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Review

Modeling and formulation/process parameters design methodological approaches for improving the performance of biocomposite materials for building, construction, and automotive applications: A state-of-the-art review

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Abstract: In today's manufacturing sector, high-quality materials that satisfy customers' needs at a reduced cost are drawing attention in the global market. Also, as new applications are emerging, high-performance biocomposite products that complement them are required. The production of such high-performance materials requires suitable optimization techniques in the formulation/process design, not simply mixing natural fibre/filler, additives, and plastics, and characterization of the resulting biocomposites. However, a comprehensive review of the optimization strategies in biocomposite production intended for infrastructural applications is lacking. This study, therefore, presents a detailed discussion of the various optimization approaches, their strengths, and weaknesses in the formulation/process parameters of biocomposite manufacturing. The report explores the recent progress in optimization techniques in biocomposite material production to provide baseline information to researchers and industrialists in this field. Therefore, this review consolidates prior studies to explore new areas.

Keywords: optimization techniques; formulation; process design; natural fibres; plastics; biocomposite material

1. Introduction

The demand for eco-friendly materials due to environmental concerns and fossil fuel depletion has recently increased [1,2]. As such, biocomposite materials are increasingly gaining attention over their synthetic counterparts in the composite industry based on their attributes such as eco-friendliness, cost-effectiveness, and renewability. Natural plant fibres are used as reinforcing materials for making biocomposite materials due to their good thermal insulation properties, lightweight, good mechanical properties, low price, durability, sustainability, and biodegradability [3,4]. Examples of plant fibres/fillers include wood powder, coconut husk, cotton stalk, shells of nuts (coconut, palm kernel), banana, hemp, flax, jute, and sisal [2,5]. Most of these biomass materials are often regarded as waste and are mostly burnt or find their destination in landfills, thereby constituting pollution [2,6,7]. However, the utilization of these agricultural materials in the polymer industry has both economic and sustainable benefits [2].

Petroleum-based plastics have been beneficial to humanity [8] in several ways, specifically in the polymer industry, where they are used to produce various polymeric goods like silicone heart valves, bottles, pipelines, plastic bags, epoxy glue, and polyethylene cups [2,9]. Compared to other materials, polymers possess better resistance to corrosion and chemicals, have a lower density, and have good thermal and electrical insulating properties [9]. However, their non-biodegradable nature and the tendency to contribute a large volume of environmental pollutants, with an annual estimation of 150 million tons globally [2], have called for great concern recently. Therefore, recycling and reusing them in the polymer industry as matrices for fibres/fillers has both environmental and economic benefits.

Recently, the field of material design has seen a remarkable transformation of biocomposite materials, which are extensively used in applications such as construction, automotive, sports, and aviation. Nevertheless, biocomposites, like every other material, are continually subjected to market competition across the globe, and this calls for continuous research [10,11] to meet customers' demands. Improvements in mechanical properties are the major concern of composite materials. However, on the premise that a single application may require several properties (such as strength, resilience, toughness, stiffness, and so on), these improvements must take into consideration the overall performance of the materials [10]. The mere mixing of components and the characterization of the properties of the resulting biocomposite materials [11] are not enough to define the overall improvement. Also, as stated by Toupe et al. [10], it is not possible to improve a particular property without influencing others. Therefore, techniques that take into consideration the simultaneous optimization of multiple responses are desirable. Generally, the mechanical performance of any biocomposite material is affected by the process parameters employed during manufacturing [10] as well as the formulation parameters, as proven by several authors [10,12–14]. To have improved performance properties, it is critical to optimize these parameters by applying the appropriate optimization technique involving mathematical modeling. However, as noted in the literature, while the majority of the studies on natural filler/fibre-reinforced polymer composites reported in published works are limited to experimental investigation, research involving empirical modeling of biocomposite is limited [15]. This claim is justified by a database search carried out in this survey. A total of 7524 research articles were retrieved from the Web of Science within the last two decades (2000–2023) for the topic "biocomposites", whereas only about 60 studies involved "response surface methodology". In this regard, it is essential to intensify research efforts. The trend of the indexed articles containing "response surface methodology" is presented in **Figure 1**.

In general, a single property of a product is not sufficient to define its quality in the presence of multiple characteristics. Also, the optimization of a specific property in the presence of multiple responses cannot be achieved without affecting others negatively [12] if a suitable optimization technique is not employed. Such a conflicting situation is usually known as a multiple-response problem. To solve such problems, a methodology that can simultaneously optimize all the responses into a single performance is required. Some authors [10,12,16], in an attempt to solve multiple response problems, have employed response surface methodology (RSM) in their research studies in the field of composites. Experimentation and modeling were used to optimize the processing and formulation conditions, as reported in the previous studies. However, the review to consolidate these prior research studies is lacking in this field. Therefore, this report presents a review of the modeling and optimization of formulation conditions as well as process parameters of manufacturing techniques based on RSM approaches for improved performance properties (mechanical, tribological, physical, and surface properties) of biocomposite materials. The study will provide researchers with the baseline information needed for the advancement of this field.

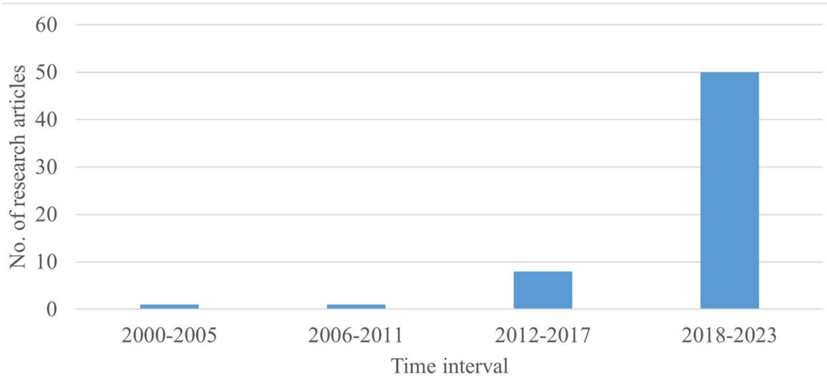

Figure 1. Trend of indexed research articles containing "response surface methodology" from 2000–2023 (Source of data: Web of Science Core Collection, accessed in December 2023).

2. Experimental design, modeling and prediction

The design of experiments (DOEs), modeling, and prediction are becoming critical aspects of product design. This is because they are suitable tools for understanding the factors-response relationships and establishing optimal conditions for maximum product quality. With such tools, robust experimentation and convincing conclusions can be reached. However, the conventional approach of mere mixing of composite elements and characterization without involving these tools can lead to inconclusive results or misleading conclusions. The reason is that the traditional method deals with the linear/main effects of the factors on the response while ignoring the quadratic and interaction effects. For example, in a study [17] on the influence of compatibilizers on the performance of WPCs, the authors concluded that it is still unknown whether the observed enhancements in the material strength are from better dispersion of wood, improved interfacial bonding, or changes in the morphology of the plastic material. However, in such a mixture experiment, non-linear behaviour like interaction amongst factors is expected to occur because most factors do not blend linearly. Such behaviour cannot be predicted by a pure factor response. Additionally, the quadratic/interaction terms of the factors can influence the response variable. Therefore, to have a better understanding of the relationships between the factors/responses, it is necessary to consider both linear and non-linear behaviours using the aforementioned tools.

2.1. Experimental design

The design of experiment (DOE) is defined as a branch of applied statistics that deals with how input factors are manipulated to examine their impacts on a performance metric by carrying out investigations of a system, process, or product. In this technique, experiments are planned, and executed, and results are analyzed and interpreted [18]. The design of the experiment is therefore a crucial aspect of experimentation and therefore should not be overlooked. Proper experimental design will promote the efficiency of the process at a reduced cost as the number of trial and error experiments is reduced.

There are two main designs of experiments, namely, one factor at a time and a factorial design. In the design of the one factor-at-a-time approach, one parameter is varied at a time while others are constrained [18]. The major drawback of this approach is that it does not involve the interactions amongst all the factors, which can automatically prevent the overall effects of all the parameters on the performance response. The factorial design is often seen as a robust method. In this approach, the total effects of the factors under consideration are observed on the performance metric. Factorial and fractional designs [19] are common examples of this approach. Many reviews [18,19] on experimental design already exist in published literature, which are also applicable in this field.

2.2. Modeling and prediction

Modeling and prediction are integral parts of optimization techniques involving the response surface methodology approach. By modeling, the relationship that exists between the factors and the quality characteristic can be established. In other words, the effects of the input variables on the performance metric can be observed.

The goodness of fit or predictive ability of a model is determined by the coefficient of correlation: R-squared (R^2) and the adjusted coefficient of correlation: R-squared adjusted R^2 (adj). A model is said to have a good fit when the R^2 and R^2 (adj) values are greater than 0.8 [12] and the absolute average deviation (AAD) between the experimental values and predicted data must be as low as possible [20]. Removal of non-significant factors from the original model [21] can be carried out to obtain the best R^2 and R^2 (adj) values. This process is called model refinement. However, care should be taken when carrying out model refinement because some factors that appear to be insignificant may have positive quadratic/interaction effects. It was reported in a previous study [10] that, based on the ordinary least square (OLS) assumptions, insignificant factors were allowed to remain in the model. Therefore, in model refinement, the total effects (main/linear, quadratic, and interactions) of all factors on the response should be considered.

3. Optimization of performance properties of biocomposites

Optimization techniques are methods that can be used to establish optimum conditions/parameters for performance improvement from a set of experimental trials. The purpose of carrying out the optimization process is to achieve maximum improvement in performance properties, including mechanical, tribological, physical, and surface characteristics, at reduced experimental trials and costs. According to Bhaskar and Sahoo [22], optimization plays a key role in the decision-making process in an industrial manufacturing process by maximizing one or more process parameters while keeping other factors within the constraints. Therefore, the importance of optimization cannot be over-emphasized as far as the manufacturing of improved products is concerned.

3.1. Types of optimization techniques

In an attempt to increase the performance of biocomposite products, several optimization techniques have been reported in the published literature, including the Taguchi method (i.e., one response-at-a-time approach) and the response surface methodology approach (viz., simultaneous optimization approaches). The various types of optimization techniques, including the Taguchi method and response surface methodology (RSM), are presented in **Figure 2**.

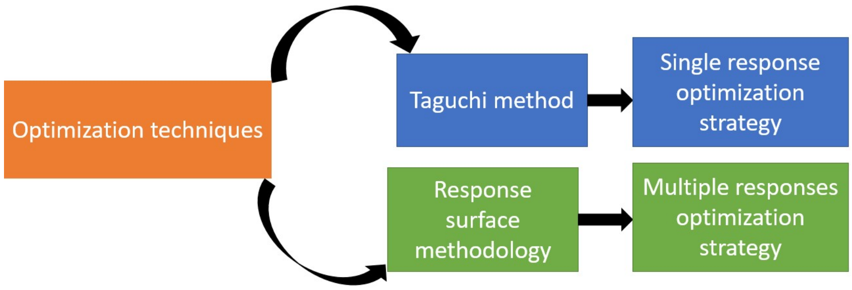

Figure 2. Types of optimization strategy.

3.1.1. Taguchi method

This is also called the one-response-at-a-time technique. It is the conventional approach of identifying optimal parameters while maintaining the other variables at a constant level [20] within the boundary conditions. In many single-response problems, the Taguchi method has been employed to find the best parameter setting, reduce response variation, and simultaneously change the mean to the desired value. Using a fractional factorial experimental design known as orthogonal arrays (OAs), it decreases the number of experimental trials within acceptable reliability and uses signal-to-noise ratio (SNR) to evaluate the performance of the responses [23,24]. The Taguchi technique offers a simple and efficient integrated method for selecting the best possible designs in terms of quality, performance, and computational cost. In this technique, parameter design is a crucial step. With the least amount of noise sensitivity, the input parameters are meant to optimize the response variables [24].

Several research studies reported in the published literature have proven that the Taguchi method, including its analysis, is a feasible and effective strategy for optimizing the formulation/process parameters for mechanical performance enhancement. For example, many researchers have reported the process conditions of injection molding technique for thin wall parts [25–28] as well as in recycled plastic products [29] for a single response problem. The major setback of this technique is that it does not involve the optimization of multiple responses simultaneously, as reported in the literature.

Most Taguchi practitioners/industrial engineers still base their decisions on mere human judgment and past experience in establishing optimal settings for multiple responses, as reported in the work of Antony [30]. The uncertainty of such a decision-making process is debatable as to whether or not the decision-maker might interfere with the process. However, product design is becoming increasingly complicated due to the intense competition in today's manufacturing sector, and therefore, the optimization of multiple responses to a product is critical [31]. The separate analysis of conflicting responses could yield incompatible solutions, and they should be optimized simultaneously [32]. For multi-response problems, the Taguchi method is insufficient due to the increasing complexity of the problem with correlated responses [23]. Therefore, to solve this problem, a response surface methodology strategy is required to establish optimal settings that will ensure simultaneous optimization of all responses.

Signal-to-noise (S/N) ratio

To evaluate the robustness of the quality characteristic (response), a signal-to-noise (S/N) ratio is introduced by Taguchi. The S/N ratio is a performance metric aimed at producing goods and processes that are not sensitive to noise factors. A higher S/N ratio suggests that the signal is stronger than the random impacts of the noise factors [24,29].

According to the Taguchi technique, the S/N ratio is classified into three categories: the smaller the better, the nominal the better, and the greater the better [24,27,29], as shown in Equations (1), (2), and (3), respectively.

$$\text{S/N} = -10\log_{10}\left[\frac{1}{n}\left(\sum_{i=1}^{n} y_i^2\right)\right] \quad (1)$$

$$\text{S/N} = -10\log_{10}\left[\frac{1}{ns}\left(\sum_{i=1}^{n} y_i^2\right)\right] \quad (2)$$

$$\text{S/N} = -10\log_{10}\left[\frac{1}{n}\left(\sum_{i=1}^{n} 1/y_i^2\right)\right] \quad (3)$$

where, y_i represents the value of the performance for the ith experimental setting, n denotes the total number of experimental trials, and s is the y_i standard deviation. However, the choice of using any of Taguchi's equations depends on the aim of the study. For example, in a work aimed at maximizing the mechanical properties of biocomposite materials, the signal characteristic of the larger is better (i.e., Equation 3) is recommendable.

3.1.2. Response surface methodology and their relevant literature

One of the major issues facing the manufacturing sector today is the problem of multi-responses due to their conflicting nature, as earlier mentioned. For instance, improving one response in multi-response problems can decrease the performance of one or more responses [33]. A methodology that can simultaneously optimize all the responses into a single response to give better performance at optimum formulation/processing conditions at a reduced cost is preferable. The multivariate strategy for solving such multiple response problems is known as response surface methodology (RSM).

Response surface methodology is a combination of mathematical and statistical methods that can be used to describe the relationships between the response and the independent variables. These interactions can be defined, either singly or in combination with the input variables. This experimental approach produces a mathematical model in addition to examining the effects of the independent variables. The name "response surface methodology" was coined as a result of the mathematical model's graphical perspective [20]. The relationship between the independent variable and the response can be expressed mathematically in the form of a quadratic Equation (4) [20].

$$Z=a+b_1y_1+b_2y_2+\ldots+b_{12}y_1y_2+b_{13}y_1y_3+\ldots+b_{11}y_1^2+b_{22}y_2^2+\ldots \quad (4)$$

where, Z is the response, y_1,y_2,y_3… are the independent variables, a is a constant (also called the Z-intercept), b_1,b_2,b_{12},b_{22}… represent the coefficients.

There are three main stages involved in the optimization study by RSM. The RSM optimization study is divided into three primary phases. The first stage consists of the preliminary work/screening experiment, whereby the independent parameters and their levels are determined. The selection of the experimental design, prediction, and validation of the model equation make up the second stage. The final step is to determine the optimal points and obtain the response surface plot/response contour plot as a function of the input factors, as detailed in the report by Baş and Boyacı [20]. The flowchart for the optimization study using response surface methodology is shown in **Figure 3**. However, this may vary slightly relative to the optimization technique used.

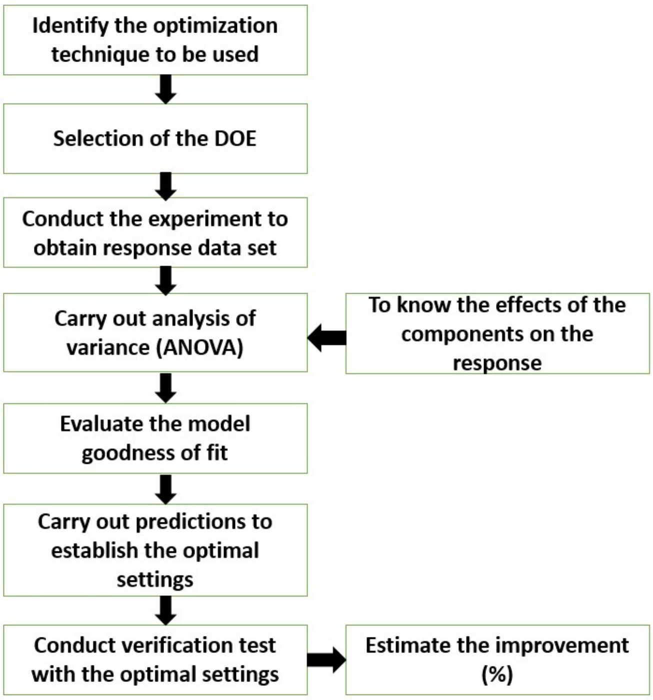

Figure 3. Optimization flowchart for RSM.

3.1.2.1. Principal component analysis

This is a multivariate approach that is suitable for combining highly interrelated criteria into a single response that includes multilateral data. It is employed in multivariate analysis to reduce the dimensionality [34] of a data set that contains highly correlated variables [24]. The data set is transformed into a new set of variables called the principal components (PCs), which are uncorrelated, orthogonal, and ordered so that the first few retain most of the variation present in the original variables. The advantage of this method is that it is sensitive to the relative scaling of the initial variables [35]. However, only components of eigenvalue (≥1) are extracted, and this cannot account for the total response variance since only a small number is used to represent the whole of the original data set.

Several authors have attempted to solve multi-response problems using principal component analysis (PCA). For example, Su and Tong [36] proposed a systematic procedure for optimizing multiple responses in the manufacturing process based on PCA. They concluded that the proposed strategy yields a satisfactory result. However, in their analysis, one component that had an eigenvalue greater than or equal to one was considered. Another study was carried out to solve the multiple response optimization problem of welding parameters in a submerged arc-welding process using Taguchi's quality loss function and principal component analysis [30]. Although the author stated that the procedure was successful, it was reported that only one component had an eigenvalue greater than or equal to one. Consequently, only one component was extracted. In most of today's complex production processes, this is no longer applicable [37].

In an attempt to extract more than one principal component, the use of the Taguchi-integrated PCA method with a coefficient of determination approach was reported [37]. The authors employed this methodology for the process parameter optimization of an injection molding technique for glass fibre-reinforced polybutylene terephthalate. Two out of four eigenvalues were found to be greater than one. However, since the principal components of all the quality characteristics were not considered, it is still arguable that the optimal condition was obtained subjectively. Additionally, in this type of approach, the total response variable might not be considered, and this could lead to an unsatisfactory compromise solution.

However, in their findings, only components that have eigenvalues greater than or equal to 1 were considered, and hence, the total response variances were not included. This might lead to an unsatisfactory compromise solution and increase the uncertainty of the result as to whether it is optimal or not which is a limitation of this method. Furthermore, the application of PCA and grey relational analysis (GRA) for the optimization of correlated multiple response processes was reported [38]. Nevertheless, the starting process conditions were assumed to be known, which is not good for designing new processes as commented by Sibalija and Majstorovic [23].

Overall, although PCA appears in the published literature as an effective and feasible technique to jointly optimize multiple responses, the objectiveness of the method is still debatable. This is because only components that have eigenvalues greater than or equal to 1 are extracted, and hence, the total response variances may not be considered. This might lead to an unsatisfactory compromise solution and increase the uncertainty of the result as to whether it is optimal or not.

3.1.2.2. Desirability function analysis

Desirability function analysis (DFA) is a simple and effective method of solving multi-objective problems. In practice, it optimizes more than one response simultaneously [22]. DFA is a less sophisticated method that is easy to understand [32] and does not involve complex mathematics or computation [39]. Thus, it is simple and can be used even by non-statisticians. Although it is claimed in the literature [30] that analysis involving relative weights of responses is often quite subjective in nature. However, using an objective weighting method such as criteria importance inter-criteria (CRITIC) [40] that is not based on the preference of the decision maker will lead to a compromise solution in an objective manner.

Many researchers have proven the feasibility and effectiveness of this technique as a method for solving multiple response problems in process engineering for the optimization of various machining process parameters, including electric discharge machining of Inconel 718 material [41], milling of glass fibre-reinforced composites [39], end milling of Inconel 718 super alloy [42], milling of rice husk fibre-reinforced composites [43], wire cut electrical discharge machining [44], drilling of polymer composite reinforced with jute fibre [45], and drilling process parameters of polymer composite reinforced with Washintonia filifera [46]. Despite the effectiveness and simplicity of this method, very few studies have employed this strategy to solve multi-response problems in the concept of biocomposite manufacturing. For example, the use of the desirability function approach for the optimization of drilling parameters of rice-husk fibre-reinforced composite (RFRC) was described [43]. The authors found that 120 mm/min was the optimal feed rate to reduce roughness as well as the input and output delamination factors. In addition, the trials' optimal point had a reasonably high desire factor of 0.678. The optimal conditions included roughness (1.75 lm), input delamination factor (1.30), and output delamination factor (1.54). The feed speed (120 mm/min), spindle speed (800 rpm), drill type (Kevlar), and type of resin (polyester) are the control parameters at the optimal point. To the author's knowledge, only Toupe et al. [12] reported the use of the Box-Behnken experimental design and desirability function approach (Derringer-Suich and Ch'ng et al. models) to establish the optimum formulation conditions based on the quality/cost ratio for flax/recycled plastic biocomposite. Using such models will require high computational skills and also involve the interference of the decision maker in terms of assigning objective weights during the process. However, DFA can be used simply and effectively by integrating the Taguchi method into it and using a weight-determining method such as criteria importance through inter-criteria correlation (CRITIC), which does not involve the preference of the decision maker. We are currently investigating such studies on biocomposite material production for improved performance in our laboratory. There are three kinds of desirability functions; nominal-the-best, larger-the-better, and smaller-the-better, as detailed in Bhaskar and Sahoo [22].

3.1.2.3. Computational-based approaches

Computational-based strategies include all approaches that involve the use of complex mathematics/computational skills. Examples include neural networks [47,48], goal programming [49], and physical programming [50,51]. Several researchers have employed the computational-based approach in their studies in an attempt to solve multi-response problems. For example, the use of an artificial intelligence (AI)-based gene expression programming (GEP) technique to predict the performance of biocomposite materials was studied [15]. The authors found that the GEP-AI model results were more accurate with strong and better predictability compared to the regression analysis techniques. In another study reported in published work, an artificial neural network (ANN) was employed to optimize the thermophysical properties of a bio-unsaturated polyester (BUP) composite [52]. In the investigation, response surface methodology (RSM) was used in the design of the experimental study plan, and both ANN and RSM approaches were used to analyze the results. The authors stated that the reliability of the theoretical model study was enhanced by comparing the results with the ANN, even though the RSM approach was used in the experiments to determine the optimization assessment. In an attempt to identify the effect of fibre loadings on the wear property of cotton fibre polyester composites, an artificial neural network was employed as the optimization technique [53]. The results of the conformation test showed that the ANN was a more useful tool than a general regression model for predicting the material's wear behaviour. Furthermore, it was reported that an artificial neural network was successfully used to estimate the specific wear rates of walnut shell powder-reinforced polyester composites [54]. Although each of these methods has its benefits, their sophisticated nature (complex mathematics/statistics), lack of algorithms used, and absence of proper guidelines make some of them unattractive and not highly practicable to practitioners, particularly non-statisticians [32].

In summary, although the computer-based approach seems promising, its complicated nature is a disadvantage since it can only be used by people with high computational/mathematical skills. Designing a mathematical model for multiple response problems that can be used by statisticians and non-statisticians and does not require complex mathematics/computational skills is most desirable in today's manufacturing sector. This will save computational costs, time, and energy and increase production outputs.

3.2. Summary of previous studies involving the optimization of biocomposites using RSM

Table 1 presents some research studies regarding the use of response surface methodology as reported in the published literature. This is to give insight into prior research in order to discover new research areas.

Table 1. Summary of previous literature involving response surface methodology.

Author (s)	Input factors	Response (s)	RSM technique	Remarks/results of the study
[43]	Screw speed, feed rate, resin type, and drill bit.	Ra, Fde, and Fds.	DFA approach.	The optimal point of the drilling process was found at the desirability of 0.678 with input variables at; spindle speed (800 rmp), feed rate (120 mm/min), resin type (polyester), type of drill bit (Kevlar) and response variables at; Ra (1.75 μm), Fde (1.30), and Fds (1.54).
[10]	Extrusion profile temperature, barrel heating temperature, and mold temperature.	Flexural modulus, tensile modulus, impact strength, and tensile stress at yield.	DFA approach using the Derringer-Suich model.	The authors reported that the optimum condition at; extrusion profile temperature is 145 °C–175 °C, barrel heating temperature of 190 °C–160 °C, and temperature of mold 35 °C.
[55]	Fibre loadings for each natural fibre (hemp, ramie, and pineapple).	Tribological properties.	CRITIC and MEW approach.	The author reported that the formulation containing 5 wt% ramie fibre is the best option for maximizing Tribological performance for the automotive braking application.
[56]	Wood waste of various amounts.	Physical, mechanical, and Wear properties.	Hybrid entropy-simple additive weighting method.	The authors reported that the best combination was found with a composite containing 2.5 wt% of wood waste.
[12]	Flax fibres, coupling agent, and impact modifier.	Flexural modulus, tensile modulus, impact strength, and tensile stress at yield.	DFA approach using the Derringer-Suich model.	The optimal formulation was obtained at; 45 wt% of flax fibre, 4 wt% of coupling agent, and a 25 wt% of impact modifier.
[57]	RWF, Rpp, MAPP, and UV stabilizer. The lubricant was kept constant.	Mechanical properties.	D-optimal mixture experimental design approach.	The authors reported that the optimal formulation was found at 50.3 wt% Rpp, 44.5 wt% RWF, 3.9 wt% MAPP, 0.2 wt% UV stabilizer, and 1.0 wt% lubricant.
[43]	Screw speed, feed rate, resin type, and drill bit.	Ra, Fde, and Fds.	DFA approach.	It was reported that the optimal point was found at Ra 1.75 μm, Fde 1.30, and Fds 1.54 with a desirability index of 0.678.

To have a robust and quality product, the optimization techniques must be suitably reviewed and designed. Although there is no universal guideline for choosing the best optimization strategies for a given application [58], a proper selection of the optimization techniques and design of experiments will yield high-performance properties for the resulting product. A simple and effective method that does not involve the preference of the decision-maker and could be used by both statisticians and non-statisticians is highly recommended. The desirability function-integrated Taguchi approach fits into this description based on this survey.

3.3. Applications of biocomposite materials

Biocomposite products have found wider applications as a class of infrastructural and structural materials in various sectors, including building, construction, and automobile industries, owing to their sustainability, ease of production, as well as their cost and environmental benefits [2]. Compared to wood, wood-plastic composites (WPs) are receiving more attention as building materials in applications such as decking and flooring owing to their better mechanical properties and stability [7]. Decking is the major market for WPCs. There are growing numbers of applications in the areas of residential, automotive, infrastructural, and railroad ties [59]. According to Mohanty et al. [60], biocomposites are emerging as a viable substitute for glass fibre-reinforced polymer composites in the automobile industry because of their favourable non-brittle fracture upon impact-a feature that is necessary for the passenger compartment and lightweight. Also, the automobile sector is taking big steps in the transition to a more environmentally friendly supply chain by using natural fibers as base materials for auto parts like boot linings, door panels, spare tires, and seat backs [61]. Natural fiber composites have been employed in structural and infrastructure applications to produce load-bearing components such as beams, roofs, multipurpose panels, water tanks, and pedestrian bridges [62]. Examples of biocomposite materials are presented in **Figure 4**. From the survey, it is evident that there is a growing market for biocomposite materials globally, which requires more research efforts. However, to have a good quality product that meets customers' demands, employing a suitable optimization technique in the product design is critical.

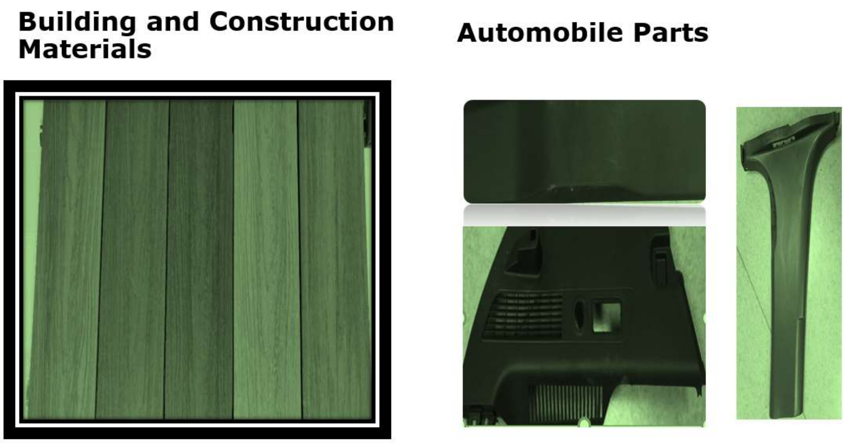

Figure 4. Biocomposite materials [2].

4. Conclusion/future perspective

In order to have robust and good mechanical performances of biocomposite products suitable for use in the building, construction, and automobile sectors, the optimization techniques must be suitably reviewed and designed. Proper selection of the optimization methods and design of experiments will yield composite materials with improved performance properties. Therefore, the decision maker must be prudent in selecting the optimization techniques and design without interference. From the survey, it seems that DFA-integrated Taguchi with CRITIC methodology is a better option when considering optimization techniques. This is because such a methodological approach is feasible, effective, and objective in nature. Additionally, it involves the total response variable, unlike the PCA, where only components with eigenvalues greater than or equal to one are extracted. Compared to computer-based approaches like neural networks or goal programming, DFA-integrated Taguchi with the CRITIC method does not require complex mathematics/computational skills and can be carried out using Minitab software and Excel.

Response surface methodology approaches have been frequently used in process engineering; however, only a few research studies have been reported on the concept of polymer-based biocomposites, considering the myriad of natural fibres/fillers. Most composite designers/industrial engineers today still base their engineering judgment on the Taguchi method of single optimization of response and past experience. However, in today's world of manufacturing, industries are being faced with multi-response problems, and only the Taguchi technique is not enough to solve such complex challenges. Also, employing past experience in the decision-making process is debatable, as the preference of the decision-maker cannot possibly be avoided. To overcome these challenges, a response surface methodological approach is required. However, the methodology for optimizing the multiple performance of a product is yet to be fully explored in the field of biocomposite, as very few studies involving the use of mathematical modeling of performance properties compared to the traditional experimental investigation approach are reported in the literature to the best of the author's knowledge. From the survey, it appears that the desirability function-Taguchi approach is a better optimization approach for multiple responses due to its simplicity, effectiveness, feasibility, and economic benefits. Also, there is no defined standard rule for choosing the best optimization technique for a given application. Therefore, efforts should be intensified to improve on the existing methodology and discover new ones to achieve quality biocomposite products for building, construction, and automobile applications.

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Abbreviations

RWF: Rubberwood flour.
Rpp: Recycled polypropylene.
MAPP: Maleic anhydride polypropylene.
UV: Ultraviolet.
Ra: Roughness.
Fde: Input delamination factor.
Fds: Output delamination factor.
CRITIC: Criteria importance through inter-criteria correlation.
MEW: Multiplicative exponent weighting.
RSM: Response surface methodology.
DFA: desirability function analysis.
PCA: Principal component analysis.
GRA: Grey relational analysis.
WPCs: Wood plastic composites.
PBT: Polybutylene terephthalate.
GEP-AI: Gene expression programming-artificial intelligence

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