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An Application of Data Envelopment Analysis in the Selection of the Best Response for the Drilling of Carbon Fiber-reinforced Plastic Composites

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ABSTRACT

In the drilling operation, defects such as delamination at exit and entry are very disturbing responses that impact the efficiency of the drilling process. Without control, an exponential growth in the amount of drilled components with defect quantities may result. Thus, the process engineer has input in attaining the desired production levels for components in the drilling process. Consequently, this article deploys a novel method of data envelopment analysis to evaluate the relative efficiency of the drilling process in reducing the defects possible in the producing components from the CFRP composites. The high-speed steel drill bits were utilized to process the CFPs, while the responses considered are the entry and exit determination, thrust force, and torque, among others. Literature experimental data in twenty-seven experimental counts were summarized into fewer groups and processed through the data envelopment analysis method. The results show that capturing the CFRP composite responses is feasible, providing an opportunity for enhanced efficiency and a situation where undesirable defects in the CFRP composite production process may be eradicated. The article’s uniqueness and primary value are in being the foremost article in offering an updated vast representation of the comparative efficiency of CFRP composite parameters within the literature for the composite area. The work adds value to the CFRP composite literature by envisaging and understanding the comparative efficiency for the parameters, identifying and separating the best from the worst decision-making unit. It also reveals how the parameters are linked by their relative placements. The article's novelty is that using data envelopment to compare the efficiency in reducing drilling defects such as entry and exit determination, among others. The method’s utility is to provide information for cost-effective drilling operations during the planning and control phases of the operation.

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1. INTRODUCTION

In the drilling of carbon fiber reinforced plastic (CFRP) composites, the emergence of defects from processed components could be very disturbing as it erodes the company's profit, reputation, and workers’ morale

(Suzuki et al., 2019; Shi et al., 2020). However, the majority of intervention approaches are experimental (Seo et al., 2020; Sridhar et al., 2021; Mura & Dini, 2021). In some cases, fracture toughness tests are conducted where a reduced toughness of the material has defects (Liu et al., 2022; Ning et al., 2022; Song et al., 2022; Yao et al., 2022). Furthermore, by following the metallurgical route, the XRD and SEM tests provide useful information to conclude whether or not the processed component has defects (Hernandez et al., 2017; Lin et al., 2022). Other research focuses on chip formation, cutting forces, hole quality, and tool wear (Brinksmeier & Janssen, 2002; Seo et al., 2020). Next, the concerns for high hardness CFRPs include long service life, fast cycle time, and bore integrity (Voss et al., 2016). Unfortunately, these approaches are very expensive to implement in practice, given the wide range of components to process using the CFRP components.

Besides, this experimental approach fails to relate the drilling operation's efficiency with the system's defect production. Nevertheless, this linkage of efficiency and defect detection as an approach helps reduce product rejects, boosts the company's profit, and stimulates improved morale and the company’s reputation enhancement. Furthermore, by avoiding the efficiency measurement of the drilling decision-making limit, the sustainability of the drilling operation may be compromised. However, viewing from the efficiency perspective of the drilling input, a superior practical instance is guaranteed with sustainability in context. Today, the concern for drilling efficiency is more compelling than ever to introduce in the industry because of regulating requirements for good governance and sustainability in the industry.

Furthermore, the process engineer is currently in a dilemma on whether to increase production or retain the small-scale production pattern practiced in the past few months despite the increasing component demand, which could lead to increased profit for the organization. However, the process engineer is threatened by the possible emergence of defects that may be proportional to the volume of component production. Unfortunately, control of the efficiency of the drilling process relating to defect reduction seems presently non-existent. Despite the documented benefits of such a control mechanism for the defect occurrence in drilling CFRP composites, extremely few reports in the drilling literature addressed the efficiency problem. However, no report has been given on applying data envelopment analysis to assess drilling operations efficiency for carbon fiber-reinforced plastic composites.

In this article, the data envelopment analysis is proposed to relate the efficiency of the drilling decision unit to the defects emanating from the drilling process while processing the carbon fiber-reinforced plastic composites. Literature data on the drilling operation of the carbon fiber-reinforced plastic composites using high-speed steel drill bits are used. Consequently, this study applies the theory of data envelopment analysis that projects the diverse efficiency types in the drilling production system. It is argued that the responses may assume decision-making units (DMUs), and such responses include the defects such as the entry and exit determination, among others (Aggarwal et al., 2021; Pranesh et al., 2013). With credit for the first-time development and application given to Micheal Farrel in the year 1957, the great utility of the DEA method stimulated significant research efforts of their research workers, namely Abraham Charles, William W. Coopers, and Edurado Rhodes, two decades after the emergence of the method to develop what is widely recognized today as Charles, Coopers, and Rhodes method, named after their surnames.

In previous studies, some authors have deployed various analytical methods to position the important factors in the drilling operation of carbon fiber-reinforced plastic (CFRP) composites for important drilling decisions. For instance, Odusoro and Oke (2021a) benefited from the hierarchical framework of the analytic hierarchical process to layout the drilling factors and inform the machining engineer on how to better focus on specific criteria. Besides, Odusoro and Oke (2021b) established the possibility of removing the vagueness and uncertainty in drilling decision-making through the deployment of the fuzzy analytic hierarchy process. In the method, the pairwise matrices are combined first by instituting an aggregated weight-determining mechanism and afterward evaluating a single weight vector: However, the drilling problem while processing the CFRP composites involves diverse resource constraints to which the linear-programming-based data envelopment analysis (DEA) generates a good solution for decision making. However, the opportunity to explore the robustness of this method had not been explored for the drilling of the CFRP composites.

This study explains the DEA method as an advanced linear programming application used on the CFRP composite drilling problem. The DEA method is used to evaluate the comparative efficiency of operating units, where the factors, which are responses that reflect the drilling system's performance, are viewed as the operating units. Here, the factors have the same objectives for the system, including the drilling of high-quality outputs of the CFRP composite processed, measured using the average roughness parameters, among others, using the quality measurement idea. In the particular case examined, the responses torque, entry delamination, exit delamination, eccentricity, and surface roughness. Now, the DEA method may be used in comparing the degree of compliance of each response to the goal of producing high-quality drilled components. This is referred to as a relative performance analysis. Besides this advantage of being a good fit to compare the relative efficiency of the responses (factors) considered in drilling the CFRP composite, it demonstrates the advantage of exhibiting and capability to tackle multiple inputs and multiple outputs. In the application considered here, as many as five responses are considered here as outputs of the drilling problem.

In the drilling area, it is often challenging for the machining engineer to establish which of the responses among torque, entry delamination, exit delamination, eccentricity, and surface roughness are inefficiently achieved at the desired levels (Alabi et al., 2007; Adeniran

& Oke, 2022; Ighravwe & Oke, 2022; Abiola & Oke, 2022). The multiple inputs of manhours, materials, equipment hours, lubrication quantities, etc., may not be efficiently converted into multiple outputs (responses) as indicated. As this problem interests the machining community, the DEA method is a suitable tool to adopt to solve the problem.

This research is important and substantial, with the potential to solve a previously unrecognized problem in the drilling operation. It provides a framework that explicitly states an important omission in the drilling operations literature concerning the evaluation of the technical efficiency of the drilling unit and its relationship with the defects produced within the system. It provides significant details for process engineers in the drilling industry regarding the building blocks of efficiency in the decision-making units of the system. Also, by tackling the efficiency problem and defect analysis for the carbon fiber reinforced plastic composites, the ignored and weak aspects of the literature with the performance analysis domain promotes future research.

Based on the proceeding discussions, the contributions of these articles involve the following. First, it highlights factors and the attributes of the drilling operations regarding efficiency, which was unclear, and this broadens the comprehension of process engineers in the performance assessment of drilling operations. Second, it establishes the drilling operation’s research flaws and helps to locate new research goals.

2. LITERATURE REVIEW

By understanding the literature, the authors have reviewed groups of studies that discuss the multicriteria concepts, determination of the resistance studies, and drilling types. Additional studies are those that consider coating the carbon fiber-reinforced plastics as well as the tool drills. Thus, this section provides a review of the literature on the performance attributes of carbon fiber-reinforced plastic (CFRP) composites during the drilling process.

At present, several original developments are noticed in the CFRP composite research domain. Through these developments, industrial practices and research have changed. There are pros and cons to this research body. For example, a group of studies has adopted the multicriteria approach where the outcome of the studies is often expressed as ranks. Odusoro and Oke (2021a) an example of such a study where an analytic hierarchy process was used to rank the parameters in a drilling operation on CFRP composites. In Odusoro and Oke (2021b), the authors engaged in factor selection while drilling CFRP composites, but the emphasis was on tracking imprecision and uncertainty in the drilling operation's measurement. A set of responses were ordered in ranks similar to the outcomes of a previous study by Odusoro and Oke (2021a). Furthermore, Odusoro and Oke (2021c) considered using the PROMETHEE method to classify the responses from drilling CFRP composites obtained from experimental data generated in the literature.

The above studies revealed that results obtained from methods such as the AHP, FAHP, or PROMETHEE might be a substitute for one another in a drive to ascertain the comparative importance of responses, including defects emanating from the drilling process. Furthermore, by considering the pros of these studies, for instance, crisp numerical values of responses have been the mode of analyzing these responses for a long time. Quantifying imprecision and errors was impossible due to the equipment and humans operating the system. However, the literature has made information available to process engineers on tackling uncertainty and imprecision and regulating them to improve the quality of drilled components. Such studies in the literature save the company's losses, adding to profit since the reduction in error promotes higher acceptance quality levels of components. Notwithstanding this merit of the drilling operation's composite literature concerning the CFRPs, the aspects of efficiency and defect monitoring and tracking through methodical research are serious weaknesses of the literature. Through an input and output analysis of multiple items, it is possible to deploy an efficiency-based method with the capability of evaluating the efficiency of the drilling process and linking it to the defects. This issue is not possible to date, but this has substantial potential.

In another group of studies, the measurement and enhancement of delamination resistance of the CFRP composites were made in this context. Suzuki et al. (2019) examined the possible production of materials with delamination defects. The material examined is a woven metal wire tool, which was drilled with a 20 mm diameter core on a CFRP plate. It was reported that no delamination or burr existed when the exit and entry positions on the CFRP were viewed. Besides Shi et al. (2020)**,** a delamination study was instituted to study the toughness performance to enhance delamination resistance for the CFRP composites. In this situation, the optimization toughness responses were examined based on parametric input quantities of diverse feed rates, concentration changes, thrust force, and torque histories. Low delamination was reported, especially when subjected to the utmost feed rate situation. Furthermore, Karnik et al. (2008) studied the delamination performance of CFRP plates at the entry position of the samples by deploying the artificial neural network method, which focuses on the parameters of point angle, rotational speed, and feed rate. It was discovered that the artificial neural network method provided a useful tool to evaluate the effect of the drilling parameters on the delamination factor.

Interestingly, the mentioned studies showed the importance of establishing and controlling the delamination factors while drilling carbon fiber-reinforced plastic composites. Notwithstanding, delamination is only one measure of defects, but its relative importance to other drilling defects is yet to be fully investigated. This implies the need for a study that evaluates the relative importance of response, particularly those responsible for defects in machined components.

The next group of studies considers the different drilling types, some of which are compared with the conventional drilling system. In Mura and Dini’s (2021) study, cryogenic drilling was examined, which employs a pre-cooling process of the composite before the machining process commences. The purpose is to produce a constant refrigerated material. The authors compared the quality of the drilled hole subjected to dry machining in conventional drilling and what was obtained when cryogenic-based cooling was exercised. The several indices of drilling considered are dimensional accuracy of the drilled holes, delamination, thrust force, feed rate impact, surface roughness, and tool wear. Furthermore, in another study, ultrasonically aided drilling, which is the addition of vibration drilling and classical drilling, was examined by Makhdum et al. (2012). The authors compared the performance of outputs from machined CFRP and Ti6Al4V using conventional drilling and ultrasonically-motivated drilling. It was affirmed that the ultrasonically-aided drilling exhibited superior performance than the classical drilling system in achieving all-lower delamination, cutting forces requirements, and the required process temperatures. It also had a superior surface finish in both tested materials of Ti6Al4V and CFRP components. In another study, Voss et al. (2016) introduced orbital drilling and compared the drilling results with that of the traditional drilling system. The feasibility of the approach is confirmed. Thus, this group of studies has demonstrated the supervisor performance of some emerging drilling types, such as cryogenic, ultrasonic, and orbital drilling operations. It should be noted that despite the uniqueness of the drilling methods, it is unable to differentiate the drilling defects from one another regarding their importance and relative weights.

Coating of carbon fiber-reinforced plastics prepare is an emerging dimension of research in developing delamination-resistant carbon fiber reinforced plastics composites through toughening materials, which are later cured mostly by hand. Layups, as indicated by Shi et al. (2020). The poly (methyl) methacrylate solution was the chosen experimental sample by Shi et al. (2020). The above description relates to the coating of the workpieces. However, studies have also reported the coating of the tool drill as contained in Harigai et al. (2021) that blended films of reinforced plastic drills. An upward surge in the drilling efficiency of the drills to process carbon fiber-reinforced plastic was reported. From these studies, coating either the workpiece or the total or both were found to have enhanced the processing of carbon fiber-reinforced plastics. Nonetheless, no study has dissociated such efficiency studies with the defects produced from such coated workpieces/tools, and particularly no study has classified the defects according to their importance.

In sum, the determination of weights of responses, particularly composite defects, is an interesting idea to reduce the composite defects produced when linked with the efficiency of the drilling operation while drilling the carbon fiber-reinforced plastic composites. Accordingly, from the reviewed papers above, it is clear that the efficiency of the drilling operation is a potential candidate to enhance the overall drilling performance and the positioning of the drilling defects in important analysis. To date, only a few studies analyze the importance scale of damage defects exists. Besides, no research has detailed the study relating damage defects and efficiency analysis regarding carbon fiber-reinforced plastics. Consequently, this research creates an avenue to study the influence of drilling operations efficiency on the damage defects for the carbon fiber reinforced plastic composites. Particularly damage defects such as eccentricity, delamination at entry, and delamination at exit are considered. However, additional responses such as thrust force, torque, and surface roughness are included as they have an impact on the damage defects (Ighravwe & Oke, 2015; Abiola & Oke, 2021).

Furthermore, the DEA method is a prominent contemporary tool in the efficiency measurement domain. Table 1 reveals the diverse natures of applications regarding the DEA method that is of scientific value and important contributions to the literature. For a deep insight into the DEA method, readers are advised to consult Liu et al. (2013) for familiarisation with the DEA research area.

3. METHODS

In installing the data envelopment analysis to the CFRP composite efficiency measurement, three possible perspectives of efficiency evaluations are possible, namely technical efficiency, allocative efficiency, and economic efficiency. Usually, economic efficiency is obtained using the product function of the technical and allocative efficiencies. The allocative efficiency concerns how the composite engineer manages the inputs into the production process relative to the prices of the components produced from the CFRP composite production process. In technical efficiency, the measurement of efficiency after production is made. Concerning the data needed, production data is enough for production efficiency, and no price data is desired to compute the technical efficiency. However, for allocative efficiency, the price data is a primary requirement for computing efficiency. Then through the analysis of data involving technical and allocative efficiency, the result of the economic efficiency may be obtained. In developing an analysis for technical efficiency, two bases of descriptions are possible, namely the input-oriented approach and the output-oriented approach. However, with respect to the CFRP composite, what do we mean by the input-oriented approach, and what is the output-oriented approach? To explain this phenomenon, an input, and an output are taken at a time. For illustration purposes, the input, such as the drilling hours, is represented on the *x*-axis, while an output, such as the exit delamination, is shown on the y-axis. Often, from the experimental data, the hours spent on production for a particular sample population are noted. However, the quality of the produced output is also measured. For each same, the possible occurrence or absence of delamination at the point that the product is discharged from the machine is also evaluated. The whole exit delamination may be evaluated by adopting any of the following methods: infrared imaging, visual inspection, and radiography, tap testing (through sounding and ultrasound). After obtaining the data, it is plotted as scattered data, explaining that a particular amount of dulling hours is used. In the process, it is possible to generate a particular

Table 1. Applications of data envelopment analysis

S/No.	Reference(s)	Application area
1	Peykani et al. (2021)	Investment ranking
2	Khodadadipour et al. (2021)	Thermal power plant
3	Chen et al. (2021a)	Research and development of green innovation in the Chinese high-tech industry
4	Nedaei et al. (2020), Wegener and Amin (2019)	Oil and gas well drilling. Oil and gas
5	Yesilyurt et al. (2021)	Hospital
6	Melo et al. (2020)	Soyabean haulage
7	Li (2020)	Banks
8	Mariani and Visani (2019)	Hotel
9	Zhou et al. (2019)	Chinese industry
10	Ebrahimi and Hajizadeh (2021)	Stock exchange
11	Luo et al. (2022)	Construction project
12	Chen et al. (2021b)	Academic journal evaluation
13	Goto and Sueyoshi (2022)	Environmental assessment
14	Balak et al. (2021)	Banks
15	Omrani et al. (2022), Ghiyasi et al. (2022)	Hospital
16	Rodrigues et al. (2022)	School networks
17	Nong (2022)	Retail stores (fashion Industry)

amount of undesirable exit delamination value. So, lines are used to connect the data points based on those obtained. The curve that connects the points has a boundary referred to as the frontier, which is the maximum value possible and can be interpreted at every point within the solution space. Having connected many points of the scattered data with a curve. It may be observed that certain points lie below the frontier. Each of these points is called a situation where the composite engineer is inefficient in production. Perhaps one or two points are above the frontier curve. Such points are still regarded as being efficient points since they at least have values equal to the frontiers and could be approximated to them. The interpretation is that at points above this frontier, the production of delamination is comparatively less than desired and, therefore, acceptable.

Now, recall that it was mentioned earlier that two types of perspectives are possible, notably the input and output-oriented approaches. However, the description above is the input-oriented approach, and from that point, the output-oriented approach is discussed. The output-oriented technical efficiency considers only the output, and it is the method adopted in the present article. There, the exit delamination given the delamination at two points (the highest and another point) is considered, and their ratio is evaluated. Consider a situation where the production hours at certain levels generate a particular exit delamination value. Also, the production hours at a different level produce another exit delamination value. The focus is to divide the delamination value of the first (highest possible) instance with that of the second instance, and the quotient obtained is the technical efficiency of the system. This idea is the dominant expression used in this particular article and used for all responses.

Furthermore, in this article, the data envelopment analysis is applied to the experimental data of Krishnamoorthy (2011), in which the drilling of carbon fiber-reinforced plastics is considered using high-speed steel drill bits. However, in this section, the procedure for the implementation of the data envelopment analysis in a practical drilling situation is discussed based on the experimental data previously mentioned. Here, the authors are working with six responses: thrust force, torque, entry delamination, exit delamination, surface roughness, and eccentricity, which are drilling responses. However, except for the thrust force, torque, and surface roughness, the other three responses are damage defects. Nevertheless, it is desired to minimize all these responses in drilling CFRP composites. In analyzing using the DEA method, it is conventional to classify and utilize data as inputs and outputs while the decision-making units are recognized and the efficiency indices measured. As will be observed from the analysis, the basis of the analysis is to use g and h, and when the final figures for these terms and 1 each, it implies that the best and most efficient positions are reached. Otherwise, the system is described as inefficient. Furthermore, while working with the DEA method, the method shares the attributes of multicriteria methods by depending on beneficial and non-beneficial criteria as present in the PROMETHEE method.

The beneficial criterion is used for a factor whose numerical increase is favorable to the drilling process and is desired. In the present case, there is no factor available to serve the purpose. Still, innovatively, the signal-to-noise ratios are argued to be a good beneficial term since increases in its value are always desired and favorable to the system. Hence, borrowing ideas from the Taguchi methodology, the signal-to-noise ratios were computed, but extracts of their results are included in the relevant tables in this section. Furthermore, the non-beneficial criterion is used as a factor whose numerical increment will not favor the drilling system. However, the working mechanism of the DEA method is that there should be inputs and outputs, and then the efficiency of the decision-making units could be computed. To comply with this format, the innovatively developed signal-to-noise ratios and taken as the output of the drilling process, while the responses are used to resemble the inputs of the drilling system. Then, the decision-making units (DMUs) are evaluated for efficiency, and the efficient DMUs are established.

Based on the preceding discussion on the procedure for implementation of the DEA method, the following steps are defined:

Step 1. Identify the non-beneficial criteria (input) and the beneficial criteria (output). DMU is considered inefficient if it fails to attain minimum input and maximum output.

The beneficial criteria are those wishing to be maximized, while the non-beneficial criteria are those wishing to be minimized or reduced. In this work, the non-beneficial criteria are thrust force, torque, entry delamination, exit delamination, surface roughness, and eccentricity, while the beneficial criterion is the Signal to Noise Ratio (SNR). Often represented by acronyms such as SNR, and S-N ratio, the phenomenon of the signal-to-noise ratio is the foundational element of the Taguchi method that is applied in consideration of the efficiency of the decision-making units of the data envelopment analysis method. In this section, the SNR is used to represent the signal-to-noise ratios discussed here. A brief explanation of the SNR is given here to appreciate the applicability of the SNR to the efficiency measurement regarding responses associated with carbon fiber-reinforced plastic. The SNR is based on the motion based on the experimental data of Krishnamoorthy (2011). It is expected that some of these experimental data yield signals while others yield noise. Regarding the drilling problem, the good data is assigned as a signal, while the bad data from the experimental data collection gives noise. Often, it is generally assumed that as more data on the CFRP is obtained, the researcher or drilling engineer is helped to decide better on the drilling decision. This may not be so if the level of noise in the additional data on CFRP composite drilling obtained contains more noise than the level obtained previously before the enlargement of the data. In reality, the signal is desired to be separated from noise. However, this separation may be achieved in the time element. The SNR is obtained to be utilized as the output parameter (since the output parameters are usually the beneficial parameters. Without the SNR values, all the parameters which happen to be non-beneficial will constitute the input leaving no output. Since the parameters are non-beneficial, the SNR obtained is achieved using the smaller, the better criterion, Equation (1):

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

From Equation (1), S/N represents the signal-to-noise ratio, n indicates the number of factors/parameters, and y_i^2 stands for the factors.

Step 2. Normalize the decision matrix as given in Equation (2):

$$N_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}^2}} \quad (2)$$

Step 3 Apply the DEA-CCR model

This is done by using Equations (3) to (8):

$$g_k = \min \sum_{i=1}^{m} v_r x_{ik} \quad (3)$$

Subject to

$$-\sum_{r=1}^{s} u_r y_{rk} + \sum_{i=1}^{m} v_r x_{ik} \geq 0 \quad for\ j = 1,\ \dots,\ n \quad (4)$$

$$\sum_{r=1}^{s} u_r y_{rk} = 1 \quad (5)$$

$$u_r \geq 0,\ r = 1,\dots,s \quad (6)$$

$$v_i \geq 0,\ i = 1,\dots,m \quad (7)$$

$$h_k = \frac{1}{g_k},\ h_k \text{ is the } k^{th} \text{ DMU efficiency} \quad (8)$$

where n is the number of alternatives/DMU, m is the number of input criteria, s represents the number of output criteria, x_{ik} and y_{rk} are the values of i^{th} input criterion and r^{th} output criterion for k^{th}.

u_r, and v_r are non-negative variable weights to be determined by the solution of the minimization problem.

Step 4 Solve the linear programming equations using Matlab (to find g_1 and h_1 for a start). The schematic for the research is represented in Figure 1.

Linear programming is used at the design stage during the carbon fiber-reinforced plastic composite development program. However, one of the components of the linear program is the objective function, which is a vehicle to minimize the negative effects of defects on the quality of the CFRP composite. Numeric values are dealt with in this kind of analysis. To further understand the usefulness and attributes of the objective function, consider the CFRP composite development project. The cost of the project, profit values, or materials shared (waste avoided from the CFRP composite fabrication process is reflected in the objective function of the data envelopment analysis framework proposed in this article. With the objective function of the DEA solution approach, the composite design engineer is attempting to arrive at a target in terms of profit to be anticipated from the CFRP composite fabrication process and the expected output from the mixtures of inputs for the CFRP composite development process. It could also target resource usage during the fabrication of the CFRP composites. In solving the problem formulated by the DEA method, the process/fabrication engineer needs to understand the relationship of the objective function with constraints and limitations within the CFRP composite development system. These may include the limits of production capacity, the availability of the CFRP raw materials and associated materials to aid fabrication, or the CFRP composite technology. Now, regarding the DEA model, the technical representation of the objective function is Equation (3), which expresses 9_k as a function of v_r and x_{ik}. The following observation exists by looking closely at the individual component of Equation (3), which is a minimization function. The v_r is the coefficient that matches the r^{th} variable, while x_{ik} is the i^{th} decision variable in the k^{th} period. To further explain, if the composite development manager/engineer wishes to maximize the profit of the fabrication process, x_{ik} is a likely activity in the composite development process. The i merely shows which activity it is, either the 10^{th} or the last activity. The index i may be conceived as a slot in a list of items of interest. The term v_r is the net value the activity produces, which could be the 10^{th} or the last activity. By reflecting on Equation (3) once again, the sign a symbol instructs us to add everything. This means that all activities and net values actively participating in the computation are recognized. It should be understood that no activities will provide value or contribute. For example, if a coefficient of zero is considered, it does not add to what is being considered. However, the coefficient should be non-zero to add to the obtained values. Also, the activity starts from the first item to the m^{th} activity. Furthermore, Equations (4) to (7) are referred to as constraints where the number of the quantitative description graphs the solution to a problem. Suppose there are three constraints, it could be graphed by a triangle, and a solution space is defined by relating it to the objective function. Equation (8) further describes how g_k is obtained as the reciprocal of h_k.

There are individual elements that make up the decision-making unit (DMU) in a system whose goal is to produce carbon fiber-reinforced plastics with the least negative influences of responses such as excessive torque, existing delamination, entry delamination, eccentricity, surface roughness, and excessive thrust force. In the CFRP composite quality performance drive, the DMUs are recognized as active participating responses in the manufacturing decision process. The key players in the DMU are explained as follows. The first key player is the torque. Torque reveals a measure of the force that triggers the carbon fiber-reinforced plastic sample to rotate around a point. During the fabrication of material, there may exist a turning exercise to produce the required shape and size of the material being fabricated. The term torque is appreciated if we consider the material to be turned by two different turning objects of the same kind of different sizes. For instance, a small wrench may find it hard to turn the material when used. However, a large wrench will find it easy to do so. However, using the large wrench may produce more than the required torque as a result of the increased distance the large wrench has compared with the small distance of the small wrench. Therefore, there is a size of wrench that will just produce enough torque, which is force multiplied by distance.

Another key player to consider is delamination, which may occur at the exit or entry. However, the explanation of delamination applies to either. The failure mode of the CFRP composite is referred to as delamination. As composites consist of layers of different material, the phenomenon that applies to composites, such as impacts and repeated cyclic stresses, stimulate the separation of composite layers. These separate layers resemble mica and possess reduced mechanical toughness, and this is referred to as delamination. Next is another key player of the DMU, notably thrust force. The thrust force could be understood by reflecting on the forces observed while the drilling machine drill acts on a CFRP composite material. In fixing the material to align on the surface where it is placed before drilling, it may require a little push forward foto align the drill bit to the center of the drill. This is sometimes accomplished by using a hammer to knock the metal carefully. The pushing force is acting downwards. If good drilling is to be accomplished sometimes, the material is fixed to be the base of the drilling bed, and a hammer may be used on some wood to fix it to the floor (bed). The forces produced by the hammer are acting perpendicular to the surface. Here, the summation of all forces acting perpendicular to the surface of the drilling bed is called the thrust force.

Eccentricity is the next key player discussed here. Usually, holes are drilled in perfect circles on the CFRP composites. However, there are many situations where perfect circles may not be obtained, but instead, eccentric circles are undesirably drilled due to machine vibration and the poor still of the machinist. Any drilled parameter that refuses to follow the circular path of hole drilling is considered eccentric. This motion of the hole, in this case, behaves in an odd manner sometimes for many an eclipse, which is undesired. The eccentricity is a measure of how nearly the hole produced in circular. Important measures of eccentricity include the distance from the center to the vertex and the focus of the ellipse. Next, surface roughness is discussed as a key player DMU. Surface roughness refers to the height of the micro and the irregularities present on the surface after machining. Surface roughness could be evaluated by using appropriate instruments which express it quantitatively.

4. RESULTS AND DISCUSSION

4.1. Pre-application and application modes of the DEA-CCR model

The working model of the DEA method is that the non-beneficial criteria are considered inputs while the beneficial criteria are considered outputs. Consequently, in this article, the signal-to-noise ratios need to be generated using the smaller, better criterion. This is then used as the output because using the SNRs will be beneficial to the drilling process of the carbon fiber-reinforced plastic composites. Thus, there are six inputs and one output considered in the present article. The results may be observed in the second column of Table 2.

Furthermore, the following computations are useful for the implementation of the DEA procedure:

The $\sqrt{\sum_{j=1}^{n} X_{ij}^{2}}$ SNR is computed as follows:

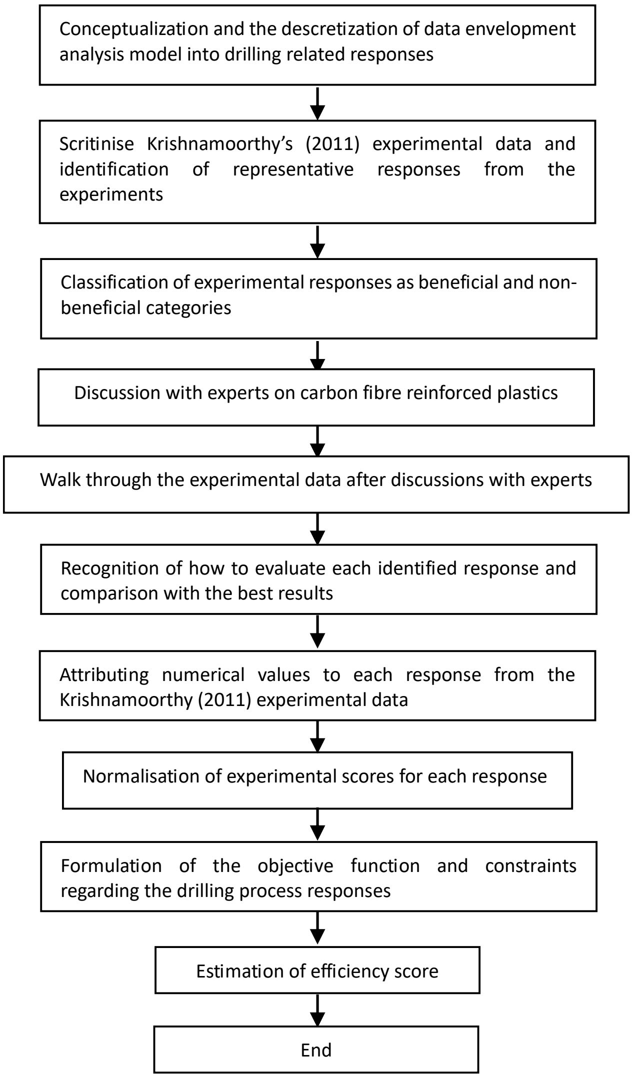

Figure 1. Research scheme in DEA application to the drilling process of CFRP composites

Table 2. Averaged experimental table (Krishnamoorthy, 2011)

Expt	SNR	Thrust Force	Torque	Entry Delamination	Exit Delamination	Eccentricity	Surface Roughness
1	4.373	0.601	0.611	0.656	0.635	0.599	0.515
2	6.670	0.374	0.653	0.442	0.417	0.473	0.364
3	5.141	0.497	0.588	0.581	0.593	0.578	0.470
4	3.747	0.558	0.808	0.645	0.652	0.647	0.555
5	4.054	0.575	0.716	0.657	0.658	0.622	0.514
6	6.653	0.247	0.816	0.405	0.382	0.420	0.289
$\sqrt{\sum_{j=1}^{n} X_{ij}^{2}}$	12.83631	1.204	1.753	1.405	1.390	1.378	1.129

$$\sqrt{\sum_{j=1}^{n} X_{ij}^{2} = 4.373^{2} + 6.670^{2} + 5.141^{2} + 3.747^{2} + 4.054^{2} + 6.653^{2}}$$

which gives 12.83631.

Besides, the same computation is extended to the thrust force, torque, entry delamination, exit delamination, eccentricity, and surface roughness to obtain the following respective values, 1.204, 1.753, 1.405, 1.390, 1.378, and 1.129. Furthermore, the normalized decision in Table 3 is shown.

The second step involves normalizing the decision matrix, which is obtained by dividing each of the values by the square root of the sum of the squares of all the values. This was first obtained one by one, as shown in the last row of Table 1. They also expatiate further such that how the results arrived at can be clear.

The next phase of the work is to normalize the decision table by dividing each of the values by the value previously obtained in the last computation discussed here, which is the square root of the sum of the squares of

Table 3. Normalized decision matrix

Expt	SNR	Thrust Force	Torque	Entry Delamination	Exit Delamination	Eccentricity	Surface Roughness
1	0.3407	0.499	0.391	0.467	0.457	0.435	0.457
2	0.5196	0.310	0.373	0.314	0.300	0.343	0.322
3	0.4005	0.413	0.335	0.413	0.427	0.419	0.416
4	0.2919	0.463	0.461	0.459	0.469	0.470	0.492
5	0.3158	0.477	0.408	0.468	0.474	0.451	0.455
6	0.5183	0.205	0.466	0.288	0.275	0.305	0.256

all the values. In this way, all the values will be less than 1. Then the normalized decision table is shown in Table 2. Notice that Table 2 shows the process of normalization, which were the values in Table 1 divided by the square root of the sum of the squares of all the values for that particular factor.

For example, for SNR, for all the values, the squares are found, then the squares are summed up, and the square foot is found. To explain Table 3 in more detail, consider experiment 1, column 1 has the signal-to-noise ratio. Here, the denominator has been obtained from the previous table. The denominator is the square root of the sum of the squares of all the SNRs, which is 12.8363. Then the numerator is the initial signal-to-noise ratio in Table 2. The procedure remains the same to compute the value under the thrust force. Here the 0.601 is from Table 2 (i.e., numerator) then the denominator is also the square root of the sum of the squares of all the thrust force obtained from Table 3. So in Table 4, the writing out the values of the results of the mathematical operation carried out in Table 3 is done. These are the results of certain divisions.

Afterward, the linear programming is generated by applying the DEA-CCR model. This model has some steps that should be followed. The first step is to attempt to formulate the linear equations. Thus, by applying the idea of the formulation in step 3 to Table 3, Equations (9) to (21) are obtained:

$$g_1 = min\ (0.499v_1 + 0.391v_2 + 0.467v_3 + 0.457v_4 + 0.435v_5 + 0.457v_6) \quad (9)$$

Subject to:

$$-0.3407u_1 + 0.499v_1 + 0.391v_2 + 0.467v_3 + 0.457v_4 + 0.435v_5 + 0.457v_6 \geq 0 \quad (10)$$

$$-0.5196u_1 + 0.310v_1 + 0.373v_2 + 0.314v_3 + 0.300v_4 + 0.343v_5 + 0.322v_6 \geq 0 \quad (11)$$

$$-0.4005u_1 + 0.413v_1 + 0.335v_2 + 0.413v_3 + 0.427v_4 + 0.419v_5 + 0.416v_6 \geq 0 \quad (12)$$

$$-0.2919u_1 + 0.463v_1 + 0.461v_2 + 0.459v_3 + 0.469v_4 + 0.470v_5 + 0.492v_6 \geq 0 \quad (13)$$

$$-0.3158u_1 + 0.477v_1 + 0.408v_2 + 0.468v_3 + 0.474v_4 + 0.451v_5 + 0.455v_6 \geq 0 \quad (14)$$

$$-0.5183u_1 + 0.205v_1 + 0.466v_2 + 0.288v_3 + 0.275v_4 + 0.305v_5 + 0.256v_6 \geq 0 \quad (15)$$

$$0.3407u_1 = 1 \quad (16)$$

$$0.5196u_1 = 1 \quad (17)$$

$$0.4005u_1 = 1 \quad (18)$$

$$0.2919u_1 = 1 \quad (19)$$

$$0.3158u_1 = 1 \quad (20)$$

$$0.5183u_1 = 1 \quad (21)$$

$$u_1, v_1, v_2, v_3, v_4, v_5, v_6 \geq 0 \quad (22)$$

The mathematical formulation contains an objective function expressed as g_k and the constraints. The idea is to minimize g_k subject to the constraints as shown. Having this in mind, the g_k has been broken down according to the different decision-making units (DMUs). Here, there could be g_1 to represent the first DMU. According to the DEA method, all the DMUs will be treated one by one. In the line containing the first DMU, the reader will find the objective function being stated and the constraints (linear equations). Notice that the linear equations were obtained from the table. In these equations, the that U represent refers to the signal-to-noise ratios while those with v show that they are inputs (responses). Recall that it was stated earlier that non-beneficial criteria are the inputs, such as exit delamination, entry delamination, eccentricity, thrust force, torque, and surface roughness. In contrast, the beneficial criteria are the signal-to-noise ratios. Thus, what is to be minimized is considered the input, and what is beneficial to be maximized is considered the output. These are the conventions for applying the DEA method. To further expatiate the constraints, -0.3407 follows how the constraints are arranged. The u_1 denotes the outputs, which are the criteria beneficial to the drilling operation of the carbon fiber-reinforced plastic composites. These are to be maximized—notice also that u_1 is the signal-to-noise ratio in this case. So v_1 to v_6 refers to the thrust force, surface roughness, and other response. Notice that six DMUs also give rise to the six constraints formulated for the method. To simplify this explanation, the first DMU is for the first constraint. The second DMU is for the second constraint, and so on, until the sixth DMU is used to represent the sixth constraint. From the equations, the reader may observe the expression $0.3407u_1 = 1$. This expression still follows from the working of the DEA-CCR model. As can be seen, the values for the various u are equated to 1. However, for the case study, only one output is considered, and this is the reason why only a variable is considered, and this variable multiplied by its coefficient is taken to be equal to 1. The next step is to solve the linear programming problem using Matlab software.

The next step is to solve the formulated linear programming model using Matlab software. The aim is to minimize g_1 and to achieve this. The researcher needs to obtain six parameters to be put into the linprog function to solve the linear programming problem. The first parameter to consider is parameter A, Table 4. This parameter A is a matrix, a 6 x 7 matrix, and it is obtained from the set of constraints. However, there is a change in sign as the constraints are converted to the matrix. Consider the list of constraints. For instance, the

Table 4. Matrix A

0.3407	-0.499	-0.391	-0.467	-0.457	-0.435	-0.457
0.5196	-0.31	-0.373	-0.314	-0.3	-0.343	-0.322
0.4005	-0.413	-0.335	-0.413	-0.427	-0.419	-0.416
0.2919	-0.463	-0.461	-0.459	-0.469	-0.47	-0.492
0.3158	-0.477	-0.408	-0.468	-0.474	-0.451	-0.455
0.5183	-0.205	-0.466	-0.288	-0.275	-0.305	-0.256

Table 5. Different values of A_{eq} and f and the respective values of g_k and h_k obtained

DMU	Values for A_{eq} and f	g_k	h_k
2	$A_{eq} = [0.5196 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$ $f = [0 \quad 0.310 \quad 0.373 \quad 0.314 \quad 0.300 \quad 0.343 \quad 0.322]$	1	1
3	$A_{eq} = [0.4005 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$ $f = [0 \quad 0.413 \quad 0.335 \quad 0.413 \quad 0.427 \quad 0.419 \quad 0.416]$	1.1652	0.8582
4	$A_{eq} = [0.2919 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$ $f = [0 \quad 0.463 \quad 0.461 \quad 0.459 \quad 0.469 \quad 0.470 \quad 0.492]$	2.2000	0.4545
5	$A_{eq} = [0.3158 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$ $f = [0 \quad 0.477 \quad 0.408 \quad 0.468 \quad 0.474 \quad 0.451 \quad 0.455]$	1.7997	0.5556
6	$A_{eq} = [0.5183 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$ $f = [0 \quad 0.205 \quad 0.466 \quad 0.288 \quad 0.275 \quad 0.305 \quad 0.256]$	1	1

coefficient of u in the first case (constraints) is negative under the list of constraints, but when considered in matrix A, the coefficient of *u* becomes positive. The sign changes are due to the conversion from the inequality to the equality sign. This is basically due to the arrangement of the terms.

The details of the formulation are further expressed as follows:

$$A_{eq} = [0.3407 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0], \tag{23}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, B_{eq} = [1], \tag{24}$$

$$f = [0 \quad 0.499 \quad 0.391 \quad 0.467 \quad 0.457 \quad 0.435 \quad 0.457] \tag{25}$$

$$lb = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0], \; ub = [\;] \tag{26}$$

However, the magnitude of the values remains the same. The A_{eq} is where the output is inserted, and the inputs are left to be zero. The matrix B is a single column, and all the rows are zero. Then the B_{eq} is given the value of 1, which is also a matrix.

However, B_{eq} is a 1 x 1 matrix. The f contains all the inputs only, while the output will be zero. Assuming there were two outputs, it means that the first two outputs will be zero. However, there is only one output, and the first output is zero. Nevertheless, the arrangement is symmetry. The A_{eq} and f complement each other because if the researcher joins A_{eq} and f, the first row of matrix A is obtained. Notice that each row of the matrix represents each DMU. It follows that the first row of the matrix represents the first DMU, and the second row of the matrix represents the second DMU until the last row, which is the sixth, is reached to represent the last (sixth) DMU. Currently, the researcher is dealing with the first DMU in which the values of A_{eq} and f correspond to the first DMU. Furthermore, other symbols in the system of equations include the *lb*, which is the short form of the lower boundary. This is something that features in the DEA–CCR model. However, the values are set to be zero for all the parameters by considering the lower boundary. The other term that features in the DEA-CCR model is the *ub*, which means the upper boundary but is represented as a null matrix in work. Thus, after adding the following components in Matlab software, namely A_{eq}, B, B_{eq}, f, lb, and ub, the line of the program, which is related to the linprog, was computed at the command window. Thus, after the first computation, the Matlab software yields the following results: g_1 is given, and the inverse of g_1 is computed to yield h_1.

Additional details are as follows:

The line entered in the command window is shown below:

$$[x_1 \; g_1] = linprog\,(f \quad A \quad B \quad A_{eq} \quad B_{eq} \quad ub \quad lb) \tag{27}$$

Consequently, the two things that are important for the analysis of the DMU are the values of g_1 and h_1. Now to realize the second DMU, the A_{eq} and f will be changed. Thus, instead of putting 0.3407, the researcher puts 0.5796, while the rest values will be zero. Nevertheless, for the *f*, instead of putting 0.5796, this is omitted, and other values are inserted. Also, when computing *f*, the negative sign is ignored. This procedure is illustrated in Table 5, while the values of *g* and *h* obtained after conducting the linprog are also shown.

Table 6. Initial table of the parameters with the efficient set of parameters identified

TF	Torque	Entry D	Exit D	Eccentricity	SR	g_k	h_k
0.601	0.611	0.656	0.635	0.599	0.515		
0.374	0.653	0.442	0.417	0.473	0.364	1	1
0.497	0.588	0.581	0.593	0.578	0.470		
0.558	0.808	0.645	0.652	0.647	0.555		
0.575	0.716	0.657	0.658	0.622	0.514		
0.247	0.816	0.405	0.382	0.420	0.289	1	1

The procedure is repeated for all six DMUs. After the analysis, it turns out that two of the DMUs have values of 1 for *g* which are the second and the sixth DMUs. Here they are considered to be the most efficient. According to the DEA-CCR model, if a DMU has a score of 1, then it is efficient, and it can be chosen for further decisions like the choice set of parameters. Also, DMUs one, three, four, and five are inefficient. Table 5 shows the initial table for the output parameters even before the signal-to-noise ratios were obtained.

The result obtained is summarized as follows:

$$X = \begin{bmatrix} 2.9351 \\ 0 \\ 4.0887 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad g_1 = [1.5987] \quad h_1 = \frac{1}{g_1} = [0.6255] \tag{27}$$

To obtain the values of g_2 up to g_6 and h_2 up to h_6, the values of A_{eq} and f were changed where the other parameters were left constant, Table 6. The A_{eq} and f values were obtained from the linear programming models. In the CCR models, the DMU is said to be efficient if it achieves a score of 1. The set of parameters that have been identified to be efficient is indicated by placing their values of g_k and h_k, respectively.

In this work, two different decision-making units are considered to be efficient. However, out of these two DMUs, i.e., DMU_2 and DMU_6, it is interesting to comment on which one is better and attribute reasons for this. In the authors' view, the better of the DMUs is in the decision of the user of the method. For instance, as a user, there is a need to consider which of the responses is important to the system being analyzed. The question is which of the responses the user is more interested in minimizing. For example, if the user is more interested in minimizing the thrust force, then DMU_6 is better because it has a lower thrust force than DMU_2. However, if the user is more interested in minimizing the torque, then DMU_2 is better because it has a lower torque than DMU_6. Thus, after the efficiency has been shown, the process operator chooses based on the factors that appeal more to this user. Furthermore, two sets of DMUs have been identified as efficient to summarize the conclusion. Therefore, either of these could be chosen as the ideal. The first set of DMU is DMU_2, and the second is DMU_6. The DMU_2 has a thrust force of 0.374, a torque of 0.653, entry delamination of 0.442, exit declamation of 0.417, eccentricity of 0.473, and surface roughness of 0.364. Then DMU_6 has a thrust force of 0.247, the torque of 0.816, entry delamination of 0.405, exit delamination of 0.382, eccentricity of 0.421, and surface roughness of 0.289. These mentioned values are the efficient set of responses.

4.2. Comparison of the present work and other studies

In Odusoro and Oke (2021a), the most important response while evaluating the CFRP composite was reported as the exit determination with a net outranking flow of 0.059. However, in the current study, the DMUs, which are DMU_2 and DMU_6, equivalent to torque and surface roughness, are considered efficient and have the best results. Unfortunately, the previous results using the PROMETHEE method appear consistent with the present study's outcome. The principal reason may be due to the difference in the working of the methods. Besides, in Odusoro and Oke (2021b), the thrust force with a height of 0.415 was regarded as the most important response while evaluating the responses in a drilling exercise. The result is the outcome of applying the fuzzy AHP method to the drilling responses. Interestingly, another result from the literature places the thrust force as the most important response while applying the AHP method to evaluate the responses from the drilling of CFRP composites. The result of the present study is, however, that places importance on torque and surface roughness are at variance with the other methods' outcomes, such as the use of the PROMETHEE method, fuzzy AHP, and AHP approaches.

4.3. Advantages of data envelopment analysis

This article develops an input-output-based approach named the data envelopment analysis to take full advantage of its capability to absorb a multiplicity of drilling inputs and outputs where the outputs regarding the defects of the drilling process are taken as the multiplied decision-making units whereby the efficiency of the system are related to them to generate measures where the defects are classified quantitatively according to the order of their numbers and then used for the further decision-making process.

Since the production of carbon fiber analysis is better than the conventional approach of performing costly experiments through fracture toughness, XRD, and SEM tests, it significantly creates a fast reaction to implementing tasks that would have been delayed for weeks, which it takes to conduct and process experimental data on defect detections. Moreover, compared with the traditional approach, the data envelopment analysis attains improvements in the efficiency objectives of the drilling process. This completely proves the effectiveness of introducing data envelopment analysis into the drilling operation.

Reinforced plastic composites are often accompanied by defects. Therefore, to respond to this problem, this article makes some improvements to understanding the link between the efficiency determination of the drilling process and the defects produced. It contributes to the data envelopment analysis as an approach to solving the problem. The responses consist of defects and other measures. However, the rating distinguishes each of them, thereby establishing how much the defects impact the quality of the drilled carbon fiber-reinforced plastic composites. It could be noticed that the analysis is based on the data envelopment.

4.4. Managerial implications

While the available data on the prioritization of responses for the CFRP composites during drilling optimization exercises is scarce, embarking on more knowledge exploration in the area is expected to assist process engineers, managers, and drilling equipment operators in being more accountable and efficient in managing drilling resources. A glaring implication of the results of applying the efficiency evaluation method of the DEA is to sharpen the sense of responsibility of the resource managers in the drilling of CFRP composites. Scarce resources are often distributed to various jobs and operators arbitrarily without considering the importance of various responses considered in this work. By implementing this study, similar to the proposal by Odusoro and Oke (2021c), resource distributors ought to pay closer attention to the distribution of resources and allocating drilling resources only to deserving workstations, activities, and operators by measurable quantities. Next, a new consciousness of waste-avoidance strategy in the management of the drilling workstation is created so that every spent resource is accompanied by an answer to the question of whether this quantity distributed avoids waste. By how much? Again, there is a recognition that what gets measured gets improved, and as such, this is tried to the consciousness in resource distribution.

5. CONCLUSION

In this article, the DEA-CCR model has been applied to the drilling operation of carbon fiber-reinforced plastics to obtain efficient decision-making units such that the results could be deployed to process the material for improved decision-making. In this work, the efficient output parameters have been identified, which are the thrust force, torque and delamination values, eccentricity, and surface roughness for experiments 2 and 6. This means that to repeat subsequent machining operations, the input parameters that gave rise to those values can be considered ideal for the particular machining operation.

The work reveals the most important decision-making units about the drilling operation of carbon fiber-reinforced plastic composites. Besides, in this work, using the signal-to-noise ratios to represent the output of the drilling operation is a novel issue contributed by this work to the literature. Furthermore, the signal-to-noise ratio was important because, without this, the problem would have been left without output from the perspective of applying the DEA method in this work. This is because all the responses are to be minimized but to apply the DEA method, apart from minimizing the inputs, the output must be specified, which should be maximized. So applying a signal-to-noise ratio provided an opportunity for the output to be specified. This is making up for the shortcomings of the DEA model. In sum, the challenge initially encountered was a situation where only the inputs could be noticed from the data while formulating and solving the problem using the DEA method. There was no concrete output. However, upon generating the signal-to-noise ratios for all the responses, it serves as an output, which was absent in the framework initially observed. This enabled the implementation of the DEA method. However, before this time, it is not possible to implement the DEA method on the data successfully. Further, the novelty of this article is considered. What can be considered new in this work pertains to the introduction of the signal-to-noise ratio to represent the output of the drilling process. Here, the operation that is being optimized is drilling, and it is particular to the carbon fiber-reinforced plastic composites. Thus using the data envelopment analysis to analyze and combine several responses and attempting to arrive at efficient machining parameters for the carbon fiber-reinforced plastic composites is new in the drilling operations literature. It has been shown that there is a clear way to arrive at the ideal efficiency indices for the decision-making units, considering multiple responses for the drilling operation.

Although the idea of using DEA to choose the best response for the drilling of CFRP composites is interesting, a weakness of the article is that the data used for illustration are taken from another source instead of performing an experiment. Thus, the latitude and flexibility to create valuable insights are limited. However, future studies may improve on this by using multiple data sources or conducting experiments to allow flexibility in research. Besides, in the future, it is essential to confirm the model's validity by comparing it with multicriteria models such as the EDAS method.

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