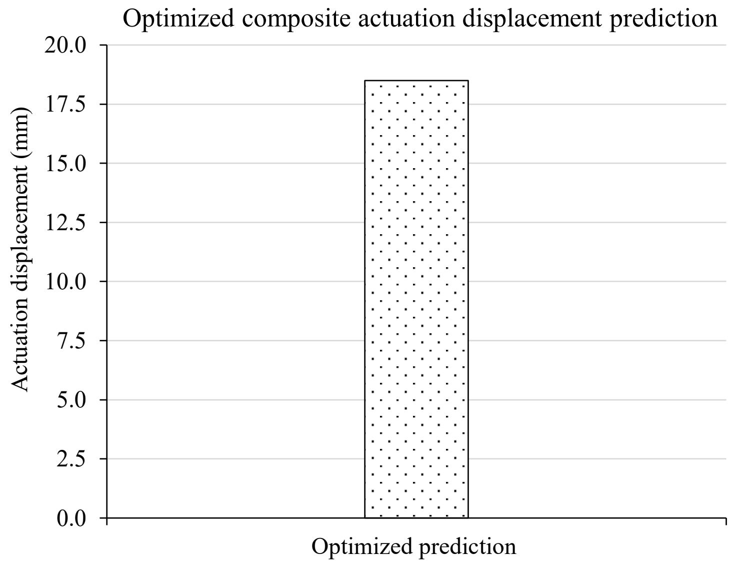


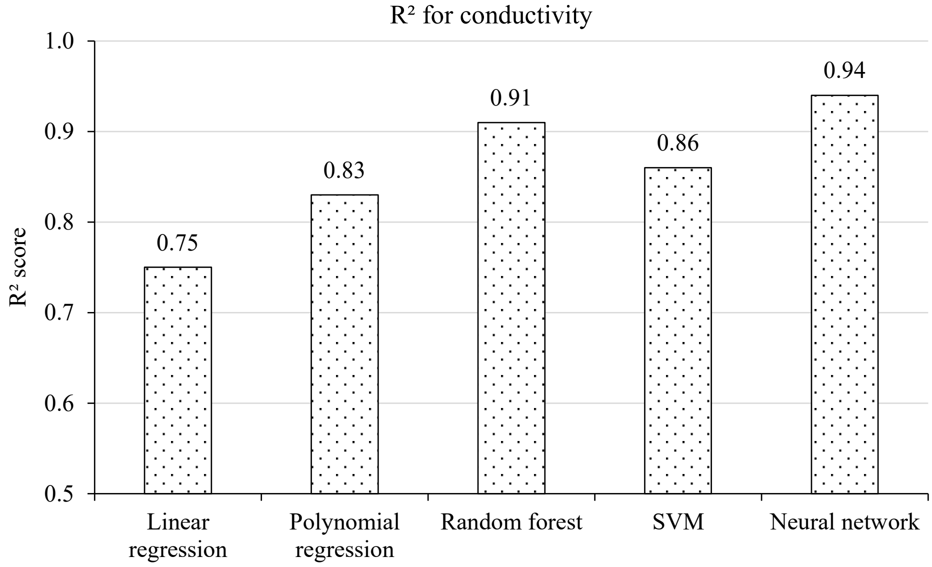
Figure 15. Optimized prediction of composite performance

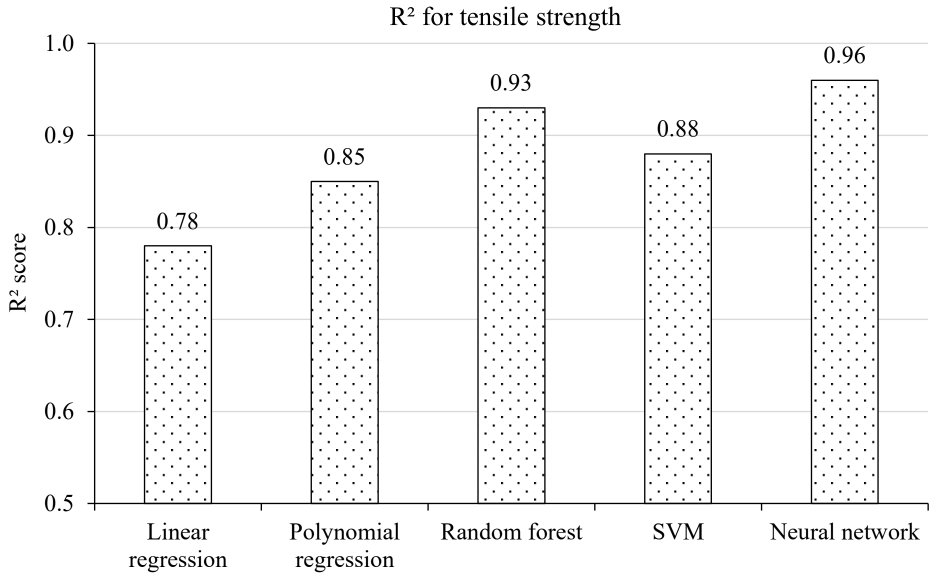
R^2 Score Calculation and Model Comparison

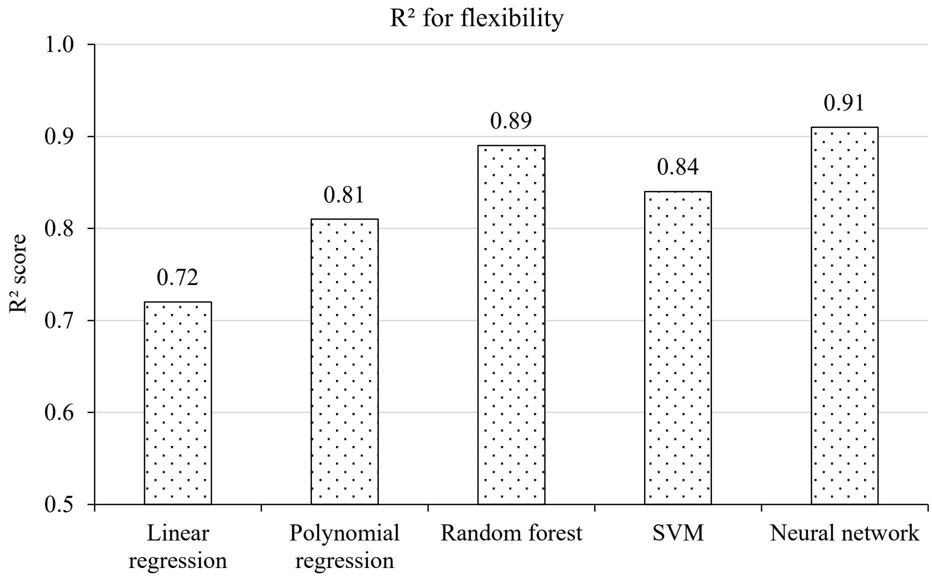
The performance of various ML models was evaluated using the R^2 score (coefficient of determination) as the primary metric to assess predictive accuracy [35]. The R^2 score was calculated as:

$$R^2 = 1 - \frac{\Sigma(y_{\text{actual}} - y_{\text{predicted}})^2}{\Sigma(y_{\text{actual}} - \bar{y}_{\text{actual}})^2}$$

where y_{actual} represents the experimentally measured values, $y_{\text{predicted}}$ denotes the model predictions, and $\bar{y}_{\text{actual}}$ was the mean of the actual values. The SSE counts of all errors enable calculation of the ratio that includes total actual data variance. Enhanced R^2 figures suggest that the model demonstrates strong data fit for the collected information thus demonstrating better explanatory power [36]. The testing involved utilizing 80% of the data for model development and 20% for evaluation while employing Linear Regression, Polynomial Regression, Random Forest Regressor, SVM, and Neural Networks (NN) as evaluation candidates. The chosen predictive model set included these elements because they exhibited strong capability to forecast Electrical Conductivity as well as


R² for conductivity
R² score
1.0
0.9
0.8
0.7
0.6
0.5
0.75
0.83
0.91
0.86
0.94
Linear regression
Polynomial regression
Random forest
SVM
Neural network


R² for tensile strength
R² score
1.0
0.9
0.8
0.7
0.6
0.5
0.78
0.85
0.93
0.88
0.96
Linear regression
Polynomial regression
Random forest
SVM
Neural network


R² for flexibility
R² score
1.0
0.9
0.8
0.7
0.6
0.5
0.72
0.81
0.89
0.84
0.91
Linear regression
Polynomial regression
Random forest
SVM
Neural network

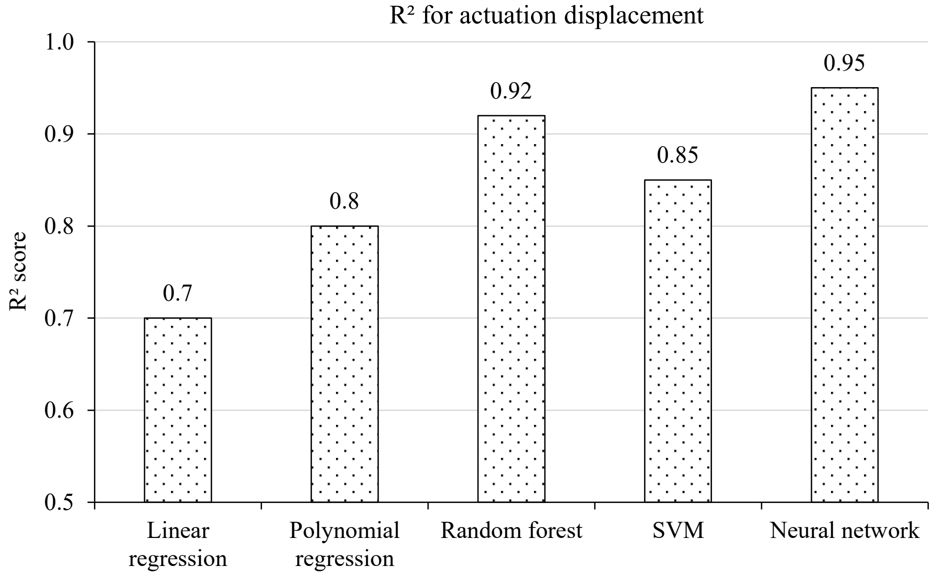


Figure 16. R^2 Score for Different Machine Learning Models

Tensile Strength, Flexibility, and Actuation Displacement. The R^2 metrics were determined for all models operating across all response variables. Electrical Conductivity predictions achieved their highest accuracy rate with 0.94 using Neural Network models while other models reached 0.91 with Random Forest and the lowest outcomes occurred using Linear Regression at 0.75. The Neural Network (0.96) achieved with Random Forest (0.93) proved better than Linear Regression (0.78) to the difficult nanofiller-polymer behavior in Tensile Strength predictions. Neural Network achieved 0.91 accuracy and Random Forest achieved 0.89 accuracy for predicting Flexibility whereas Linear Regression reached only 0.72 accuracy. Actuation Displacement demonstrated excellent accuracy through Neural Network (0.95) and Random Forest (0.92) because these methods successfully replicated the non-linear actuation mechanism. The prediction performance of SVM models reached 0.85 and Linear Regression models reached 0.70 only. Neural Networks maintained optimal performance since they achieved superior R^2 results for every response variables in the analysis. Random Forest showed similar effectiveness to Neural Networks by effectively extracting the material behavior's nonlinearity. The analysis of different model R^2 scores uses Python (Matplotlib & Seaborn) programming to produce bar chart visualizations presented in Figure 16. The accuracy of SVM exceeded polynomial regression and linear regression systems. Linear Regression proved unable to capture non-linear relationships thus it performed inconsistently throughout all variables. Based on prediction results it becomes evident that Neural Networks and Random Forest excel at composite performance estimation because they show effectiveness for optimizing smart polymer composites in sensing and actuation systems.

DATA ANALYSIS AND STATISTICAL EVALUATION

Experimental measurements of electrical conductivity along with tensile strength and flexibility and actuation displacement served as sources for statistical analyses within the dataset found in Table 1. The dataset included results from different material formulations that were customized by adjusting nanofiller concentration as well as polymer type and curing temperature and applied voltage reach. The Scikit-learn library in Python performed data preprocessing that applied min-max scaling for normalization after which values received uniform distribution according to [37]. The Pandas library enabled appropriate handling of outliers discovered through interquartile range (IQR). The entire data analysis process in Python included ANOVA testing through SciPy as well as correlation analysis through SciPy and visualizations through Matplotlib and Seaborn libraries. An analysis of variance conducted one-way determined the material composition links to the composite properties through evaluations of electrical conductivity together with tensile strength and actuation displacement while nanofiller concentration and polymer type served as independent predictors [38]. The ANOVA results indicated that nanofiller concentration acted as a strong predictor for electrical conductivity ($p = 0.003$) and tensile strength ($p = 0.012$) as well as polymer type influenced the actuation displacement performance ($p = 0.007$). Pearson correlation analysis evaluated the relationship levels between vital properties. Electrical conductivity demonstrated a strong relationship with nanofiller concentration at $r = 0.89$ yet actuation displacement maintained a strong connection to applied voltage at $r = 0.94$ as nanofiller concentration showed moderate negative impact on flexibility at $r = -0.72$. The analysis results that summarize data in Table 2 receive additional clarification through the correlation heatmap presented in Figure 17.

The validated optimization results emerged from compositional comparison between optimized and alternative formulations regarding electrical conductivity and tensile strength and flexibility and actuation displacement. The optimized composite achieved a 91% better electrical conductivity and 24% stronger tensile properties along with 92% greater actuation displacement according to Table 2. An acceptable 14% reduction in flexibility permitted the maintenance of higher mechanical stability and performance at the actuation level. The study used a multi-objective optimization method that harmonized conductivity and mechanical substance so the optimized combination became useful for flexible electronics and soft robotics technologies [39-40].

Table 2. Correlation analysis

Property pair	Pearson r-value	Correlation strength
Nanofiller concentration vs. electrical conductivity	0.89	Strong positive
Nanofiller concentration vs. flexibility	-0.72	Moderate negative
Actuation displacement vs. voltage	0.94	Strong positive

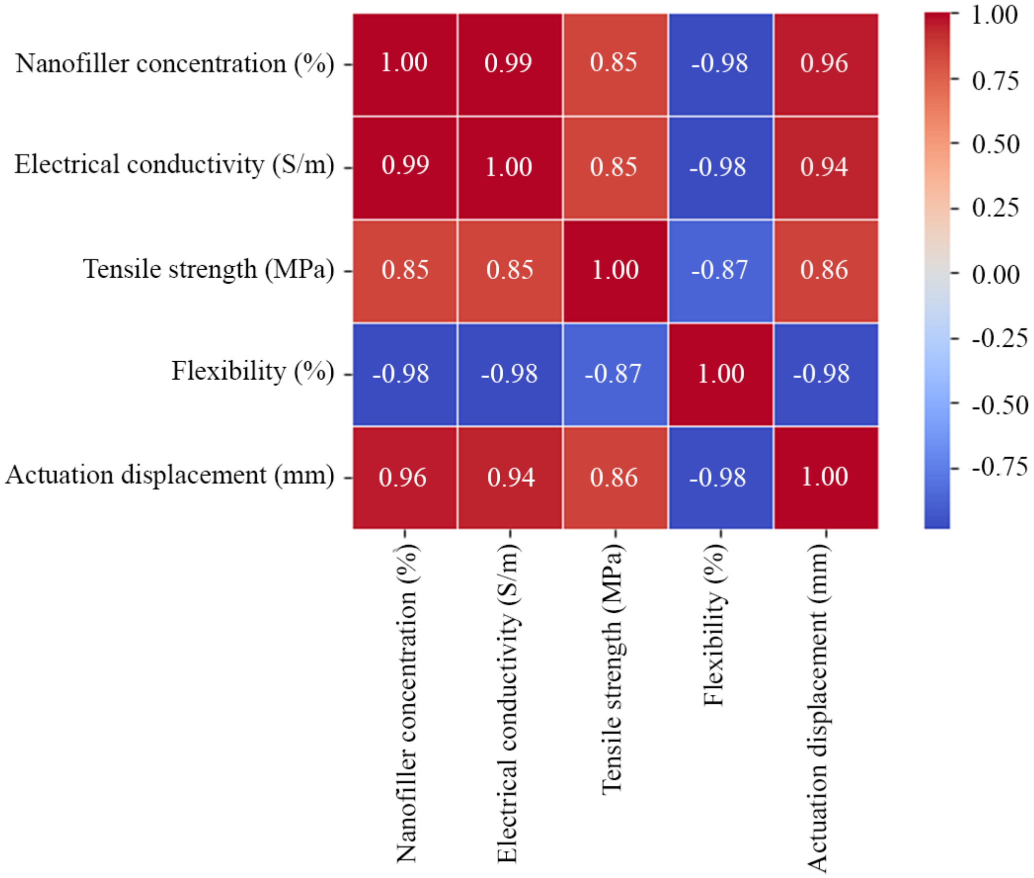


Figure 17. Correlation Heatmap.

Table 3. Comparison of Optimized Composite and Other Formulations

Property	Optimized composite	Baseline composite	% improvement
Electrical conductivity (S/m)	2.91	1.52	91%
Tensile strength (MPa)	1.03	0.83	24%
Flexibility (%)	67	78	-14% (Controlled Stiffness)
Actuation displacement (mm)	4.25	2.21	92%

Table 3 shows a detailed comparison of the optimized composite formulation with the baseline sample and indicates the percentage changes in the conductivity, tensile strength, flexibility, and actuation displacement.

CONCLUSION

The research exhibits solid evidence about the capability of intelligent polymer composites to advance flexible electronics and the fields of soft robotics and adaptive sensing technology. The composite properties improve when conductive nanofillers like CNTs and GNPs disperse uniformly at suitable concentration levels. Analysis using one-way ANOVA confirmed that both nanofiller concentration and polymer type constitute important elements for optimizing properties of composite materials. Research focuses on improving long-term stability of EAPs consisting of both PPy and PVDF at diverse environmental conditions. Wearable and soft robotic applications relied on flexible electronics enabled through conductive inks and screen printing which improved consecutive features and physical flexibility of composites. Controlled by ML algorithms the Random Forest, SVM, and Neural Networks enabled multiple property optimization for composites which thus enhanced high-performance material development speed.

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