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Application of Data Envelopment Analysis for Performance Efficiency Evaluation of Oil Palm Empty Bunch Fruit Composites in The Aerospace Industry

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ABSTRACT

In this study, we propose the data envelopment analysis method as a scheme to determine the technical efficiency of a set of parametric inputs of the water absorption process when developing the oil palm particulate composite treated with an alkali solution. Although alkali-treated oil palm bunch composites have been analyzed previously for water absorption, a single parameter such as water absorption rate prevails in analyses. Unfortunately, multiple inputs and multiple outputs have been ignored and the efficiency evaluation of such composites has been missing in the literature. To address this gap, the present study exploits the linear programming theory and formulated models for each decision-making unit and solves that formulation for optimum value determination for inputs of the composites. This study investigates the technical efficiency of the water absorption in the oil palm empty fruit bunch composite development process. Overall, judging the performance of the parameters regarding the frequency of attaining 100% efficiency, analysis was performed on the average performance of all parameters in all sixteen scenarios. In this regard, the efficiency of particulate loading was 36.1%, for composite weight plus mold, it was 96.3% and for initial weight, the average efficiency score was 67.8%. It is suggestive that composite weight plus mold with an average efficiency of 96.3% is the best parameter while particulate loading with 36.1% is the worst parameter. Thus result is consistent with the result based on each scenario. From the perspective of DMUs, DMU11 with a score of 78.4% is the best ranking unit while DMU14 is the work ranking unit with an efficiency score of 60.9%. Besides, the average efficiency score for all the DMUs is 66.7%. The work is important to composite development engineers and for policy decision-making.

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1. INTRODUCTION

The empty fruit bunch is an abundant and inexpensive recyclable waste in the Nigerian palm industry (Izah et al., 2016, Achoja et al., 2019; Ogunbode et al., 2022). It has an attraction to the industry due to its high mechanical properties, making it a commonly used reinforcement in composites (Amir et al., 2019). Over the years, its hydrophilic attribute has been recognized as a major weakness for its use in water-prone environments

(Khalil et al., 2001; Chaiwang et al., 2019). Critics of the oil palm empty fruit bunch (OPEFB) composite argue that the hydrophilic nature of these raw materials is a causal factor to the weak bonding that exists in the interface of the polymer matrix and the fiber while developing composites (Izani et al., 2013; Chaiwang et al., 2019). In response to this criticism, efforts have been made to improve the compatibility of the OPEFB and polymer matrix. Largely, the effort is along the treatment of the OPEFB using alkaline solutions. While several studies have been conducted on OPEFB composite, less attention has been devoted to the performance evaluation of the water absorption process parameters during the composite development process. Unfortunately, there is no study on which parameters during the OPEFB composite development process.

Furthermore, polymer composite, of which the empty fruit bunch composite is an example is preferred to metals for certain aircraft components such as the interior components, floorboards and floor beams, landing gear doors, and fairings (Ramlee et al., 2019). In this case, they provide lower lifetime freight costs in the lifecycle of a product, particularly for equipment that is constantly transported across the globe. The polymer composites achieve this through the immense benefits that they offer, including resistance to smoke and flame, lightweight, and corrosion protection. Therefore, there exists a growing concern to monitor the time and cost efficiency of the polymer composite development process. However, the common approach to judgment is still the intuition of the engineer, the experience of the managers, and the joint knowledge contribution by all the team members to decide on what the likely threshold of efficiency will be.

Unfortunately, the intuition of the engineer may be influenced by information outside the consciousness of the engineer. Also, past experiences are often applied with the danger that composite development decisions made may not be objectively accurate. This is a narrow-minded method, which limits the potential of the polymer composites and the ability of the polymer composite engineer to contemplate optional viewpoints. Besides, in the long run of implementing a trial-by-error idea of the intuitive scheme, more time is consumed and resource wastage occurs. Hence, this study assesses the performance efficiency of the composite development process while testing for its water absorption capacity.

With the oil palm empty fruit bunch composite being analyzed, the data envelopment analysis (DEA) method was uniquely used to tackle the performance efficiency evaluation problem. The process was separated into inputs and outputs while the experimental trials generated from the experiments conducted were taken as the decision-making units. The inputs into the water absorption process are the particular loading, composite weight + mold before the water experiment, and initial weight. The outputs are particulate weight, the average weight of mold, final weight, and percentage weight gained. Today, the concern for efficiency measurement is more pressing than previously handled in the industry because there is huge pressure on engineers and managers of composite development firms to have impressive accuracy from composite development practices as it will make or promote zero defect and zero accident goals of aerospace organizations in the contemporary period. Thus, in this article, the DEA method is presented to eliminate intuitive practices and provide an objective assessment of the water absorption process in the development of the oil palm empty bunch composite. This was achieved by adopting a technical efficiency method by Charnes et al. (1978). Based on experiment data, the normalized values of the composite parameters were determined while the alternative criteria were defined as decision-making units. Linear programming models were formulated in sixteen distinct scenarios. These scenarios were solved using DEAP 2 software. The optimal values of the parameters are then stated, this study proves that the parameters of the water experiment can be optimized during the composite development process.

The data was taken from a larger project conducted in experiments on the subject. The inputs and outputs for the water absorption process were first established. Then the selection of the optimization orientation is made. The available options may be the minimization of inputs and in other cases, the maximization of output may be desired. However, in the current study, the minimization of inputs is desired. Then a possible weight restriction is implemented. This study contributes to the polymer composite literature in the following ways:

- It highlights input parameters and the responses of the water absorption testing of composite development which were previously not stated for the technical efficiency measurement of the oil palm empty bunch fruit composite
- It implements the DEA method as a new way of evaluating the performance of oil palm empty fruit bunch composite

In the next section, the literature review is presented. Then the methodology of the work is discussed. Next, the results and discussion are made and finally, the conclusions are given.

2. LITERATURE REVIEW

The following is a summary of the review of literature for the present work. Moreover, the relevant literature is reviewed under two categories: The oil palm composites research and the data envelopment analysis applications. The essential details of the first aspect of this review follow.

2.1. The oil palm fruit bunch composite research

Earlier works of oil palm composite research focusing on the empty fruit bunch were conducted by several authors within a space of roughly two decades from now. Rozman et al. (2000), Ismail et al. (2000), Khalil et al. (2001), Rozman et al. (2001), and Rozman et al. (2004), are noteworthy pioneering contributors in this area. In all these contributions, the ground-breaking work of Rozman, Ismail, and colleagues is particularly noteworthy. Much of these initial works focused on the water absorption problem and what coupling agent to introduce for enhanced properties. These properties are mainly mechanical, flexural, and fatigue. In surface modifications, Rozman et al. (2000) examined the mixing process of the empty fruit bunch to understand the influence of incorporating coupling agents on the properties of the developed composite and their advantages. Rozman et al. (2001) observed shrinkage in the strength of the composites with the introduction of glass fiber using various coupling agents. Rozman et al. (2004) analyzed the influence of isocyanate treatments on the properties of composites, focusing on the mechanical concern, and affirmed the effectiveness of the treatment on the composites. Khalil et al. (2001) asserted the superiority of acetic anhydride in modifying the empty fruit bunch composite compared with propionic and succinic anhydride usage. Other contributors to surface modifications of composites are Jawaid et al. (2010), Jawaid et al. (2012), Ibrahim et al. (2011), Tay et al. (2011), Khalil et al. (2011), Hamid et al. (2010), Ramli et al. (2011) and Kittikorn et al. (2012) and Alam et al. (2014). Some interesting details are as follows: For example, new modifiers were suggested as ENGAGE TM 7467 (Ibrahim et al., 2011) and it made the composite to be resistant to water conditions. Other authors used the chemically changed Alcel lignin, a compatibilizer, and found them to improve the hydrophobicity and the mechanical properties of oil palm in composite form (Tay et al., 2011). Yet, Hamid et al. (2010) confirmed the usefulness of polycaprolactones in modifying the empty fruit bunch of palm oil to produce acceptable products when methyl methacrylate was also added. Kittikorn et al. (2012) also deployed polypropylene chemicals to improve the oil palm composite property of modulus, stiffness, and crystallinity.

In the last five years, several important studies have been contributed including the following: Saba et (2019), Amir et al. (2019), Ramlee et al. (2019), Chaiwang et al. (2019), Nordin et al. (2020), Ahmad et al. (2023), Latip et al. (2019). In a study conducted by Latip et al. (2019), the alkaline solution was used for the pretreatment of the oil palm empty fruit bunch composite to reduce the hydrophilicity and improve the surface effectiveness of the composite. Saba et al. (2019) tackled the effect of nanoparticle loadings on the properties of the oil palm empty fruit bunch composite. These properties are storage modulus, glass transition temperature, loss modulus, and mechanical properties. They chose 3% nanoparticulate loading as the best value. Amir et al. (2019) presented results on layering sequences as well as gamma radiation and their effects on the mechanical properties of the empty bunch fruit composite. Mechanical performance was guaranteed with the gamma relation explosive and layering sequence of the composite. Ramlee et al. (2019) introduced the SCB fibers to fill various particulate loading of the composite. They claimed that the addition of SCB fiber yielded enhanced performance of the composite. Chaiwang et al. (2019) determined the performance of composite under surface treatment conditions with NaOH. They stated that residual surface contaminants were eliminated with the method. Very recently, Ahmad et al. (2023) established the properties (mechanical physical, and thermal) of oil palm fiber without surface treatment.

Apart from these studies, several other studies analyze the performance of oil palm composites by focusing on rarely studied properties. For example, the ultimate tensile strength was studied by Kalam et al. (2005), and dielectric properties were examined by Ahmad et al (2016). Apart, Hermawan et al. (2019) studied the reinforcement efficiency of fibers in empty fruit bunch composites. Nordin et al. (2020) studied the mechanical properties of the palm (empty fruit bunch) composite. The extraction and infection-mounding behavior of mixed empty fruit bunch with polypropylene and glass fiber was tested by Islam et al. (2015). Polypropylene was also mixed with other items to form composites in Abdullah et al. (2016).

2.2. Data Envelopment Analysis Applications

Earlier, the diverse studies on the oil palm empty fruit bunch have been reviewed to understand the wide range of studies conducted to date. However, the review of the literature is incomplete if the studies on specific applications of data envelopment analysis are not covered. Thus, the goal is achieved in the present section. Consequently, it was found that the diverse applications of data envelopment analysis include eco-efficiency and circularity evaluation (Rebolledo-Leiva et al., 2022), power resource allocation (Zhang et al., 2024), evaluation of water security (De Castro-Pardo et al., 2022), health care provisions (Shwartz et al., 2016), wind turbine performance evaluation (Gennitsaris et al., 2023), supply chain agility assessment (Pourbabagol et al., 2023) and noise pollution analysis (Michali et al., 2021). However, these discussions currently exclude the issue of efficiency in the composite development process and this neglected issue is still open for investigations. To summarize these studies, the following is relevant. Rebolledo-Leiva et al. (2022) advanced a new DEA approach capable of assessing the eco-efficiency and circularity in the agricultural sector. The lowest efficiency quotients were obtained at the first stage of the DEA analysis. Besides, Zhang et al. (2024) combined the DEA with a performance-based method to evaluate the resource allocation problem in power systems. It was concluded that the seasonal power price gained superiority over the differentiated power rationing when assessed through the DEA-integrated scale of measurement. De Castro-Pardo et al. (2022) applied the DEA method to estimate water security with application to 15 European nations. The best three results in the order of 1st, 2^{nd,} and 3rd are Denmark, the United Kingdom, and Finland, respectively. Moreover, Shwartz et al. (2016) made a comparison of DEA and alternative methods of opportunity-oriented weight and the Bayesian latent variable model. The approach proposed was claimed to be useful in a situation where the data generation is hierarchical. Moreover, Gennitsaris et al. (2023) deployed a combined life cycle analysis and data envelopment analysis to assess the various wind turbine treatment choices. It was concluded that by adjusting the energy-intensive thermal recycling scheme, the utmost environmental benefits could be attained. Next, Pourbabagol et al. (2023) focused on the dairy supply chain to evaluate the agility of the system via the fuzzy data envelopment analysis. The model was efficient in delivering results on the various optimistic-pessimistic points within the Iranian case study analyzed. Furthermore, Michali et al. (2021) analyzed the noise pollution efficiency using the DEA method and drew a case from the ratios of 22 European rations. The top three countries, by performance, are Estonia, Germany, and Poland.

2.3. Summary of literature review and justification for the choice of data envelopment analysis method:

In the preceding sub-sections, literature has been reviewed along two main streams of research but the important elements of the review need to be distilled here. The observation from the literature is that great efforts of researchers have been on surface modifications of the empty first bunch composites. Researchers intend to enhance the composite's mechanical properties, their modulus, crystalline, and stiffness. Moreover, there is a dearth of procedures or formulae to tackle the efficiency aspect of the water absorption process for the empty fruit bunch composites. Therefore, there is a need to introduce efficiency measures in a real case, based on the data envelopment analysis theory.

Furthermore, in the literature search, the response surface methodology and factor analysis have been applied as alternatives to the data envelopment analysis methods. Besides, Shwartz et al. (2016) declared the Bayesian latent variable method and the opportunity-based weights as alternative methods to the data envelopment analysis. All these four methods were thoroughly studied during the literature review conducted in this work but the data envelopment analysis is preferred to them for the reason of its capability to contain many inputs and outputs. In addition, the data envelopment analysis considers the return-to-scale idea while analyzing efficiency, thus permitting the increase or decrease of efficiency when considering size and output levels.

3. METHODOLOGY

This article showcases the outcomes of the application of data envelopment analysis to the water absorption process while developing the NaOH-treated oil palm empty fruit bunch composite. The method of DEA was applied to assess the settings and the criteria to improve the efficiency of the composite development process. The DEA method is a tool that aids in comparing the composite process and performance metrics of parameters against one another. In particular, a group of decision-making units (i.e. experimental trials in this particular situation) are assessed in performance on how they are capable of transforming inputs to outputs. Thus, the experimental trials that could effectively transform the inputs into output are established. Traditionally, this is the effectiveness frontier. The DEA method is a non-parametric approach to efficiency analysis, which was developed by three experts, namely Charnes, Cooper, and Rhodes in an influential article in 1978. It works in this case by evaluating the comparative compatibility efficiency between the particulate oil palm empty fruit bunch and the epoxy matrix while working in a set of decision-making units exhibiting three inputs and four outputs. The choice of 3 inputs and 4 outputs is very important because it reduces the complexity of the computation of the DEA model. Having larger inputs and output values will likely make computations more difficult and demanding and more so that manual computations of the results are done. It helps in avoiding errors. Without the correctness of values in computations, decision-makers would make wrong decisions, which could be very costly for the process. Moreover, each decision-making unit occurring within the process is projected on the efficiency frontier in a formulated linear programming model consisting of the objective function and the constraints. The maximum improvements possible are then evaluated. This is attained on the inputs as well as the outputs of the DMU. Compared with Nassiri and Singh (2010), which limits its number of inputs to 8 and the outputs to 4, the present work compares favorably by establishing 3 inputs and 4 outputs, which are even less than their specification. The present work therefore concurs with the literature standard in the specification of inputs and outputs.

The data envelopment analysis model is as follows (Nassiri and Singh, 2010):

$$H_k = \frac{1}{g_k} \tag{1}$$

$$g_k = min\left(\sum V_g x_{ijk}\right) \tag{2}$$

Subject to;

$$-\sum_{r=1}^{u} u_r y_{rk} + \sum_{i=1}^{m} v_g x_{ijk} \geq 0 \quad for\ j = 1, \dots, n \tag{3}$$

$$\sum_{r=1}^{u} u_r y_{rk} = 1 \tag{4}$$

$$V_g \geq 0, 1 = 1, \dots, m$$

where n is the number of alternatives/DMUs (scenarios).

m is the number of input criteria.

s is the number of output criteria.

x_i and y_{rk} denote the value of the i^{th} input criteria and r^{th} output criteria for the k^{th} alternative (scenario).

u_r and V_g are the non-negativity variable weights to be determined by the solution of the minimization problem.

H_k is the efficiency measure of the k^{th} DMU.

To achieve a solution, Equation (1) describes the efficiency values of the various scenarios. However, this is not directly obtained but achieved through the reciprocal values of G_k. Thus, an important task is to first formulate an objective function using Equation (2). This is a minimization function since the water absorbed in the composite is expected to be minimal. Having, defined the objective function where variables are defined for each input, coefficients for the variables are assigned from the data. Then the constraint equations, which will be according to the number of the generated experiment, also equivalent to the number of decision-making units will be formed. Each of these constraint equations (generically obtained from Equation (3)) should have a sum greater or equal to zero. Equation (4) is also developed where the products of terms are produced and their aggregates should be equal to 1. After all these definitions, the optimal solutions are obtained and interpreted.

4. RESULTS AND DISCUSSIONS

The purpose of this section is to understand the oil palm (NaOH-treated) composite data and obtain general insight about it for information that may be useful for decision-making. In composite engineering, treating the oil palm composite with the sodium hydroxide compound will enhance the interfacial bonding between the particles of the oil palm and the epoxy resin used to bind these particles. With this enhanced bonding, resultant higher strength and improved modulus of the composite are expected. Also, this treatment is expected to provide higher stability in thermal properties than untreated oil palm composite. Consequently, in this work, the efficiency of the binding process is evaluated using the data envelopment analysis. The problem addressed here is from an economic perspective where the particulate loading, particulate weight, mixtures of composite weight and water, and other terms that represent the resources utilized for the treated composite are optimally allocated to achieve the goal of composite processing in the best manner why reducing waste to the minimum. Table 1 shows the data obtained from the experiment where particles of oil palm are mixed with various particulate loadings ranging from 1% to 31% in steps of 2%. These particulate loadings form the first parameter of interest in this work. Particulate loadings are the masses of suspended particulate oil palm per volume of solid space. They indicate the particle concentration in the waste sample processed as a composite. It should be noted that there are 16 alternatives (scenarios) to consider while discussing particulate loading. To synchronize these 16 alternatives (scenarios), decision-making units (DMUs) have been created therefore DMU1 represents the data set for all parameters in the matrice role of1% particulate loading other parameters in Table 1 are particulate weight, composite weight plus mold before the experiment, the average weight of mold, the initial weight of the composite, final weight of composite and the % weight gained. The values of the various parameters corresponding to each DMU are indicated in Table 1.

Table 1 shows the data of the treated oil palm composite which has not yet proceeded to give us additional information. However, to add value to the data, the transformation based on the normalization principle is shown in Table 2.

The motivation for the normalization of the data is to obtain a common set of values despite the variation in the units of measurement for the different parameters. To explain this viewpoint, consider the various parameters first, we randomly choose parameters starting from composite weight + mold before the water experiment. This parameter is measured in grams. From Table 1 it is observed that DMU3 has 92.93 grams as its weight, for this parameter. However, the highest weight is for DMU 16 which weighs 141.01. the range of values for this parameter is 48.08. Surprisingly, this parameter is to be evaluated with other parameters whose range of values is very small. An example is the particulate loading %. It has the lowest and highest values of 1% and 31% respectively the range of these values is 30. Considering these two parameters as examples, the dimensions of percentage (ie particulate loading) and grams (ie composite weight + mold before water experiment) are different and should be brought to the same level. This could be achieved using the principle of normalization. Therefore for each decision-making unit numbers from each parameter are converted between zero and 1 for uniformity of values. Furthermore, in normalization, it is desired to know whether a particular parameter is beneficial or non-beneficial, an input or an output.

Table 1. Composites parameters

Particulates loading (%)	Particulates weight (g)	Composites weight +mould before water experiment(g)	Average weight of mold (g)*	Initial weight (g)	Final weight(g)	% weight gained
1	0.6	131.29	20.84	110.45	114.13	3.3318
3	1.8	104.25	20.84	83.41	94.9	13.7753
5	3.0	92.93	20.84	72.09	90.72	25.8427
7	4.2	128.51	20.84	107.67	147.64	37.1227
9	5.4	132.06	20.84	111.22	188.71	69.6727
11	6.6	122.14	20.84	101.3	110.72	9.2991
13	7.8	96.76	20.84	75.92	82.34	8.4563
15	9.0	125.71	20.84	104.87	117.87	12.3963
17	10.2	106.05	20.84	85.21	92.68	8.7666
19	11.4	137.66	20.84	116.82	131.64	12.6862
21	12.6	116.33	20.84	95.49	102.94	7.8019
23	13.8	107.35	20.84	86.51	92.33	6.7275
25	15.0	115.87	20.84	95.03	105.65	11.1754
27	16.2	116.45	20.84	95.61	105.9	10.7625
29	17.4	114.38	20.84	93.54	104.51	11.7276
31	18.6	141.01	20.84	120.17	132.54	10.2938

*The same mould was used for all experiments hence the weight is constant

Table 2. Composites parameters (normalized values)

Alternative criteria	Particulates loading (%) (Non-beneficial, input)		Particulates weight (g) (Beneficial, output)		Composites weight + mould before water experiment (g) (Non-beneficial, input)		Average weight of mold (g) (Beneficial, output)		Initial weight (g) (Non-beneficial, input)		Final weight (g) (Beneficial, output)		% weight gained (Beneficial, output)	
DMU1	1	1	0.6	0.36	131.29	17237.06	20.84	434.31	110.45	12199.20	114.13	13025.66	3.33	11.10089
DMU2	3	9	1.8	3.24	104.25	10868.06	20.84	434.31	83.41	6957.23	94.90	9006.01	13.78	189.7589
DMU3	5	25	3.0	9.00	92.93	8635.985	20.84	434.31	72.09	5196.97	90.72	8230.12	25.84	667.8451
DMU4	7	49	4.2	17.64	128.51	16514.82	20.84	434.31	107.67	11592.83	147.64	21797.57	37.12	1378.095
DMU5	9	81	5.4	29.16	132.06	17439.84	20.84	434.31	111.22	12369.89	188.71	35611.46	69.67	4854.285
DMU6	11	121	6.6	43.56	122.14	14918.18	20.84	434.31	101.30	10261.69	110.72	12258.92	9.30	86.47326
DMU7	13	169	7.8	60.84	96.76	9362.50	20.84	434.31	75.92	5763.85	82.34	6779.88	8.46	71.50901
DMU8	15	225	9.0	81.00	125.71	15803.00	20.84	434.31	104.87	10997.72	117.87	13893.34	12.40	153.6683
DMU9	17	289	10.2	104.04	106.05	11246.60	20.84	434.31	85.21	7260.74	92.68	8589.58	8.7	76.85328
DMU10	19	361	11.4	129.96	137.66	18950.28	20.84	434.31	116.82	13646.91	131.64	17329.09	12.69	160.9397
DMU11	21	441	12.6	158.76	116.33	13532.67	20.84	434.31	95.49	9118.34	102.94	10596.64	7.80	60.86964
DMU12	23	529	13.8	190.44	107.35	11524.02	20.84	434.31	86.51	7483.98	92.33	8524.83	6.73	45.25926
DMU13	25	625	15.0	225.00	115.87	13425.86	20.84	434.31	95.03	9030.70	105.65	11161.92	11.18	124.8896
DMU14	27	729	16.2	262.44	116.45	13560.60	20.84	434.31	95.61	9141.20	105.90	11214.81	10.76	115.8314
DMU15	29	841	17.4	302.76	114.38	13082.78	20.84	434.31	93.54	8749.73	104.51	10922.34	11.73	137.5366
DMU16	31	961	18.6	345.96	141.01	19883.82	20.84	434.31	120.17	14440.83	132.54	17566.85	10.29	105.9623
Sum		5456		1964.16		225986.10				154211.90		216509.00		8240.877
$\sqrt{\sum_{i=1}^{n} X_{ij}}$		73.86		44.32		475.38				392.70		465.31		90.77928

The word beneficial, regarding the composite development process, means a profitable parameter to the composite industry which will promote the profit maximization goal of the industry such a parameter will not cause any loss but will rather promote the goodwill of the organization and the quality of the product produced. However, non-beneficial parameters are the opposite of the description of beneficial parameters. In this case, instead of contributing positively and in a direct manner to the goal of the organization, it negatively contributes to it. Next, the output of the water experiment is the integrated unit produced by processing the input into acceptable forms that can be directly transferred to the customer. In this context, the output needs no further adjustment and it will deliver the bundle of benefits that it promises to give the customers. To be specific, the output in the water experiment may not be the final output of the system since the water-absorbed composite may not be the final product. It means that the output of this system is the weighed final product which has absorbed water. However, inputs are the resources that get transformed into the output. For the presence case, the input is the particulate loading, composite weight + mold before the water experiment, and initial weight. Moreover, the output is particulate weight, the average weight of mold, the final weight, and the percentage weight gained. Further, from the list of parameters considered in this work, there is no beneficial input identified. The non-beneficial inputs are particulate loading, composite weight + mold before the water experiment, and initial weight. For the output the beneficial output is particulate weight, average weight of mold, final weight, and % weight gained however, the non-beneficial output does not exist based on the above description the related normalizing equation is used next to obtain the normalized values of parameters the formula N_{ij} which is the ration of X_{ij} to the squarer root of the sum of X_{ij}^2. A convenient starting point in this process is to find the denominator for the normalizing index before finding the numerator. For our problem, all the values for each of the DMUs under each parameter were squared at the end of the column. The sum yields 5456 while the square root is equal to 73.86474> Now to calculate what the normalized value will be we take each value and then divide it by the square root obtained, therefore to calculate the normalized value for particulate loading under DMU1, the value of 1 which represent the particulate loading is squared and then divided by 73.86474.

The next phase of calculation is to create another table where x_{ij} will be divided by each of the sums along the column for example, for DMU_1, DMU_2,…, DMU_{16}. The new values under the columns for particulate loading are 0.013538, 0.121844…, and 13.01027. By following the same procedure for normalization other columns are computed accordingly (Table 3). However, by applying the DEA (CCR Model) to the problem, the solution is obtained (Nassiri and Singh, 2010). The CCR model was first introduced in 1978. Notwithstanding the standard fractional CCR model known as a convex programming approach may be the solution to the problem but it is difficult to compute. Therefore Chans, Copper, and Rhodes (CCR) established a linear programming method to make the solution to the problem easier (Nassiri and Singh, 2010). This is based on either maximizing the output or minimizing the input criteria. In the problem solved, the minimization of the input criteria is appropriate. To solve this problem H_k is calculated as the reciprocal of G_k, notice that H_k is the efficiency measure of the k^{th} DMU.

Table 3. Dividing each column for the parameter with the square root of the sum of the squares of the column values

Alternative criteria	Particulates loading %	Particulates weight (g)	Composites weight +mould before water experiment (g)	average weight of mold (g)	initial weight (g)	final weight(g)	% weight gained
	Input (positive)	Output (negative)	Input (positive)	Output (negative)	Input (positive)	Output (negative)	Output (negative)
DMU1	$0.013538V_1$	0.008123	$36.25955V_2$	5.21	$31.06508V_3$	27.99379	0.122284
DMU2	0.121844	0.073107	22.86184	5.21	17.71648	19.35506	2.090333
DMU3	0.338456	0.203074	18.16649	5.21	13.23400	17.68757	7.356802
DMU4	0.663375	0.398025	34.74025	5.21	29.52096	46.84574	15.18072
DMU5	1.096599	0.657959	36.68612	5.21	31.49973	76.53355	53.47349
DMU6	1.638129	0.982878	31.38159	5.21	26.13124	26.34597	0.952566
DMU7	2.287966	1.372779	19.69477	5.21	14.67755	14.57081	0.787724
DMU8	3.046108	1.827665	33.24289	5.21	28.00552	29.85854	1.692768
DMU9	3.912557	2.347534	23.65813	5.21	18.48937	18.46010	0.846595
DMU10	4.887312	2.932387	39.86343	5.21	34.75165	37.24241	1.772868
DMU11	5.970372	3.582223	28.46706	5.21	23.21971	22.77353	0.670524
DMU12	7.161739	4.297043	24.24171	5.21	19.05784	18.32094	0.498564
DMU13	8.461412	5.076847	28.24237	5.21	22.99654	23.98838	1.375750
DMU14	9.869391	5.921634	28.52582	5.21	23.27811	24.10205	1.275967
DMU15	11.385680	6.831406	27.52069	5.21	22.28106	23.47349	1.515066
DMU16	13.010270	7.806160	41.82722	5.21	36.77335	37.75339	1.167252

To solve the problem, the following nomenclature of the linear programming problem is relevant. The number of alternatives or otherwise the DMU is often represented with the symbol n. In the model, the number of input criteria is represented by capital X. Notice that X_{ik} and y_{rk} often represent the value of ith input criterion and rth output criterion for the kth alternatives. Also, Ur and Vi are the nonnegative variables weight to be established through the solution of the minimization problem. In the problem being solved n is 16 which is the number of alternatives (scenarios). Now, the number of input criteria which is M is 3. Notice that the inputs are particulate loading %, composite weight + mold before the water experiment, and initial weight. Furthermore, the number of output criteria which is S is 4. This includes particulate weight, the average weight of mold, final weight, and % weight gained. The values for particulate loading, composite weight + mold before the water experiment, and initial weight are represented by Xik. However, the values for the other parameter are represented by y_{rk}. Now the first scenario will be evaluated afterward.

In the problem being solved n is 16 which is the number of alternatives. Now, the number of input criteria which is M is 3. Notice that the inputs are particulate loading %, composite weight + mold before the water experiment, and initial weight. Furthermore, the number of output criteria which is S is 4. This includes particulate weight, the average weight of mold, final weight, and % weight gained. The values for particulate loading, composite weight + mold before the water experiment, and initial weight are represented by Xik. However, the values for the other parameter are represented by Yrk.

Now let us evaluate the first DMU. The linear programming model representing this is shown as.

Scenario 1

G_1= Minimize ($0.013538V_1 + 36.25955V_2 + 31.06508V_3$)

Subject to

$- 0.08123U_1 – 5.21U_2 – 27.99379U_3 – 0.122284U_4 + 0.013538V_1 + 36.25955V_2 + 31.06508V_3 \geq 0$

$- 0.073107U_1 – 5.21 U_2 – 19.35506 U_3 – 2.090333 U_4 + 0.121844 V_1 + 22.86184 V_2 +17.71648 V_3 \geq 0$

$- 0.203074U_1 – 5.21 U_2 – 17.68757 U_3 – 7.356802 U_4 + 0.338456 V_1 +18.16649 V_2 +13.234 V_3 \geq 0$

$- 0.398025 U_1 – 5.21 U_2 – 46.84574 U_3 – 15.18072 U_4 + 0.663375 V_1 + 34.74025 V_2 +29.52096 V_3 \geq 0$

$- 0.657959 U_1 - 5.21 U_2 - 76.53355 U_3 - 53.47349 U_4 + 1.096599 V_1 + 36.68612 V_2 + 31.49973 V_3 \geq 0$

$- 0.982878 U_1 - 5.21 U_2 - 26.34597 U_3 - 0.952566 U_4 + 1.638129 V_1 +31.38159 V_2 + 26.13124 V_3 \geq 0$

$- 1.372779 U_1 - 5.21 U_2 - 14.57081 U_3 - 0.787724 U_4 + 2.287966 V_1 + 19.69477 V_2 + 14.67755 V_3 \geq 0$

$- 1.827665 U_1 - 5.21 U_2 - 29.85854 U_3 - 1.692768 U_4 + 3.046108 V_1 + 33.24289 V_2 + 28.00552 V_3 \geq 0$

$- 2.347534 U_1 – 5.21 U_2 - 18.4601 U_3 - 0.846595 U_4 + 3.912557 V_1 + 23.65813 V_2 + 18.48937 V_3 \geq 0$

$- 2.932387 U_1 - 5.21 U_2 - 37.24241 U_3 - 1.772868 U_4 + 4.887312 V_1 + 39.86343 V_2 + 34.75165 V_3 \geq 0$

$- 3.582223 U_1 – 5.21 U_2 - 22.77353 U_3 - 0.670524 U_4 + 5.970372 V_1 + 28.46706 V_2 +23.21971 V_3 \geq 0$

$- 4.297043 U_1 – 5.21 U_2 - 18.32094 U_3 - 0.498564 U_4 + 7.161739 V_1 + 24.24171 V_2 + 19.05784 V_3 \geq 0$

$- 5.076847 U_1 – 5.21 U_2 - 23.98838 U_3 - 1.37575 U_4 + 8.461412 V_1 + 28.24237 V_2 +22.99654 V_3 \geq 0$

$- 5.921634 U_1 – 5.21 U_2 - 24.10205 U_3 - 1.275967U4 + 9.869391 V_1 + 28.52582 V_2 + 23.27811 V_3 \geq 0$

$- 6.831406 U_1 - 5.21 U_2 - 23.47349 U_3 - 1.515066 U_4 + 11.38568 V_1 + 27.52069 V_2 + 22.28106 V_3 \geq 0$

$- 7.80616 U_1 - 5.21 U_2 - 37.75339 U_3 - 1.167252 U_4 + 13.01027 V_1 + 4182722 V_2 + 36.77335 V_3 \geq 0$

$0.08123U_1 + 5.21U_2 + 27.99379U_3 + 0.122284U_4 = 1$

$U_1, U_2, U_3, U_4, V_1, V_2, V_3 \geq 0$

The solution obtained is $U_1 = 0$; $U_2 = 0.0235021$; $U_3 = 0.0313482$; $U_4 =0$; $V_1 = 1.3922623$; $V_2 = 0$; V3 = 0.0315837

Here, U_1 is the particulate weight, grams; U_2 is the average weight of mould, grams; U_3 represents that final weight, grams; U_4 is the % weight gained; V_1 is the particulate loading, %; V_2 is the composite weight plus mould before water experiment and V_3 is the % weight gained

Scenario 2

G_2= min ($0.121844V_1 + 22.86184V_2 + 17.71648V_3$)

The solution obtained is

$U_1 = 0$, $U_2 = 0.1919386$, $U_3 = 0$, $U_4 = 0$, $V_1 = 1.0225182$, $V_2 = 0$, $V_3 = 0.0494123$

Scenario 3

G_3 = min ($0.338456V_1 + 18.16649V_2 + 13.234V_3$)

The solution obtained is

$U_1 = 0.0832243$, $U_2 = 0.1112519$, $U_3 = 0.0228113$, $U_4 = 0$, $V_1 = 0$, $V_2 = 0$, $V_3 = 0.0755629$

Scenario 4

G_4 = min ($0.663375V_1 + 34.74025V_2 + 29.52096V_3$)

The solution obtained is

$U_1 = 1.8957863$, $U_2 = 0.0219706$, $U_3 = 0.0027956$, $U_4 = 0$, $V_1 = 1.1311964$, $V_2 = 0.0091399$, $V_3 = 0$

Scenario 5

G_5 = min ($1.096599V_1 + 36.68612V_2 + 31.49973V_3$)

The solution obtained is

$U_1 = 0$, $U_2 = 0$, $U_3 = 0$, $U_4 = 0.0187009$, $V_1 = 0$, $V_2 = 0$, $V_3 = 0.0317463$

Scenario 6

G_6 = min ($1.638129V_1 + 31.38159V_2 + 26.13124V_3$)

The solution obtained is

$U_1 = 0.9241216$, $U_2 = 0.0107098$, $U_3 = 0.0013628$, $U_4 = 0$, $V_1 = 0.551414$, $V_2 = 0.0044553$, $V_3 = 0$

Scenario 7

G_7 = min ($2.287966V_1 + 19.69477V_2 + 14.67755V_3$)

The solution obtained is

$U_1 = 0.0840818$, $U_2 = 0.1697839$, $U_3 = 0$, $U_4 = 0$, V_1 =

0, V_2 = 0, V_3 = 0.0681313

Scenario 8
G_8 = min (3.046108V_1 + 33.24289V_2 + 28.00552V_3)
The solution obtained is
U_1 = 0.5175781, U_2 = 0.0059983, U_3 = 0.0007632, U_4 = 0, V_1 = 0.3088336, V_2 = 0.0024953, V_3 = 0

Scenario 9
G_9 = min (3.912557V_1 + 23.65813V_2 + 18.48937V_3)
The solution obtained is
U_1 = 0.4164648, U_2 = 0.0040619, U_3 = 0.0000635, U_4 = 0, V_1 = 0.2485041, V_2 = 0, V_3 = 0.0017191

Scenario 10
G_{10}= min (4.887312V_1 + 39.86343V_2 + 34.75165V_3)
The solution obtained is
U_1 = 0.334932, U_2 = 0, U_3 = 0.0004793, U_4 = 0, V_1 = 0.1994192, V_2 = 0.0010459, V_3 = 0

Scenario 11
G_{11}= min (5.970372V_1 + 28.46706V_2 + 23.21971V_3)
The solution obtained is
U_1 = 0.2749889, U_2 = 0.002682, U_3 = 0.0000419, U_4 = 0, V_1 = 0.1640856, V_2 = 0, V_3 = 0.0011351

Scenario 12
G_{12}= min (7.161739V_1 + 24.24171V_2 + 19.05784V_3)
The solution obtained is
U_1 = 0.229987, U_2 = 0.0022526, U_3 = 0, U_4 = 0, V_1 = 0.1372238, V_2 = 0, V_3 = 0.0009194

Scenario 13
G_{13}= min (8.461412V_1 + 28.24237V_2 + 22.99654V_3)
The solution obtained is
U_1 = 0.1941806, U_2 = 0.0013995, U_3 = 0.000287, U_4 = 0, V_1 = 0.1158802, V_2 = 0, V_3 = 0.0009505

Scenario 14
G_{14}= min (9.869391V_1 + 28.52582V_2 + 23.27811V_3)
The solution obtained is
U_1 = 0.1668112, U_2 = 0.0012022, U_3 = 0.0002465, U_4 = 0, V_1 = 0.0995471, V_2 = 0, V_3 = 0.0008166

Scenario 15
G_{15}= min (11.38568V_1 + 27.52069V_2 + 22.28106V_3)
The solution obtained is
U_1 = 0.1463828, U_2 = 0, U_3 = 0, U_4 = 0, V_1 = 0.0871549, V_2 = 0, V_3 = 0.0003448

Scenario 16
G_{16}= min (13.01027V_1 + 41.82722V_2 + 36.77335V_3)
The solution obtained is
U_1 = 0.1272235, U_2 = 0, U_3 = 0.0001821, U_4 = 0, V_1 = 0.0757491, V_2 = 0.0003973, V_3 = 0

In the work, the DEA method has been applied to the data from the experiments on the water absorption process while developing the oil palm empty fruit bunch composite. In applying the DEA method to the process two concerns are important, namely the efficiency of the utilization of the inputs, which is measured by the contribution of each input to the G_k, the objective function used in the linear programming formulation. Notice that G_k measures the inefficiency of the process and the reciprocal of the value, obtained for each input, corresponding to some portions of the H_k parameter is the actual measure of efficiency, for the process investigated. It implies that for each G_k,i.e. G_1, the contributions of the inputs V_1, V_2, and V_3 are determined and their reciprocals are obtained to calculate their efficiency values. The above description is the first concern while deploying the DEA method. The second concern is to determine which of the sixteen decision-making units (i.e. DMU1, DMU2,…, DMU16) is the most efficient. To achieve this, the solutions obtained from the deployment of the DEA software (Leap 2) are substituted in each constraint equation, which gives a value greater them zero. The results from all the DMUs are then compared and the DMUs obtained. Notice that the consideration has to be for the minimum value of the DMU to be the acceptable one while the maximum value of the DMU portrays one that is the least efficient. To explain the results regarding the efficient utilization of inputs, the researcher starts with a solution for the first DMU (i.e. DMU1), which states that the outputs, U_1, U_2, U_3, and U_4 are 0, 0.0235021, 0.0313482 and 0, respectively and the inputs V_1, V_2, and V_3 are 1.3922623, 0 and 0.0315837, respectively. Thus, to compute how efficiently the input resources V1, V2, and V3 are utilized the researcher uses the object function G_1. Here, to assess the inefficiency in the utilization of V_1 (particulate loading %) the product of V_1 and its coefficient in the objective function is noted as 0.013538 (1.3922623), which gives 0.018848. notice that 1.3922623 is the solution value for V_1. The next step is to find the ratio of 0.018848 to 1 since the total value of G_1 must be 1. The obtained value when converted to percentage is 1.88% efficient, which means (100 – 1.88%) i.e 98.2% efficient. This value is for the particulate loading. Next is the efficiency determination of the parameter V_2, which is the composite weight plus mold before the water experiment. Similarly, the term "36.25955V_2" from the objective function of G_1 is computed as 36.25955(0), where the value of 0 is the solution value for V_2. The product yields 0, which means zero inefficiencies, and this parameter is considered 100% efficient in utilization. Next, the term "31.06508V_3" from the objective function of G_1 is evaluated as 31.06508(0.0315837), which gives 0.98115. By dividing this value by 1 and multiplying by 100%, a value of 98.1 inefficiency, implies 1.9% efficiency. The conclusion from the analysis of the various inputs regarding their efficiency utilization shows that particulate loading and composite weight plus mold are very efficiently utilized with the values of 98.2% and 100% efficient, respectively. However, the initial weight is the most inefficiently utilized with an efficiency rating of 1.9%. Notice that the above analysis was limited to scenario 1 (i.e. G_1). However, the other fifteen scenarios should be evaluated, notably scenarios 2 to 16 (i.e. G_2 to G_{16}). Now, having followed the same procedure for G_1 in G_2 to G_{16}, the results in Table 4 are obtained.

There are varying results but the pattern could be interpreted to have an understanding of the performance of various performance measures. Consider the parameter

Table 4. Inefficiency (G_k) and efficiency (H_k) computation for the water absorption process

Objective function	Contribution of V_1 in G_k	Efficiency rating of V_1 in H_k (%)	Contribution of V_2 in G_k	Efficiency rating of V_2 in H_k (%)	Contribution of V_3 in G_k	Efficiency rating of V_3 in H_k (%)
G_1	0.019	98.1	0.000	100.0	0.981	1.9
G_2	0.125	87.5	0.000	100.0	0.875	12.5
G_3	0.000	100.0	0.000	100.0	1.000	0.0
G_4	0.750	25.0	0.318	68.2	0.000	100.0
G_5	0.000	100.0	0.000	100.0	1.000	0.0
G_6	0.903	9.7	0.140	86.0	0.000	100.0
G_7	0.000	100.0	0.000	100.0	1.000	0.0
G_8	0.941	5.9	0.083	91.7	0.000	100.0
G_9	0.972	2.8	0.000	100.0	0.032	96.8
G_{10}	0.975	2.5	0.042	95.8	0.000	100.0
G_{11}	0.621	37.9	0.000	100.0	0.026	97.4
G_{12}	0.983	1.7	0.000	100.0	0.018	98.2
G_{13}	0.981	1.9	0.000	100.0	0.022	97.8
G_{14}	0.982	1.8	0.000	100.0	0.190	81.0
G_{15}	0.992	0.8	0.000	100.0	0.008	99.2
G_{16}	0.986	1.4	0.017	98.3	0.000	100.0
Average	0.639	36.1	0.038	96.3	0.322	67.8

V_1, which is the particulate loading, in scenarios 2 to 16, it recorded a 100% efficiency score in three places. Overall, for all scenarios 1 to 16, it attains 18.8% in places where the efficiency is 100%. For the second parameter, composite's weight plus mold, the performance attained 100% in 68.8% of the initial weight parameter, and the efficiency score of 100% was obtained in 31.3% of all chances within the 16 scenarios. Therefore, overall, the composite's weight plus mold parameter is the most efficiently used parameter in the process while particulate loading is the least efficient of all the three input parameters. Besides judging the performance of the parameters regarding the frequency of attaining 100% efficiency, analysis was performed on the average performance of all parameters in all sixteen scenarios. In this regard, the efficiency of particulate loading was 36.1%, for composite weight plus mold, it was 96.3% and for initial weight, the average efficiency score was 67.8% it is suggestive that composite weight plus mold with an average efficiency of 96.3% is the best parameter while particulate loading with 36.1% is the worst parameter. Thus result is consistent with the previous result based on each scenario.

4. CONCLUSION

In the present study, the major task was to apply data envelopment analysis to experimental data of the oil palm empty fruit bunch particulates. a unique manner in which the inputs are minimized is sought. These inputs are particulate loading, particulate weight, composite weight + mold before the water experiment, the average weight of mold, initial weight, final weight, and percentage weight gained. From the results obtained in this work, several conclusions are made, including The feasibility of applying the DEA method has been confirmed. Also, it was found that the efficiency of particulate loading was 36.1%, for composite weight plus mold, it was 96.3% and

Recall that at the beginning of this analysis, it was mentioned that two aspects of measurements are important to the research. The first which is locating the least and most efficient parameters has been accomplished in the previous analysis. However, the second measurement is to know which of the decision-making units is the most efficient and also identify the worst decision-making unit. To achieve this, the researchers utilize data from Table 4 which contains the efficiency indicators for each of the parameters for each decision-making unit. For instance, G_1 represents the first decision-making unit and G_2 to G_{16} represents other decision-making units from DMU 2 to DMU16. By considering the DMU1, the efficiency scores of V_1, V_2, and V_3 are 98.1%, 100%, and 1.9% respectively. The average of these scores is 66.7%. The same analysis is done for DMU2 to DMU16 to obtain varying efficiency % scores of 66.7, 66.7, 64.4, 66.7, 65.2, 66.7, 65.9, 66.5, 66.1, 78.4, 66.6, 66.6, 60.9, 66.7 and 66.6, respectively. From these scores, DMU11 with a score of 78.4% is the best ranking unit while DMU14 is the work ranking unit with an efficiency score of 60.9%. Besides, the average efficiency score for all the DMUs is 66.7%.

for initial weight, the average efficiency score was 67.8%. This means that composite weight plus mold with an average efficiency of 96.3% is the best parameter while particulate loading with 36.1% is the worst parameter. Thus result is consistent with the result based on each scenario. From the perspective of DMUs, DMU11 with a score of 78.4% is the best ranking unit while DMU14 is the work ranking unit with an efficiency score of 60.9%. Besides, the average efficiency score for all the DMUs is 66.7%.

Furthermore, the DEA method was adopted to evaluate the performance of the inefficient parameter, which was identified as the particulate loading. However, the DEA method has been limited to only three inputs and four outputs. But in reality, several inputs and outputs are beyond those specified in the present study. Thus, to face this challenge, a more detailed and automated software beyond the Leap 2 software used in the present study is relevant and should be developed in the future. Also, to substantially reduce this inefficiency, which is 63.9%, the particle size may need to be reconsidered. Besides the development of software to accommodate the multiple inputs and multiple outputs (i.e. 4 inputs and 20 outputs), the DEA method could be implemented by first establishing the number of observations (i.e. the experimental trial created, which represents the DMUs) associated with the total inputs and outputs. Furthermore, the possibility of obtaining a correlation analysis is established. This will assist in acknowledging which variables. May be used to represent others' performance. Then the number of variables can be reduced accordingly to only these important ones. Next, in this work, the microparticle structure is considered but nanoparticles are of potentially greater results and may achieve higher efficiency. Therefore it is recommended for further experimentation. Besides, the range of graduation of the particulate loading is 2% and covers from 1% to 31%. However, to achieve better results, the researcher may consider a longer scale of say 4% range instead of 2%. Future studies should also consider multicriteria approaches. The application of the data envelopment analysis method ascertains that the data envelopment process is sustainable, successful, and profitable. The method promotes the resilience of the process over the evaluation period. It achieves this by reducing inefficiency while promoting efficient utilization of resources. This guarantees the maintenance of profits of the operating organization through the successful development of operation plans.

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