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Influence of Artificial Intelligence on the Design of Composite Materials for Industrial and Automotive Applications: A Review

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Abstract

It has been observed recently that a new shift has taken place in composite design for industrial and automobile applications due to inclusion of artificial intelligence(AI) into material design for engineering applications. Traditional composite design methods usually depend on data driven modelling and experimentation which are very costly, time wasting, and always have limited optimization capacity. This review analysed how AI approaches, such as deep learning(DL), machine learning(ML), data driven optimization can expedite material design, forecasting and performance enhancement. With the integration of AI, it could be possible to evaluate complex dependencies between processing factors, material constituents, and performance features that include thermal behaviour, mechanical properties, stiffness, and weight efficiency. Experimental efforts through optimization of filler selection, reinforcement dispersion with the use of big data sets and algorithm can be minimised with the help of AI models. This makes it very easier develop lightweight composite materials that has enhanced strength to weight ratios for automobile applications which raises fuel economy and lessen emissions. AI-driven design in manufacturing environments promote growth of advanced materials with custom-built elements for certain conditions. The failure analysis, longevity prediction, real time monitoring of composite parts can be evaluated with AI and this improves maintenance plans and reliability. Accuracy and adaptivity in composite development can be further improved by integrating AI with advanced technology methods such as intelligent manufacturing systems and additive manufacturing. This study clearly reviews how applying AI significantly reduces development times, reduces material waste, and increases the effectiveness of composite material design. The findings demonstrate that AI-driven techniques offer a powerful path toward next-generation, high-performance composite materials, enabling businesses to meet the growing needs for productivity, sustainability, and innovation.

1. Introduction

Over the course of the three industrial revolutions, our industries underwent a complete change, going from producing goods totally by hand using human effort to building machines that operated, and finally producing goods in enormous quantities utilising assembly lines and structured production.(George & George, 2020; Kurt, 2019; Mohajan, 2019; Mokyr, 2001). However, because they operate the machinery and monitor everything, people are still essential to the production process even when machines are used. Machines just reduce human intervention. The primary reason they cannot yet completely replace people is their inability to think and behave

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in accordance with the situation. Robots cannot make decisions that need a comprehensive understanding and study of many factors that impact a decision's acceptability and effectiveness since they lack brains.

(Adebayo, Ajayi, & Chukwurah, 2024; Broadbent, 2017; Kaupp, Makarenko, & Durrant-Whyte, 2010; Rizvi, Haleem, Bahl, & Javaid, 2021).For example, a machine cannot modify production in response to variations in demand, even if it is programmed to produce "x" units of a thing each day. Another illustration is that a car's parking sensors are only able to assist the driver; they are unable to park the vehicle independently. Similar to this, an automobile's sensors are only able to determine the least congested path; they are unable to control the brake, accelerator, or steering wheel without a human driver(Reif, 2014). Even the most advanced technologies are unable to fully replace humans; they can only aid them in the process(Murali, Kaboli, & Dahiya, 2022).

Because of people's insatiable drive for maximum comfort and the ongoing growth of technology, systems that can completely replace people and perform activities independently must be developed. Artificial intelligence, or robots or software that can think, understand, and make decisions like humans, was thus created.

(Shabbir & Anwer, 2018). Even though artificial intelligence has not yet reached its highest level of development, inchoate systems have been employed in many different industries(Mhlanga, 2021; Olawale et al., 2023). The deployment of increasingly sophisticated AI systems will eventually alter the automotive industry. The automotive industry uses AI outside of the assembly line and manufacturing site, in contrast to other industries. AI offers a lot of potential applications in the car itself, various after-sales services, and the design process. The well-known billionaire and CEO of Tesla, Elon Musk, has already made progress toward developing a completely autonomous car that can drive itself on public highways(Clausen & Olteanu). For example, if a Tesla model finds that any worn-out or broken parts need to be replaced, it can order spare parts. The tireless efforts of scientists will undoubtedly result in the development of incredibly comprehensive, clever, and perceptive AI systems within a few decades, and the things that now appear like science fiction will eventually become our reality(Liao, 2022). However, we need strong, resilient, safe, and high-performing automobiles in order to use these contemporary technologies. This enables us to discover novel and cutting-edge materials that can be utilised to produce various automobile components that are more dependable and efficient than those already in use. For instance, the majority of the top producers of sports cars now create their bodywork out of carbon fibre rather than metals like steel or aluminium. This is because the car is lighter due to the carbon fiber's comparatively low density, which raises the power-to-weight ratio. Additionally, certain carbon fibre composites are stronger than traditional metals. Because carbon fibre offers greater strength for less body weight, the vehicles are both tough and quick.

1.1 Objectives

The main objectives of this study are:

1 To review the current state of composite design with the application of AI

2 To substantiate the impact and efficiency of AI-based optimization when compared with traditional techniques/approaches through review

3. To give workable solutions for implementation in industries and automobile sectors

4. To identify emerging avenues for future research and constraints of current AI approaches

2. Literature Review

2.1 Review of Artificial Intelligence on prediction of composite materials properties

The ability of machines to comprehend events, think, and make appropriate judgements is known as artificial intelligence(Korteling, van de Boer-Visschedijk, Blankendaal, Boonekamp, & Eikelboom, 2021; Rich & Gureckis, 2019). It seeks to create machines that can learn from their experiences and carry out jobs similar to those of humans. To some extent, more advanced AI systems are even able to predict future occurrences of specific events. Netflix, Siri, and driverless automobiles are a few popular instances of AI systems. AI may be roughly divided into four groups according to its degrees of sophistication.

Artificial intelligence (AI) has become a revolutionary force with transformative potential in recent years, affecting many fields globally(Alabdulatif, 2024). AI's wide range of applications indicates that it has the potential to significantly alter a number of fields. John McCarthy first used the phrase "artificial intelligence" (AI) in 1955(Tewari & Bose, 2023).

AI is the branch of computer science that makes it possible for computers to simulate human intelligence functions including learning, reasoning, and self-correction (Alkatheiri, 2022). This can be applied in various polymer based composite material designs(Jayaraman Krishnamurthy, 2023).

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The measure, dispersion, and form of strengthening components can have a significant effect on the mechanical and thermal properties of polymer-based composites(Saba & Jawaid, 2018; Thakur, 2011). According to the study carried out by Spanu et al.(Spanu & Abaza, 2022), LabVIEW software was used in their research which used artificial neural network (ANN) model to predict tensile behaviour of glass fiber reinforced polymer based composites. This model was trained to use numbers in the range of 3-50 neurones in two hidden layers with the volume fraction of glass fibres used as 30%, 40% and 50% respectively which were assigned as independent variable. In order to optimised the model, sigmoidal activation function and resilient propagation(RProp) learning algorithm model was adopted for optimization. From the review of the work, the outcome of the research suggested that ANN model could do an accurate estimation of tensile strength with the use of experimental data, even with percentage of error less than 5%. Also for instance, a significant degree of agreement predicted tensile strength by ANN architecture 1-15-7-1 (R2 less than 0.99) and experimental tensile strength values was observed.

2.2 Composite Materials

composite comprise of two or more elements with different chemical and physical properties. These elements or materials are in form of reinforcement, laminate configuration, and hybrid structure. When these materials are combined, they manifest distinctive properties distinct from those of the individual constituents(Ajayi, Turup Pandurangan, & Kanny, 2023; Perov & Khoroshilova, 1995; Ramesh, Selvan, & Saravanakumar, 2025). Each type of composite material consists a matrix and reinforcement material which include metal matrix composites, ceramic matrix composites, bio-composites and wood composites. Due to the advancement of smart manufacturing, it has been discovered that composites can be applied extensively in various engineering applications(Arulprasanna & Omkumar, 2024). Their capacity to overcome constraints associated with single materials, especially in the area of their thermal and mechanical behaviour has made them essential and fundamental in aerospace, automotive, electronics(Ajayi, Turup Pandurangan, Kanny, & Ramachandran, 2023; Mallik, Ekere, Best, & Bhatti, 2011). In the field of material science and engineering, there is current ongoing research in composites with improved mechanical properties to meet up with more sophisticated and rigorous requirements of applications. The analysis of material mechanical property is the central point of interest in efficiently employing and manufacturing these composites. In the process of mechanical and thermal research, some studies have been conducted through experimental and theoretical analyses by recommending mathematical models(Rajak, Pagar, Menezes, & Linul, 2019). These models usually entail regular geometric shapes, boundary conditions, and material responsivity expressed through explicit expressions. They assist to abstract real and complex mechanical problems into mathematical models, and thereafter the closed-form solutions of the problem are sought. Nevertheless, as the intricacy of the composites expands, their mechanical performance becomes more complex, posing difficulties in resolving problems with more complex geometrical models and boundary conditions

2.3 Construction of Constitutive Model

Constitutive models are structure or networks utilized to explaining the material mechanical and thermal behaviour and by that means facilitating to comprehend their mechanical, thermal and physical reactions under various conditions. In terms of complex materials, progressive enhancement of constitutive models improves our understanding of complex interplay between material arrangement and property(Trusov, 2021). This thorough investigation of constitutive models for composites is critical for advancements of materials science. The study of constitutive models for composites is important in material research because it does not only promote the explanation and forecast/prediction of material properties but also increases the speed of discovery and application of materials. Presently, this aspect of material science has seen the advancement of numerous theoretical and empirical models for composites(Chen, Zhao, Li, Guo, & Dong, 2021; Rique, Liu, Yu, & Pipes, 2020). Traditional constitutive models are usually represented by detailed mathematical functions, frequently needing modelling based on fundamental physical mechanisms of material combined with some specific assumptions. The model specifications are then measured through experimental analysis making the establishment of the model straightforward when mechanical properties are explicit understood. However, when carrying out research on complex composites, understanding and investigating the mechanical behaviour of complex nonlinear systems poses a considerable difficulty in scientific research. This means that conventional methods face difficulties in dealing with emerging complexity, in as much as both empirical and theoretical constitutive models need incorporation of increasing number of specifications, thereby restricting their practical usefulness.

Machine learning possesses exceptional abilities in illustrating complex mapping relationships and simulating complex physical constitutions. Based on adequate amount of training data, machine learning models can understand complex nonlinear mappings from high-dimensional attribute vectors to the targeted outcomes(Salmenjoki, Alava, & Laurson, 2018). The construction of constitutive models in machine learning mostly relies on experimental data and allows the establishment of highly nonlinear relationships between composite variables. Machine learning has develop into a centre point of interest in the research efforts on

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constitutive models for different materials(Gao, 2018; Maia, Rocha, Kerfriden, & van der Meer, 2023; P. Zhang, Yin, & Jin, 2021). Therefore, numerous studies have utilized machine learning methods to construct constitutive models for composites, maximizing the flexibility and suitability of machine learning techniques.

3. Traditional AI methods for predicting Mechanical properties of Composites

Overview of the application ML methods for forecasting mechanical properties of polymer-based composite materials was presented in this section.

- The k-nearest neighbour (k-NN) method is ML method that is captured under group of non-parametric and instance-based approaches. It could be used for both classification and regression tasks. KNN stores all instances associated with the training data in n-dimensional space which is different from other methods that construct a general internal model. The distance between new data and training data in a descriptor hyperspace are measured using eucliden distance in K-NN in which the output is predicted based on the values of the nearest K instances.
- Decision tree is another widely accepted non-parametric monitored ML method used for both regression and classification purposes. Decision tree models consist of leaf nodes, root nodes and branches as described in Figure 1. Input data was represented by root of the tree and a potential decision was represented by each of the branch. The leaves of the tree correspond to the output produced by the algorithm.

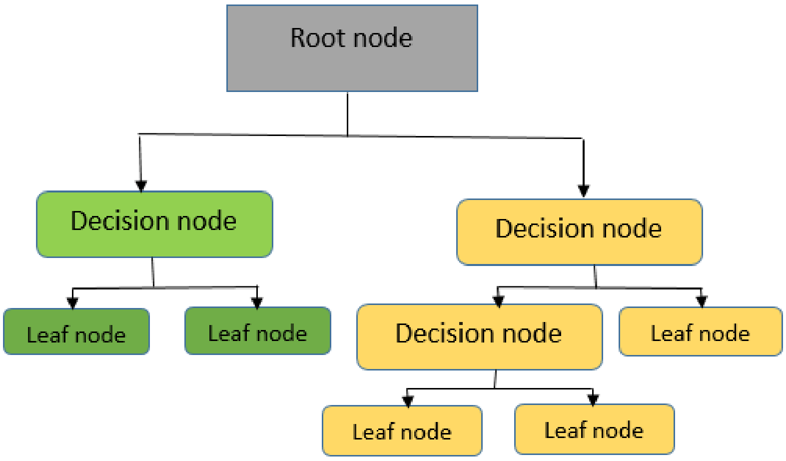

Figure 1. Schematic of decision tree

- Artificial neural networks(ANNs) which are the most popular monitored ML method, and were inspired by the biological neural network. The architecture of ANNs constitute of an input layer, hidden layer with an output layer as shown in Figure 2. The neurons of the input layer take input features, while output neurons give predictions. In the hidden layer, each neuron receives input data from input-layer neurons and the data were integrated and then the results were used in a straightforward computation.

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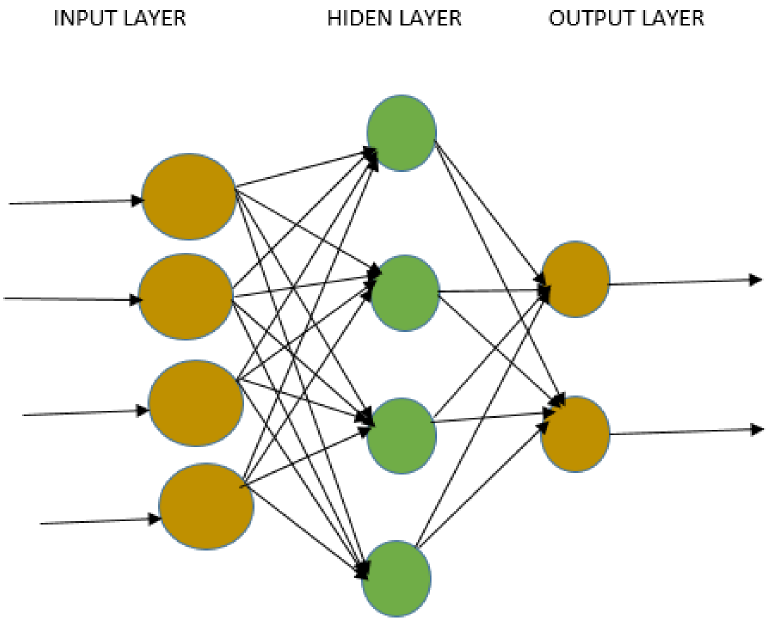

Figure 2. Architecture of ANN model

4. Observation, Challenges and Future Directions

In the preceding sections, the publications of AI especially ML and deep learning (DL) algorithms in the forecast of the polymer based composite materials was discussed. In the field of forecasting thermal and mechanical properties of composite materials, AI algorithms have proven to be promising and have produced valuable insights(Abdulhussein, Şentürk, Topbasoglu, & Altayli, 2026; Karuppusamy et al., 2025). According to the analysis presented in the studies, traditional ML methods such as support vector machines and artificial neural networks have shown a very good forecast results when compared to experimental measurements and numerical simulations. These ML approaches can efficiently learn from small experimental data and identify nonlinear, multi-dimensional relationship without prior assumptions about their nature. Nevertheless, it is necessary to note that while conventional ML methods have strengths, they also have weaknesses as described in Table 1. It is necessary to understand these weakness and strengths so as to assist in making the right choice for appropriate learning method for predicting mechanical properties of polymer base composite materials.

Table 1. Strengths and weaknesses of common shallow learning methods in the prediction of material properties(Kibrete, Trzepieciński, Gebremedhen, & Woldemichael, 2023)

Traditional ML Methods	Strengths	Weakness
Support Vector Machine (SVM)	High prediction speed and accuracy for small datasets Ability to handle high-dimensional data Relatively memory efficient	Inefficient for large datasets Not suitable for noisy data
k-Nearest Neighbor (k-NN)	Simple structure and easy implementation Robust to noise Mature theory	Slow performance with large-volume datasets Computationally expensive Poor performance with high-dimensional data Requires significant storage space Performance influenced by the choice of k
Decision Tree	Easy to understand and interpret Good visualization of results	Prone to overfitting Longer training period Requires additional domain knowledge

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Random Forest	Easy to understand and interpret Low computational cost Good performance with high-dimensional data	Prone to overfitting
Artificial Neural Network (ANN)	Parallel information processing capability High prediction accuracy and speed Effective approximation of complex nonlinear functions Suitable for relatively large datasets	Computationally expensive Prone to overfitting with small datasets Lack of transparency due to the "black box" nature of training procedures

Also, as a particular type of ML, deep learning methods have gained attention because of their capability for automated feature extraction from nonlinear and multi-dimensional material data. This approach has been used to forecast thermal and mechanical properties of polymer-based composite materials(Choudhary et al., 2022). It could be seen in Table 2 that the strengths and weaknesses of DL methods applied in forecasting material properties, and understanding this behaviour assist those carrying out research in this area to make accurate and informed decisions when selecting DL methods for predicting material properties (Table 2)

Table 2. Strengths and weaknesses of common deep learning methods in the prediction of material properties(Kibrete et al., 2023).

DL Methods	Strengths	Weaknesses
Convolutional Neural Network (CNN)	Well-suited for multi-dimensional data, particularly images Effective for extracting relevant features Excellent performance in local feature extraction	Complex architecture, requiring longer training times Requires a sufficient amount of training data Prone to overfitting
Recurrent Neural Network (RNN)	Suitable for sequential data analysis Can capture temporal changes and patterns effectively Well suited for time series data.	Difficult to train and implement due to complex architectures
Auto-Encoder (AE)	Easy to implement Computationally efficient Can learn enriched representations	Requires a large amount of training data Ineffective when relevant information is overshadowed by noise Performance can degrade if errors occur in the initial layers
Deep Belief Network (DBN)	Well suited for one-dimensional data Extracts high-level features from input data Performs well with complex data without requiring extensive data preparation The pre-training stage removes the need for labelled data.	Training can be slow due to complex initialization and computational expense Inference and learning with multiple stochastic hidden layers can be challenging
Generative Adversarial Network (GAN)	Efficient at generating synthetic data with limited training data	Difficult to train and optimize Limited data generation ability when the training data are extremely limited

In general, AI algorithms play a vital role in forecasting the properties of composite materials in design. Both ML and DL methods aim to learn patterns and relationships for input material data to make accurate predictions. ML algorithms perform well in any situation with limited data and offer interpretable models. In contrast, DL

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algorithms are better suited for handling extensive and complex datasets, automating feature extraction and capturing complex relationships.

5. Application of AI in Design and Manufacturing

AI is revolutionising high-value manufacturing and high-value design industries with its data-driven decision-making skills as production becomes less about muscles and more about brains (Table 3).

Table 3. Significant applications of artificial intelligence (AI) in intelligent design and manufacturing.

Applications	Tools/Techniques	Description
Intelligent Design	Knowledge-based engineering (KBE) with CAD/CAM TRANS-FORM Failure Modes and Effect Analysis (FMEA) Knowledge-based engineering (KBE) with CAD/CAM	KBE enables the automation of the design process by integrating knowledge about design and manufacturing engineering and other relevant concepts upfront with the product designing process. Chrysler Corporation was amongst the first companies to use KBE to gain knowledge about design and manufacturing engineering and other relevant concepts upfront with the product designing process. Chrysler Corporation was amongst the first companies to use KBE to develop a Cooling System Design Assistant (Coolsys). It was created to aid the Design Engineer by structuring the process and analyzing it against pre-existing design standards. Jaguar also uses KBE for designing their headlights (S. Zhang, Xu, Gou, & Tan, 2017)
Intelligent Assembly Line	Global Study Process Allocation System (GSPAS), Direct Labour Management System (DLMS)	The reduction in cost and maximization of the efficiency of the assembly line is a crucial factor to any car manufacturer. This led to the development of an AI integrated assembly line. It was developed to enhance the assembly line planning process. GSPAS set a standard methodology and similar business practices for vehicle assembly and design to be followed worldwide. GSPAS has an AI component known as the Direct Labour Management System (DLMS) which sets the standard labour times required by various labour classes for vehicle assembly. Along with reducing costs and maximizing efficiency, AI also takes care of the ergonomic problems associated with the vehicle(Huo, Chan, Lee, Strandhagen, & Niu, 2020; Y. Zhang et al., 2019)
Vehicle Production Sequencing	Constraint programming, Genetic algorithms, ILOG	Typical assembly line produces around 1200 vehicles daily. This consists of different vehicle types (sedan, wagon, hatch, SUV, etc.), each composed of various parts (engine, spoiler, body, upholstery, exhaust, etc.). These different cars are to be painted in an assortment of colours. All these operations are performed simultaneously, and this requires proper planning to sequence the production of vehicles. Vehicle production sequence is crucial to any supply chain to keep a smooth supply–demand curve. The complex nature of the operation makes it a suitable target for implementing AI. Various techniques like constraint programming, genetic algorithms and ILOG are used to develop an intelligent assembly line process planning(Toader, 2017)
Intelligent Control over Production	Integrated Paint Quality Control System (IPQCS), Fuzzy Reasoning, Multi-Variable rule-based Fuzzy Controller	Overproduction is a significant factor in lowering an organization's efficiency. The production process needs control over it both quantitatively and qualitatively. The number of vehicles and the quality of each part needs to be analysed and managed. Ford's

		IPQCS utilizes an algorithm called RBIC (Rule-Based Initial Control) Intelligent Control System to control the paint quality. It consists of paint applicators and paints film thickness measurement integrated into a closed-loop feedback control system and contains the surface finish quality and paint film thickness (Altenmüller, Stüker, Waschneck, Kuhnle, & Lanza, 2020; Cioffi, Travaglioni, Piscitelli, Petrillo, & De Felice, 2020)
Supply Chain and Inventory Management	Data Mining, Virtual Enterprise Systems	For a few years, automotive manufacturers have drawn their attention towards developing an efficient and agile Supply Chain. Several AI-based supply chain management techniques have been developed, such as virtual enterprise systems and soft computing techniques for automobile supply chain management. Ford used data mining techniques to study past data about supply needs and devise methods to minimize suppliers' material requirement variations. The technique is called 'Stability of Supplier releases'. This increases the operational efficiency of the Supply Chain and reduces costs (Ashima, Haleem, Bahl, Nandan, & Javaid, 2022; Oh & Jeong, 2019)

6. Conclusion
As days go by, we keep moving closer to achieving our dream of having many more modern autonomous cars on the roads. The studies related to the applications and working of AI in the automobile industries is of great importance. New results gotten from the new studies makes our understanding of a concept clearer and comprehensive and no new technology can be developed directly without having enough theoretical knowledge. Bearing in mind the steep technological developments, we are very close to creating fully autonomous cars, consequently having a more secure car travel experience. However, the blending of advanced materials in manufacturing car bodies and components for cars has achieved substantial drive. Many foremost automobile producers worldwide use polymer composite reinforced with natural and synthetic fibres, carbon fibre, and advanced good strength steel to make various body parts. From this study, it can be concluded that AI is very versatile field and has many practical utilizations in the automobile industries. The application of AI technologies in vehicles will ensure safe trip due to road safety improvement and lower casualties. Furthermore, automobile safety can be provided by using responsive materials like polymer composites and ultra-high strength steel in the bodies of these vehicles. In conclusion, it can be stated that integrating AI and intelligent materials in automobiles will complement the safety and protection of road travel. Consequently, these technologies have a broad scope of research and application in the automobile industry.

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