

# An Implementation of A Combined DEA-PROMETHEE Method for The Hull of A Ship Application

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## ABSTRACT

The selection of an appropriate parameter in a water absorption process experiment is an important route to reducing fabrication wastes and ensuring the optimum deployment of scarce process resources to the appropriate parameter. However, the literature is inadequate in providing an appropriate direction on selecting parameters for the hull of the ships' application due to the conflicting requirements of the interested parties. A novel method called the Data Environment Analysis (DEA) to overcome this problem. Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) method is deployed to establish the appropriate parameter in a water absorption process on epoxy composite. The net outranking results show that criterion B (final weight) is placed in the first position. The criterion A (initial weight), D (thickness), and C (length) are placed in the second, third, and fourth positions, respectively, while E (time) is not necessary to the achievement of the system's goals. The key novelty is the unique application of the fused DEA-PROMETHEE method to a composite using the Taguchi signal-to-noise ratio response table for the hull of a ship. The method enhances the performance of multiple inputs (parameters) and multiple outputs (responses). The results of the DEA method-PROMETHEE method established the potential of epoxy composite to be used on the ship for the hull component. This could reduce the waste generated in the system, and guided allocation of resources are made to the appropriate parameters and, consequently, enhance the shipping company's profit. Furthermore, the results could improve the shipping vessel performance and develop a sustainable practice, which will lengthen the lifespan of the shipping industry.

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## 1. INTRODUCTION

This article examines a case study to illuminate a research gap in composite water absorption literature relevant to a ship's hull (Maduekwe and Oke, 2020; Maduekwe and Oke, 2021). This is of wide interest to composite developers, surface coating engineers, materials engineers, and structural engineers (Georgiev and Pentschew, 2002; Zheng et al., 2016; Nair et al., 2017; Guo et al., 2017; Lindstad and Bø, 2018; Moreira and Soares, 2020). At present, the literature is inadequate in providing a direction on selecting an appropriate parameter (Koh et al., 1998; Kim and Chi, 2010; Lindstad et al., 2013; Hou, 2017; Jeong and Jeong, 2020). Serious

challenges are imposed on the interested party (i.e., composite development engineers) because of various options in parameters to choose from (Cerka et al., 2017; Cheng et al., 2018; Deng et al., 2021). Furthermore, the challenge to satisfy multiple and conflicting requirements by the aforementioned interested parties, such as the surface coating engineers and structural engineers, is extremely hard to tackle without an adequate scientific guide (Maduekwe and Oke, 2020; Maduekwe and Oke, 2021). Therefore, very scanty selection models are presently deployed to solve this problem, and the present success level is accomplished by the overwhelming pressure from researchers and practitioners.

Furthermore, at the conceptual design stage of the hull of a ship, several essential considerations exist, and optimization is desired (Bales, 1980; Kim and Chi, 2010; Lindstad et al., 2013; Pechenyuk, 2017; Hou, 2017; Deng, 2017; Cerka et al., 2017; Cheng et al., 2018; Feng et al., 2018; Lindstad and Bø, 2018; Oliveira et al., 2018; Jeong and Jeong, 2020). In practice, a ship is subjected to speed loss on the real seaways. This loss by the actions of wind and waves causes environmental loads on the ship and thus impair the ship's operational efficiency (Jing and Kim, 2019). Consequently, as the water resistance of the ship is considered along with the ship's speed loss under wind and waves, it is compelling to consider the composite behavior, which is proposed for the hull of a ship.

Besides, a ship's hull from composites tends to develop micro and macro cracks at the operational level from welding imperfections, corrosion, loading corrosion, loading situations, and fatigue (Zhang et al., 2016; Guo et al., 2017; Nair et al., 2017). Thus, several important factors at the design and operational stages should be considered for the most comprehensive capture of the behavior of the hull of a ship at the operational level. Unfortunately, testing all the conditions and parameters is not feasible due to the exorbitant experimental cost to institute the experiment. This makes it compelling for researchers and practicing engineers to seek guidance from the literature for economic models (Georgiev and Pentschew, 2002; Ajibade et al., 2019). These models should be comprehensive, which could save the cost of experimentation and provide the necessary information and control measures to attain the research goal of selecting the best alternative among the composite parameters. In this context, depending on the literature data and the classical Taguchi method, the parameters (the thickness of the composite, its length, the initial and final weights of the composite in water) and the immersion time of the ship hull composite in water have been relied upon (Georgiev and Pentschew, 2002; Ajibade et al., 2019).

However, knowledge concerning the best criterion of these stated criteria to evaluate the water absorption of a ship's hull may be needed (Abiola and Oke, 2021a; Abiola and Oke, 2021b; Maduekwe and Oke, 2021). To tackle this problem, the Taguchi SN ratio response table is coupled with the combined DEA-PROMETEE method to select the best criterion from those controlling the water absorption process of the composite for the development of the hull of a ship. The Taguchi SN ratio response table is the final optimization form of the water absorption process parameters of a composite whose evaluation commenced with the establishment of factors and levels, an institution of orthogonal arrays, signal to noise ratios, and the averaging of the SN ratios (Ajibade et al., 2019; Maduekwe and Oke, 2021). For the DEA-PROMETHEE method, the DEA approach the efficiency of the alternative water absorption parameters of the composite for the hull of a ship with competence to analyze several inputs and outputs. However, based on the weakness of the inability to rank the criteria in order of importance, the PROMETHEE method is introduced to correct its weakness (Maduekwe and Oke, 2021).

The PROMETHEE method is adequate to complement the strength of the DEA method and correct its weakness since it offers a total ranking of the alternatives (Babaee et al., 2015; Macharis and De Smet, 2015; Bagherikahvarin and Smet, 2016; Bagherikahvarin and Smet, 2017; Bagherikahvarin, 2019; Mahad et al., 2020). Unlike the previous reports on combined DEA and PROMETHEE methods, the present study introduces the Taguchi scheme by adopting a Taguchi SN ratio response table to optimize the alternatives while selecting the best one. This study aims to evaluate the efficiency of the water absorption parameters of the hull of a ship composite and offer a total ranking of alternatives using the DEA-PROMETHEE method.

Thus, the research novelty is implementing the DEA-PROMETHEE method to evaluate the efficiency and offer a total ranking of the investigated alternatives. This study provides information to assist in managing the ship design process more efficiently in the shipbuilding sector and the shipping industry. Efficient alternatives could be viewed as a benchmark model for other alternatives, while inefficient alternatives can imitate the paramount practice of efficient alternatives to achieve superior efficiency (Mahad et al., 2020).

## 2. LITERATURE REVIEW

This section presents a literature review to support both the method, DEA-PROMETHEE, and the case analyzed, the hull of a ship. First, a brief review of the DEA-PROMETHEE method is given, followed by the literature review on other methods used for the ship system. Then, the literature on the hull of a ship application is disclosed to support the article's novelty.

### 2.1. The DEA-PROMETHEE method

The data envelopment analysis (DEA) is an efficiency-oriented method with non-parametric characteristics, initiated in 1957 by Farwell (Fare et al., 1994; Mahad et al., 2020). However, Charnes et al. (1978) are one of the later but vastly influential contributors to extend the previous platform of alternative remains profitable in production. It lacks discrimination power such that the DEA offers a solution, which labels the decision-making units as efficient (Mahad et al., 2020). Although DEA can distinguish efficient from inefficient DMU or alternative, it lacks the competence to institute ranking for the member alternatives (Mahad et al., 2010). However, ranking alternatives and selecting the best alternative inefficiency is generally compelling to decision-makers in ship manufacturing and the shipping industry. Fortunately, there is compelling evidence on PROMETHEE as a competent tool to correct the drawback of the DEA mentioned earlier. More so, the PROMETHEE could function appropriately in the absence of rich data and therefore becomes an attractive tool to fuse to the DEA method as the DEA-PROMETHEE method. Interestingly, PROMETHEE has an impressive subscription; as of 2015, Macharis and Smet (2015) reported that roughly 1000 publication on the PROMETHEE method exists, and these are largely methodology-related.

Then, the history of the development of PROMETHEE of often linked to the initiative by Jean-Pierre Brans (1982) and has since expanded in frontiers to applications, methodological growth, and software implementation (Macharis and De Smet, 2015). PROMETHEE has several versions, while PROMETHEE I and II are two common. However, PROMETHEE II is used in this article. A multi-attribute decision-making approach establishes mutual comparison among composites' water absorption process parameters for the hull of ship application. The PROMETHEE ranks from the best case to the worst-case alternative in a situation where pairs of alternatives are compared on the basis of selection criteria (Mahad et al., 2020). Furthermore, Mahad et al. (2020) argued that a total ranking is achieved for the alternatives analyzed if PROMETHEE is integrated with the DEA. Consequently, the DEA PROMETHEE is a candidate for evaluations in many projects. For instance, Babaee et al. (2015), Bagherikahvarin and Smet (2016), Bagherikahvarin (2019), Mahad et al. (2020) and Karasakal et al. (2021).

Bagherikahvarin (2019) instituted a two-step method to rank the multiple outputs and inputs. It was shown that compatibility between the outcomes of the DEA to a more robust structure that it showcases today. Afterward, the DEA has been affirmed as effective in the efficiency appraisal of organizational decision-making units to reveal essential modifications to attain utmost efficiency (Mahad et al., 2020). For instance, Andersen and Petersen (1993) and Bal et al. (2010) support the effectiveness of DEA usage for efficiency monitoring. Unfortunately, despite the utility of DEA as a tool to ascertain that organizations remain competitive when applied to decision-making units or that the product ranking using DEA and integrated DEA-PROMETHEE approach for the case of an input and an output. The monotonicity property of the method was discussed, and a numerical example was demonstrated to compare the developed DEA-PROMETHEE and DEA-AHP methods.

In Bagherikahvarin and De Smet (2016), the restriction of weight values regarding the DEA method by deploying the multi-criteria decision analysis was made. The outcome of the method is realistic inputs/outputs weights. It enhances the model's performance compared with the traditional DEA method, while it is often experienced that extremely high or low weights are possible. The stability interval was deployed to attain the goal, and this feature in PROMETHEE II ranking was deployed for the solution. The feasibility of the approach was confirmed with examples.

Furthermore, Babaee et al. (2015) assessed the total performance of elderly drivers and ranked them using a study sample of 55 drivers. The DEA was used to compute the score representing the optimal performance of the drivers. A multi-criteria decision-making analysis was deployed to complement the work. Finally, the PROMETHEE II was introduced. It was concluded that there is a high correlation between the results. In another work, Karasakal et al. (2020) proposed two new methods based on PROMETHEE but integrated with the DEA approach. One of the approaches tackles the imprecise elements contained in criteria weights, while the second

method employs a combination of threshold and weights. The practical use of the methods was shown with examples. In another study, Bagherikahvarin and Smet (2017) showcased an approach to establish new weights using combined PROMETHEE and DEA methods. In specific terms, the authors proposed an adjustment to the "decision maker brain" concept operational in the GAIA plane. A numerical description was shown to validate the method.

In the literature on the integrated DEA-PROMETHEE method, researchers have established methodological development that warrants adjusting the feature of DEA to remove the shortcomings using the PROMETHEE method. Also, very few novel works on using the DEA-PROMETHEE method in case applications have been accomplished. The transportation case is one of the very few cases explored in the literature where old drivers were evaluated. Surprisingly, there is no case implementation on a ship's hull, which is extremely important for fuel efficiency in bulk carriers. There is a complete omission of how the DEA-PROMETHEE is used to enhance the efficiency of alternatives in the choice of composites tested for water absorption in water bodies. Thus, the parameters of water absorption of composites need to be tested as a novel adventure. Thus, the novel element of this article is the implementation of an integrated DEA-PROMETHEE method to the water absorption process parameters of composites developed and tested in a water environment.

However, despite the growing popularity of the DEA-PROMETHEE method, the gap for the hull of a ship remains unattended. But the hull of a ship is a major aspect whose information about the best parameter in its composite design remains essential. Consequently, there is an open problem of selecting parameters of composites to be solved using the DEA-PROMETHEE method for the hull of a ship.

## 2.2. Parameter selection methods

In the domain of parameter selection, several methods have been reported with success, including Taguchi methods, factor analysis, and neural networks. However, the DEA PROMETHEE method is rarely discussed. Furthermore, the case of a ship's hull with the application of the DEA-PROMETHEE method has not been reported in the literature. Yet, developing a case study for the hull of a ship based on the DEA-PROMETHEE method might be quite beneficial for the related practices for the ship manufacturer and shipping industry. Thus, the approach in this review is to analyze the literature according to the Taguchi and neural networks methods.

Although the parametric selection was not made by some researchers investigating hull form optimization while minimizing ship resistance, the influence of the hull form parameters was analyzed (Deng et al., 2021). The analysis is closely related to the Taguchi method, reviewed from the perspective of being a selection method. It is also an optimization method. The author (Deng et al., 2021) analyzed the hull form influence on the hydrodynamic accomplishment of a ship while employing a combined optimization procedure to incorporate maneuverability, ship resistance, and seakeeping in

association with the key measuring of the ship. Besides, the study concluded it is possible to attain a good parent ship using the key dimensional optimization process; also, an enhanced hull form optimization was argued as possible by combined optimization using key dimensions and hull form.

### 2.2.1. Taguchi methods for the hull of a ship

In seakeeping research activities, the optimization of various ship hull designs has been a center point of attention. The Taguchi method has been developed to fulfill this goal as an engineering design method. In the Taguchi application domain, interest has been to analyze the effect of hull form parameters on resistance displacement proportions (Georgiev and Pentschew, 2002). In this case, the 42000 TDW bulk carrier was analyzed, and the NAPA system was used to examine the ship hull design and the changes to the specification of the parameters (Georgiev and Pentschew, 2002). Furthermore, the complete analysis involves resistance for various standard speeds through the Danckward approach. Additionally, the frontier of mathematical analysis on a ship's hull has been extended to incorporate genetic algorithms by robust design (ho et al., 1998). The article by Koh et al. (1998) argued for using a genetic algorithm-based robust design to enhance the speed of the hull of a ship and advanced a practical example to validate the claim.

### 2.2.2. Related artificial neural network research in the hull of a ship

An artificial neural network (ANN) is a structure that mimics the human brain. This machine-learning algorithm could propose design solutions in shipbuilding activities through trial and error and thus predict the outputs by training from a given set of parameters. In shipbuilding, ANN has been used in hull form design with details following: Jung et al. (2019) optimized the ship dimensions from the hydrodynamic performance in waves; a non-dominated sorting genetic algorithm was introduced to reduce the resistance of the ship on its maneuvering in the seaways. The model accounts for speed loss and resistance using the slender-body theory, empirical method on-resistance due to short waves, and Maruo's far-field procedure. The use of numerical examples affirmed the feasibility of the study.

Moreira and Soares (2020) analyzed an artificial neural network to predict the bending moment and the shear force experienced by the ship's hull during the action of waves on it. Thus, the authors argued serves as a tool for a ship's motion. The principal parameters studied are the yaw rate, roll angle, heading angle, sway acceleration, vertical acceleration, and pitch angle. Furthermore, the authors deployed a mathematical model to provide the ship's motion data based on the strip theory. Nair et al. (2017) established criteria for evaluating cracks rooted in inducement parameters that affect crack initiation within the hull structure. The authors established an association between inducement parameters and the operational life of ships using a visualization method.

### 2.2.3. Water absorption studies on composites

Ajibade et al. (2019) analyzed the epoxy composites based on various agro-wastes. Maduekwe and Oke (2020) examined the ship's hull by proposing an integrated model based on the analytic hierarchy process and the PROMETHEE method. Furthermore, Maduekwe and Oke (2021) studied composites' water absorption process problem, evolving a DEMATEL-PROMETHEE method to establish the parameters of the process. Abiola and Oke (2021a) elaborated on six parameters that influenced the water absorption process parametric assessment. The mentioned factors are the weight of the initial matrix weight, particulate weight (final weight), particulate loading, rate of water absorption, and the weight after 150 days.

Furthermore, an extension of a previous study was reported in Abiola and Oke (2021b), where analysis of uncertainty and imprecision using the fuzzy analytic hierarchy process (see Hou, 2017; Karasakal et al., 2021). In this sub-section, parametric analysis relating to ship using the Taguchi and the artificial neural network methods were reviewed. Furthermore, the water absorption literature on composite with relevant studies to the ship was briefly reviewed. However, only a case was established for the selection process for composite parameters for a ship's hull in these instances. But the efficiency of the process was not analyzed, which creates a gap for further investigations.

### 2.3. Hull studies

The ship's framework is the hull but excludes the elements of sails, masts, rigging, and yards. The part of the ship rides two ways as it navigates and is on top of the water. However, expensive mild steel and manganese materials are currently deployed to construct the ship. While the percentage of carbon in the mild steel used is controlled to be within the limits of 0.15% to 0.23% carbon, a high quantity of manganese content should be maintained. Besides, the challenge of material control for the ship is complicated as the composition of the sulfur and phosphorus must be limited to less than 0.05% to avoid complications in welding the ship's hull. However, they enhance the ship's fuel efficiency, limit energy consumption, and control greenhouse gas emissions. These conventional materials have failed to satisfy ship manufacturers' global and industrial demands.

In the hull of ship research, there is a tradition of analyzing the hull's surface for enhanced performance. While some authors argued that panel redesign is essential for enhanced speed through surface adjustment of the ship (Kim et al., 2006), a recent study has diverged from this opinion to surface modification material and chemical application. In the study by Kim et al. (2016), an algorithm called the panel cutting method was established to solve the flow problem as the ship advances on the free surface of the water at a regular speed. The authors used iteration on the non-linear free surface boundary situation while considering a raised panel situation in the analysis. The principal factors considered are the wave resistance coefficients, wave heights, and wave patterns. The other aspect of surface research mentioned earlier involves blasting and surface cleaning activities for the ship's hull

from corrosion. Zhang et al.'s (2016) study are relevant to this case. The authors established a mathematical method to explain the association between various inputs and the blasting quality; interestingly, the author deployed the method of Taguchi as an effective means of analysis. From these reviews and other papers surveyed during this investigation, the hull of a ship has been extensively discussed but solving the selection problem of parameters in composites remains unresolved.

#### 2.4. Summary and observations from the literature

From the review of literature, the following observations are valid:

- The hull of a ship is a vital part of the ship and substantially influences the maneuvering and fuel efficiency of the ship.
- Substantial efforts have been invested in the design improvement of a ship's hull through surface integrity improvement, power setups, fuel enhancement, and reduction of greenhouse gas emissions and costs.
- Although the DEA-PROMETHEE method has since emerged in 2015 from the work of Babae et al. (2015), it has restricted applications, and only a case in the transportation sector has been reported so far.
- The Taguchi method with a robust economic potential to reduce the cost of experimentation has not been reportedly linked with the integrated DEA-PROMETHEE method.
- Despite the central point of hull of a ship in influencing ship's performance, the development of composites with optimized parametric setting and selection potential for the best parameter using the Taguchi method as the basis and the DEA-PROMETHEE method has not been previously documented in the ship manufacturer's literature or shipping industry in general.

### 3. RESEARCH METHODOLOGY

This section discusses the DEA-PROMETHEE method and its application to a ship's hull.

Procedure for testing the DEA-PROMETHEE method The following procedure should be observed to apply the DEA-PROMETHEE method to a problem:

*Step 1. Obtain the Taguchi SN ratios response table*  
DEA procedure (Bagherikahvarin and Smet, 2016)

*Step 2. Classification of beneficial and non-beneficial criteria*

DEA model employs the concept of system efficiency that uses output or input to establish the overall efficiency of DMU. A DMU or alternative is considered inefficient if it fails to yield maximum output and minimum input.

*Beneficial criteria* (output): These are criteria whose values are favored when increased or minimized. In this design model, criterion *E* is considered as the beneficial criterion.

*Non-Beneficial criteria* (input): The criteria favored by minimizing their values are considered non-beneficial criteria. Criteria *A*, *B*, *C*, and *D* are all considered as non-beneficial criteria.

*Step 3. The normalization of the decision matrix*

The normalization of the decision matrix is achieved through Equation (1) (Mathew et al., 2017):

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

*Step 4. Adapting the Charnes et al. (1978) (CCR) model of DEA*

Charnes et al. (1978) developed a linear programming model of CCR to replace the basic fractional CCR model. The model aims to either maximize the output or minimize the input criteria. Opting for the minimization of the input criteria, using the underlisted formulas (Charnes et al., 1978):

Minimizing the input criteria,

$$g_k = \min \left( \sum_{i=1}^n V_i X_{ik} \right) \quad (2)$$

subject to

$$-\sum_{r=1}^s u_r Y_{rk} + \sum_{i=1}^m V_i X_{ik} \geq 0 \quad (3)$$

$$\sum_{r=1}^s u_r Y_{rk} = 1 \quad (4)$$

$$u_r \geq 0, r = 1, \dots, s$$

$$v_i \geq 0, i = 1, \dots, m$$

where  $n$  is the number of alternatives/DMUs, 4, and  $m$  is the number of input criteria, 1. While  $s$  is the number of output criteria, 4,  $x_{ik}$  and  $y_{rk}$  denote the values of  $i^{\text{th}}$  input,  $r^{\text{th}}$  is output criteria for the  $k^{\text{th}}$  alternative.  $u_r$  and  $v_i$  are the non-negative variable weights to be determined by the solution of the minimization problem.

*Step 5. The efficiency measure of the  $K^{\text{th}}$  DMU is computed*

This is given by the formula (Charnes et al., 1978),

$$H_k = \frac{1}{g_k} \quad (5)$$

but,

$$W_A + W_B + W_C + W_D + W_E \leq 1 \quad (6)$$

pre-process before applying the PROMETHEE method.

*Step 6. Normalize the decision matrix to prepare for the implementation of the PROMETHEE method*

(Mathew et al., 2017; Maduekwe and Oke, 2020)

This done be classifying the factors as beneficial and non-beneficial, Equations (7) and (8):

*Beneficial:*

$$R_{ij} = \frac{[\max(x_{ij}) - x_{ij}]}{[\max(x_{ij}) - \min(x_{ij})]} \quad (7)$$

where  $i = 1, 2, 3, 4, 5$  and  $j = 1, 2, 3, 4, 5$

*Non-beneficial:*

$$R_{ij} = \frac{[(x_{ij}) - \min(x_{ij})]}{[\max(x_{ij}) - \min(x_{ij})]} \quad (8)$$

where  $i = 1, 2, 3, 4, 5$  and  $j = 1, 2, 3, 4, 5$

PROMETHEE procedure (Bagherikahvarin and Smet, 2016; Maduekwe and Oke, 2020).

*Step 7: Evaluative difference of  $i^{\text{th}}$  alternatives with respect to other alternatives*

The difference of each alternative with respect to other

Table 1. Taguchi SN ratios response table for water absorption of dual-filler composite (Ajibade et al., 2019)

Attribute/criterion		A	B	C	D	E
Alternative	1	*-30.7422	-30.7418	-30.7096	-30.7455	*-30.2670
	2	-30.7435	-30.7468	-30.7707	-30.7443	-30.6012
	3	-30.7431	-30.7438	*-30.7071	-30.7419	-30.9083
	4	-30.7431	*-30.7397	-30.7847	*-30.7403	-31.1955

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water, \*optimal level

alternatives in the same criteria/attributes is evaluated using the expression

$$D [R_i - R_j]; \quad \text{where if } i = 1, \text{ then } j = 2, 3, 4, 5. \\ \text{and if } i = 2, \text{ then } j = 1, 3, 4, 5.$$

#### Step 8. Calculation of the preference function

The preference function is calculated using the given formulae, Equations (9) and (10):

$$P_j(a, b), \text{ then } P_j(a, b) = 0 \text{ if } R_{aj} < R_{bj} \rightarrow D(R_a - R_b) < 0 \quad (9)$$

If the difference between the two alternatives is less than or equal to zero, that value automatically becomes zero.

$$P_j(a, b) = (R_{aj} - R_{bj}) \text{ if } R_{aj} > R_{bj} \rightarrow D(R_a - R_b) > 0 \quad (10)$$

If the difference between one alternative with respect to others is greater than zero, then it retains its value.

#### Step 9. Calculate the aggregated preference function

This is done by considering the criteria weights using Equation (11):

$$\pi(a, b) = \frac{\sum (W_j P_j(a, b))}{\sum W_j} \quad (11)$$

where  $\pi(a, b)$  is the aggregated preference function,  $W_j$  is the criteria weight, and  $P_j(a, b)$  is the preference function.

Notice Equation (12):

$$P_j(a, b) = P(R_{aj} - R_{bj}) \quad (12)$$

#### Step 10. Determination of leaving and entering outranking flows

Apply the formulae for the leaving (positive) and entering (negative) flows, Equations (13) and (14):

Leaving (positive) flow for a<sup>th</sup> alternative,

$$\phi^+ = \frac{1}{n-1} \sum \pi(b, a); (a \neq b) \quad (13)$$

where  $n$  is the number of alternatives, which is 4.

Entering (negative) flow for a<sup>th</sup> alternative,

$$\phi^- = \frac{1}{n-1} \sum \pi(b, a); (a \neq b) \quad (14)$$

where  $n$  is the number of alternatives, which is 4

#### Step 11. Compute the net outranking flow of each alternative

The net outranking flow is evaluated using the following Equation (15):

$$\phi(a) = \phi^+(a) - \phi^-(a) \quad (15)$$

## 4. APPLICATION OF THE DEA-PROMETHEE METHOD

The data used in the study is based on the results declared by Ajibade et al. (2019) that conducted experiments on pairs of agro-waste reinforcements in epoxy resin to form composites, which were tested in the water absorption process. The methodology of the DEA method – PROMETHEE method demands the use of experienced composite practitioners to evaluate the questionnaire as decision-makers. However, one of the authors served that purpose in the present study. The composite practitioner is expected to showcase preferences of a parameter over others on a measuring scale. So the results obtained from such an analysis were assembled and indicated in the present study. Besides, the present study is robust as it adopts a second case study to validate the method discussed.

To apply the DEA-PROMETHEE method, effort should first be directed to applying the Taguchi method to develop the response table. The steps involve identifying factors from any given set of data and creating levels for the factors taking into consideration the repeatability of data to affirm a level. Then the orthogonal array is then specified by using standard software such as the Minitab18, which helps establish the orthogonal array fit for the problem. Then the signal-to-noise ratios are developed as the criterion of smaller the better, larger the better, and nominal the best is chosen from the alternative criteria. Then the signal-to-noise ratios are summarised as the response tables. This article assumes that the ship manufacturer could establish the response table; hence, it adopts data in the final form of the Taguchi SN ratio response table from Ajibade et al. (2019) to illustrate the workability of the DEA PROMETHEE method proposed. To sum up, the parameters utilized in this work have been optimized using the Taguchi method before being used as an input to the DEA-PROMETHEE method.

Upon determining the response table (Table 1) and revising the DEA method, the base of commencement of the DEA PROMETHEE method is to establish inputs and outputs. However, there are five alternatives: initial weight, final weight, length of composites, composite thickness, and time. Since the data obtained from the literature (Ajibade et al., 2019) is limited to these five parameters, it is essential to establish an output or outputs among these parameters. Thus a strategy of identifying and distinguishing between beneficial from non-beneficial criteria is adopted. It is thought that the beneficial parameters could be the output while non-

Table 2. Normalized decision matrix of the composite

Alternative	Attribute/ criterion	A	B	C	D	E
	1		-0.5000	-0.4995	-0.4995	-0.5000
2		-0.5000	-0.5005	-0.5005	-0.5000	-0.4977
3		-0.5000	-0.4994	-0.4994	-0.5000	-0.5027
4		-0.5000	-0.5007	-0.5007	-0.5000	-0.5073

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water

beneficial parameters may be classified as inputs. But then, what are beneficial criteria in the context of the hull of a ship's composite parameters, and what are non-beneficial parameters?

From the multi-criteria literature, a beneficial parameter is one whose increase in values will benefit the water-resistance goal of the hull of a ship's composite that undergoes water absorption test demonstrated in Ajibade et al. (2019). Thus, applying the knowledge and experience of the present authors, it is thought that by increasing time, which is a characteristic of the ship that spends substantial time in the water, is beneficial. Usually, when a ship is operational on the sea, it stays on the water. Also, when the ship is docked, it is still in the environment of water. So it is difficult to separate a ship's hull from having contact with water. Hence, time is a beneficial criterion and taken as the output for this study. By argument, the initial weight desired to be as low as possible is non-beneficial. The final weight is also expected to be relatively low, being a non-beneficial parameter. The length of the hull of a ship should be reasonable in size. So, extremely long lengths are undesirable and non-beneficial to the system. Likewise, the thickness of the ship's hull is not desired to be excessive and hence classified as non-beneficial. This, using the symbolic representation from Table 1, parameter *E* is the output while the parameters *A*, *B*, *C*, and *D* are inputs. Table 1 focuses on five parameters, namely, initial weight (g), *A*; final weight (g), *B*; length (mm), *C*; thickness (mm), *D*; and time (s), *E*.

The initial weight of the composite for the hull of a ship is an important part that determines the success of the effort in overcoming resistance and attaining the desired powering of ships. It is a function of the type of composite, the properties of the material, and the fiber loading during the composite formulation. The composite fabrication for a ship's hull is subjected to depends on the temperature and atmospheric condition. The final weight is the measured value of the composite fabrication adopted, whether or not the composite is treated, and if treated, how long the treatment takes. Time refers to the extent to which the composite for a ship's hull is allowed to stay in the water and determines the amount of water absorbed. This is to test the resilience of the composite in water. The length of the composite is to reflect the size of the ship, which may be small, medium, or large. It is considered an essential element to determine the optimization and selection process of water absorption process parameters used for composites for a ship's hull.

The composite thickness is an important element in establishing the optimization and selection of the water absorption process parameters. Thicker composite strata

are found to produce heavier composites. Thickness determines how ready it is to break the composite of a ship's hull. The object of the experiment by Ajibade et al. (2019), however, is to study how a real-life structure would respond to water absorption by way of examining the influence of initial weight, final weight, the thickness of composite, length of composite, and time of composites suspension in water. As this reflects the same scenario that the ship and hull of a ship undergo in water bodies, it is adopted to illustrate the DEA-PROMETHEE method in this study.

Furthermore, the objective function is the Taguchi SN ratio response that originates from the choice among the smaller-the-better, larger-the-better, or the nominal-the-best signal-to-noise criterion. It consists of the log function of the anticipated output of the optimization cum selection process in the present study. It supports the hull of a ship's data analysis and predicts the optimum results. Besides, as the hull of a ship remains a prominent structural entity in the ship, it is conceived that optimization in design cum selection of the best parameter is a better pursuit than selection alone. Thus, the Taguchi SN ratio oversees all aspects relevant to optimizing the parameters before being used as an input to evaluate the DEA-PROMETHEE method in developing the composite for the hull of a ship.

A signal-to-noise ratio is a relationship between the signal power level and noise power, usually expressed as decibels (dB). In the Taguchi SN ratio response table, Table 1, -30.7422 dB, which is the value of the initial weight along the row for the first alternative is higher than any of the other three values of -30.7435, -30.7431, and -30.7431 dB for the initial weight of alternatives 2, 3 and 4. Higher dB values are generally preferred as they provide more useful information (i.e., signal) than undesired data (i.e., noise). This idea of signal-to-noise that originated outside the composite development area has been relevant to the water absorption parametric evaluation of a ship's hull in the present article. This idea is mentioned as it is known that even in the electrical engineering domain that the signal-to-noise originates, all components developed, including cables, exhibit a certain noise level in proportion to the signal power. Since the best electronics components are developed to maximize the SN ratio by holding the noise level to the lowest level, this idea is borrowed to the composite development of a ship's hull where the noise is made as low as possible.

Having established the inputs and output to the DEA method within the DEA-PROMETHEE framework, the next step is normalizing the decision matrix.

Table 2 is the normalized decision matrix for the problem under investigation. But then, normalization and

decision matrix may be explained in the context of the present article. The decision matrix (Table 1), which is transformed to Table 2, is a list of alternatives, namely the initial and final weight of composites length of the composite, the thickness of the composite, and the time of immersion of the composite in water. The decision matrix contains the factors along with the columns. Each alternative is scored using the average signal-to-noise ratios to obtain the decision matrix (Table 1). The scores are weights through the comparative importance of the alternatives. The scores are added up to reveal the overall score of each alternative. For example, in the normalization of the decision matrix for the hull of a ship composite's alternatives, Equation (1) is applied. Here, the numerator is the alternative value along the row divided by the overall score along the column. Consider alternative 1 in intersection with A. The normalized value is obtained as -30.7422 divided by 61.486 to yield -0.5000. This is matched against alternatives 2, 3, and 4, calculated similarly as -0.5000, -0.5000, and -0.5000, respectively. The normalized values entail ranking the SN ratio scores in the range between 0 and 1 (minus inclusive). The normalized decision matrix comprises competitive options arranged row wisely, and the average signal-to-noise ratios of the Taguchi method are taken as the rating of the alternatives. Table 2 is particularly useful as the comparative importance of each parameter (alternative) is to be determined; it allows the researcher to examine and evaluate the strength of association between the alternative parameters of the behavior of the composite in water for the hull of a ship.

DEA is employed to determine the performance efficiency of a set of entities or alternatives commonly referred to as a decision-making unit (DMU). Table 1 contains the Taguchi SN ratios response table for water absorption of dual filler composite drawn from Ajibade et al. (2019) and used to analyze the DEA-PROMETHEE method. Being motivated by the need to concurrently optimize the parameters of water absorption of composites and establish the best alternatives, the Taguchi SN ratio responses are used as the background. This response table reveals which parameter exhibits the greatest influence on the response with the corresponding level for the parameter associated with the lower or higher response characteristics values.

Since the CCR model of the DEA method has decision-making units (DMUs) as a framework, some explanation of DMUs regarding the hull of a ship composite may be necessary. The DMU originated from the novel discovery of Robinson et al. (1967) with a central notion of a buying center that assembles all participants in an organization related to the buying process of a service or product. While Charnes et al. (1978) developed the idea of DEA based on the DMUs, subsequently, DMUs have been replaced with alternatives in certain domains, such as the shipbuilding involving hull of a ship's composite. The idea of a DMU is that of an organization's buying decision where the principal players may be identified as the influencers, buyers, users, gatekeepers, and deciders. However, the benefits of using the DMU concept in this work involve that several prospective decisions have a high chance of being positive since they permit all the

players in the DMU to contribute opinions arising from their knowledge and expertise. Besides, the DMU enhances an understanding of the decision-making process. Furthermore, the players of the DMU are committed to growth for the unit since they are willing to put their best input into the process.

From the normalized results, the next step is to adopt the CCR model of the DEA method that has been discussed in the model formulation in the section on methodology. The attempt here is to apply the procedure to the data provided by Ajibade et al. (2019). Recall that the CCR model of the DEA method is a linear equation consisting of the objective function and the constraint equations, which any linear programming software may solve. However, the linprog function in the Matlab software is made. For proceeding, the linear programming equations are formulated for each decision-making unit (DMUs/alternatives 1, 2, 3, and 4). However, for the first DMU/alternative 1, the linear programming model is formulated as a minimization function since increasing the values of inputs, namely the initial weight, final weight, length of composite, and thickness, are not desirable. Usually, the objective function has decision variables coefficients that are added together. In this case, consider decision variables  $V_1$ ,  $V_2$ ,  $V_3$ , and  $V_4$  to represent the initial weight,  $A$ , final weight,  $B$ , length of composite,  $C$ , and the thickness of composite,  $D$ , it is required to find the numbers  $V_1$ ,  $V_2$ ,  $V_3$  and  $V_4$  that minimizes the sum of  $-0.5000V_1$ ,  $-0.5000V_2$ ,  $-0.4995V_3$  and  $-0.5000V_4$  subject to constraints shown hereafter.

Notice that the coefficients of these numbers,  $V_1$ ,  $V_2$ ,  $V_3$ , and  $V_4$ , are the corresponding values for alternative one along the first row, showing alternative 1 as  $-0.5000$  attached to  $A$ , while  $-0.5000$ ,  $-0.4995$ ,  $-0.5000$  are attached to  $B$ ,  $C$ , and  $D$ , respectively. But the constraint equations need to be formulated to be greater than 0. Here, the output and input are considered with the coefficients drawn from Table 2. To formulate the first constraint equation, consider  $V$  as the number representing the output whose coefficient may change depending on the alternative being considered. For example, in the forthcoming expressions of constraint equation, the first constraint equation is formulated with the coefficient of  $-0.4922$  for  $u_1$ . In contrast, the coefficients of  $V_1$ ,  $V_2$ ,  $V_3$ , and  $V_4$  are drawn from  $A$ ,  $B$ ,  $C$ , and  $D$  along the row of alternative 1. In sum, the objective of the first DMU/alternative 1 is:

$$g_1 = \min (-0.4999V_1 - 0.4999V_2 - 0.4995V_3 - 0.5000V_4) \quad (16)$$

$$\text{subject to}$$

$$-0.4922u_1 + (-0.5000V_1 - 0.4999V_2 - 0.4995V_3 - 0.5000V_4) \geq 0 \quad (17)$$

$$-0.4977u_1 + (-0.5000V_1 - 0.5005V_2 - 0.5005V_3 - 0.5000V_4) \geq 0 \quad (18)$$

$$-0.5027u_1 + (-0.5000V_1 - 0.4994V_2 - 0.4994V_3 - 0.5000V_4) \geq 0 \quad (19)$$

$$-0.5073u_1 + (-0.5000V_1 - 0.5007V_2 - 0.5007V_3 - 0.5000V_4) \geq 0 \quad (20)$$

$$\text{where } u_1, V_1, V_2, V_3, V_4 \geq 0$$

The equality constraint  $\sum_{r=1} u_r y_{rk} = 1$  is evaluated as,

$$-0.4922u_1 = 1$$

$$u_1 \geq 0$$



By following similar procedure, for the first DMU/alternative 2, the objective function and constraint equations are formulated as:

$$g_2 = \min (-0.5000V_1 - 0.5005V_2 - 0.5005V_3 - 0.5000V_4) \tag{21}$$

subject to

$$-0.4922u_1 + (-0.5000V_1 - 0.4999V_2 - 0.4995V_3 - 0.5000V_4) \geq 0 \tag{22}$$

$$-0.4977u_1 + (-0.5000V_1 - 0.5005V_2 - 0.5005V_3 - 0.5000V_4) \geq 0 \tag{23}$$

$$-0.5027u_1 + (-0.5000V_1 - 0.4994V_2 - 0.4994V_3 - 0.5000V_4) \geq 0 \tag{24}$$

$$-0.5073u_1 + (-0.5000V_1 - 0.5007V_2 - 0.5007V_3 - 0.5000V_4) \geq 0 \tag{25}$$

The equality constraint  $\sum_{r=1} u_r y_{rk} = 1$  is evaluated as,

$$-0.4977 u_1 = 1$$

$$u_1 \geq 0$$

Also, for the first DMU/alternative 3, the objective and constraint equations are developed as follows:

$$g_3 = \min (-0.5000V_1 - 0.4994V_2 - 0.4994V_3 - 0.5000V_4) \tag{26}$$

subject to

$$-0.4922u_1 + (-0.5000V_1 - 0.5000V_2 - 0.4995V_3 - 0.5000V_4) \geq 0 \tag{27}$$

$$-0.4977u_1 + (-0.5000V_1 - 0.5005V_2 - 0.5005V_3 - 0.5000V_4) \geq 0 \tag{28}$$

$$-0.5027u_1 + (-0.5000V_1 - 0.4994V_2 - 0.4994V_3 - 0.5000V_4) \geq 0 \tag{29}$$

$$-0.5073u_1 + (-0.5000V_1 - 0.5007V_2 - 0.5007V_3 -$$

$$0.5000V_4) \geq 0 \tag{30}$$

The equality constraint  $\sum_{r=1} u_r y_{rk} = 1$  is evaluated as,

$$-0.5027 u_1 = 1$$

$$u_1 \geq 0$$

Likewise, for the first DMU/alternative 4, the objective function and constraint equations are show as:

$$g_4 = \min (-0.5000V_1 - 0.5007V_2 - 0.5007V_3 - 0.5000V_4) \tag{31}$$

subject to:

$$-0.4922 u_1 + (-0.5000V_1 - 0.5000V_2 - 0.4995V_3 - 0.5000V_4) \geq 0 \tag{32}$$

$$-0.4977 u_1 + (-0.5000V_1 - 0.5005V_2 - 0.5005V_3 - 0.5000V_4) \geq 0 \tag{33}$$

$$-0.5027 u_1 + (-0.5000V_1 - 0.4994V_2 - 0.4994V_3 - 0.5000V_4) \geq 0 \tag{34}$$

$$-0.5073 u_1 + (-0.5000V_1 - 0.5007V_2 - 0.5007V_3 - 0.5000V_4) \geq 0 \tag{35}$$

The equality constraint  $\sum_{r=1} u_r y_{rk} = 1$  is evaluated as,

$$-0.5073 u_1 = 1$$

$$u_1 \geq 0$$

However, the next phase of the evaluation is to determine the efficiency measure of the k<sup>th</sup> DMU. This is obtained by Equation (5):

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

However, the problem, which may be solved using linear programming software, was solved using Matlab.

Table 3. The normalised matrix

Attribute	A	B	C	D	E
1	0	0.2960	0.0030	1	1
2	1	1	0.8200	0.7690	0.6416
3	0.6920	0.5770	0	0.3080	0.3123
4	0.6920	0	1	0	0.0043

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water

Table 4. Computations of  $D (R_i - R_j)$  based on normalised matrix

Attribute	A	B	C	D	E
1	0	0.2960	0.0030	1	1
2	1	1	0.8200	0.7690	0.6416
3	0.6920	0.5770	0	0.3080	0.3123
4	0.6920	0	1	0	0.0043
$D(R_1-R_2)$	-1	-0.7040	-0.8170	0.2310	0.3584
$D(R_1- R_3)$	-0.6920	-0.2810	0.0030	0.6920	0.6877
$D(R_1- R_4)$	-0.6920	0.2960	-0.9970	1	0.9957
$D(R_2- R_1)$	1	0.7040	0.8170	-0.2310	-0.3584
$D(R_2- R_3)$	0.3080	0.4230	0.8200	0.4610	0.3293
$D(R_2- R_4)$	0.3080	1	-0.1800	0.7690	0.6373
$D(R_3- R_1)$	0.6920	0.2810	-0.0030	-0.6920	-0.6877
$D(R_3- R_2)$	-0.3080	-0.4230	-0.8200	-0.4610	-0.3293
$D(R_3- R_4)$	0	0.5770	-1	0.3080	0.3080
$D(R_4- R_1)$	0.6920	-0.2960	0.9970	-1	-0.9957
$D(R_4- R_2)$	-0.3080	-1	0.1800	-0.7690	-0.6373
$D(R_4- R_3)$	0	-0.5770	1	-0.3080	-0.3080

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water

Table 5. The preference function,  $P_j(a,b)$ 

Attribute	A	B	C	D	E
$P(R_1-R_2)$	0	0	0	0.2310	0.3584
$P(R_1-R_3)$	0	0	0.0030	0.6920	0.6877
$P(R_1-R_4)$	0	0.2960	0	1	0.9957
$P(R_2-R_1)$	1	0.7040	0.8170	0	0
$P(R_2-R_3)$	0.3080	0.4230	0.8200	0.4610	0.3293
$P(R_2-R_4)$	0.0616	0.2000	-0.0360	0.1538	0.1275
$P(R_3-R_1)$	0.6920	0.2810	0	0	0
$P(R_3-R_2)$	0	0	0	0	0
$P(R_3-R_4)$	0	0.5770	0	0.3080	0.3080
$P(R_4-R_1)$	0.6920	0	0.9970	0	0
$P(R_4-R_2)$	0	0	0.1800	0	0
$P(R_4-R_3)$	0	0	1	0	0

Key: A – the initial weight of the composite before immersion in water, B – final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water

Table 6. Aggregated preference function

Attribute	A	B	C	D	E	$\sum_{i=1}^n w_j P_j(a,b)$	$\pi(a,b)$
Weights (from DEA method)	0.2000	0.2000	0.2000	0.2000	0.2000		
$w_j P(R_1-R_2)$	0	0	0	0.0462	0.0717	0.1179	0.1179
$w_j P(R_1-R_3)$	0	0	0.0006	0.1384	0.1375	0.2765	0.2765
$w_j P(R_1-R_4)$	0	0.0592	0	0.2000	0.1991	0.4583	0.4583
$w_j P(R_2-R_1)$	0.2000	0.1408	0.1634	0	0	0.5042	0.5042
$w_j P(R_2-R_3)$	0.0616	0.0846	0.1640	0.0922	0.0659	0.4683	0.4683
$w_j P(R_2-R_4)$	0.0123	0.0400	-0.0072	0.03076	0.0255	0.1014	0.1014
$w_j P(R_3-R_1)$	0.1384	0.0562	0	0	0	0.1946	0.1946
$w_j P(R_3-R_2)$	0	0	0	0	0	0	0
$w_j P(R_3-R_4)$	0	0.1154	0	0.0616	0.0616	0.2386	0.2386
$w_j P(R_4-R_1)$	0.1384	0	0.1994	0	0	0.3378	0.3378
$w_j P(R_4-R_2)$	0	0	0.0360	0	0	0.0360	0.0360
$w_j P(R_4-R_3)$	0	0	0.2000	0	0	0.2000	0.2000

Key: A – the initial weight of the composite before immersion in water, B – final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water

Thus, the values of  $g_k$ ,  $V_1$ ,  $V_2$ ,  $V_3$ ,  $V_4$ , and  $u_1$  can be evaluated using the linprog function of the Matlab. The obtained values are  $V_1 = -9.8904$ ,  $V_2 = -3.9851$ ,  $V_3 = 3.5917$ , and  $V_4 = 12.2844$ . But substituting the values of  $V_1$ ,  $V_2$ ,  $V_3$  and  $V_4$  into the objective function for  $g_1$ ,  $g_2$ ,  $g_3$ , and  $g_4$  yields  $g_1 = 0.9992$ ,  $g_2 = 1.0003$ ,  $g_3 = 1.0004$ ,  $g_4 = 0.9994$ . Also, it substitutes the values of  $u_1$  in the respective DMU equations reformulated and takes the average produces of  $g_5$  value as 0.9998. Hence  $H_1 = 1.0008$ ,  $H_2 = 0.9997$ ,  $H_3 = 0.9997$  and  $H_4 = 1.0006$  while  $H_5 = 1.0006$ . However, let  $W_A$ ,  $W_B$ ,  $W_C$ ,  $W_D$ , and  $W_E$  represent the weights of  $H_1$ ,  $H_2$ ,  $H_3$ ,  $H_4$ , and  $H_5$  (criteria A, B, C, D, and E), respectively. But,

$$W_A + W_B + W_C + W_D + W_E \leq 1$$

On substitution,

$$1.0008 + 0.9997x + 0.9997x + 1.0006x + 1.0006x \leq 1 \quad (36)$$

$$\text{Also, } x \leq 0.19994 \quad (37)$$

Hence,  $W_A = W_B = W_C = W_D = W_E = 0.2$

This is the final answer for the DEA method, which is fed into the PROMETHEE method to complete the evaluation of the DEA-PROMETHEE method. But the

data has to be processed by normalization before using the PROMETHEE method. The result is shown in Table 3. But normalization is done using Equation (7) for the non-beneficial parameters A, B, C, and D, and Equation (8) is used for the beneficial parameter E, Table 3.

For instance, take the initial weight A, the maximum value is -30.7422 while the minimum value is -30.7435 and the range is 0.0013, the computed  $R_{11}$  becomes zero. Then, place it at the intersection of parameter A and attribute 1. Similarly, all other values in Table 3 are computed.

Using the normalized matrix, the PROMETHEE procedure is applied. This commences with the differences evaluation of the  $i^{\text{th}}$  alternative with respect to other alternatives (Table 4).

This is obtained by considering the expression  $D(R_i - R_j)$ , whereas  $i$  is specified. It is not considered in the values listed for  $j$  and vice versa. Thus, when  $i = 1$ , then  $j = 2, 3, 4$  and  $5$ . Similarly, when  $i = 2$ ,  $j = 1, 3, 4$  and  $5$ . Other combinations of  $i$  and  $j$  and so determined. The expression  $D(R_i - R_j)$  means that the difference between the normalized values of the  $i^{\text{th}}$  and  $j^{\text{th}}$  alternatives are

Table 7. Outranking flow

Aggregate preference function	A	B	C	D	E	$\phi^+$ Leaving flow
A	-	0.1179	0.2765	0.4583	-	0.2843
B	0.5042	-	0.4683	0.1014	-	0.3579
C	0.1946	0	-	0.2386	-	0.2166
D	0.3378	0.0360	0.2	-	-	0.1913
E	-	-	-	-	-	-
$\phi^-$ Entering flow	0.3455	0.0777	0.3149	0.2661	-	-

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water, Ranking the most important criteria\*

Key: A – the initial weight of the composite before immersion in water, B - final weight of the composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water, and E – time of the composite immersion in water, Ranking the most important criteria\*

Table 8. Net outranking

Alternative	$\phi^+(a)$	$\phi^-(a)$	$\phi(a)$	Rank
<b>A</b>	0.2843	0.3455	-0.0612	2
<b>B</b>	0.3579	0.0777	0.2802	1
<b>C</b>	0.2166	0.3149	-0.0983	4
<b>D</b>	0.1913	0.2661	-0.0748	3

Key: A – the initial weight of composite after immersion in water, B – final weight of composite after immersion in water, C – length of the composite after immersion in water, D – thickness of the composite after immersion in water

calculated and placed in the table. Consider the row containing  $D(R_1-R_2)$ . Two rows are involved in the computation: row 1 (written as  $R_1$ ) and row 2 (written as  $R_2$ ). Row 1 (i.e.,  $R_1$ ) is the immediate row under attribute, with values of 0, 0.296, 0.003, 1, and 1. Row 2 (i.e.  $R_2$ ) is following, which starts with 1 (under A) and contains other values such as 1 (under B), 0.820 (under C), 0.769 (under D) and 0.641609 (under E). For obtaining  $D(R_1-R_2)$ , each value in a column from row 2 is subtracted from the corresponding value in row 1. Consider column A, under row 2, 1 is found while 0 is observed under row 1. Thus, the difference between 0 and 1 as row 2 is subtracted from row 1 is -1. Thus value is placed on the row containing  $D(R_1-R_2)$  but under column A. Similarly, the whole Table 4 is completed with the differences between one row and the other. Notice that the attributes are only four, which are 1, 2, 3, and 4. Therefore the differences relate to  $R_1, R_2, R_3,$  and  $R_4$  only, and only twelve observations are involved. The next step is to calculate the preference function. For attaining this goal, two rules are followed. The first rule is to observe the calculated entries for the  $D(R_i-R_j)$  (i.e., twelve sets of computations). There is a need to replace any value of  $D(R_i-R_j)$  negative with zero, Equation (9). Consider Table 4 again to develop Table 5.

Once the row containing  $D(R_1-R_2)$  is observed, the first value under "A" is -1, which will be replaced with zero according to the rule. Also, -0.7040, which is the value under B, is replaced with zero. -0.8170 is also replaced with zero (value under C). However, 0.2310, which is the value under D, is retained according to the second rule. Likewise, 0.3584 is retained according to the second rule,

Equation (10). Thus, with the application of the two rules (Equations (9) and (10)), Table 5 is produced. The following computation phase develops the aggregated preference function by considering the criteria weights, Equation (11). However, Equation (12) needs to be applied.

Also, note that the summation of weights, with the above information, Table 6 could be built up. Recall that Table 6 builds on Table 5. The second row of Table 6 is the weights of the alternatives extracted from the DEA method's output. The next row multiplies the weight of each alternative with what was previously computed in the corresponding cell in Table 5. Consider the intersection of  $w_jP(R_1-R_2)$  and A; here, the intersection value of  $P(R_1-R_2)$  and A from Table 5 is 0. As zero is multiplied with 0.2000, it yields zero, placed at the intersection of  $w_jP(R_1-R_2)$  and A.

The rest of Table 6 for B to E is computed using a similar procedure. However, the next column to E sums up the obtained values under A to E. For the row containing  $w_jP(R_1-R_2)$ , the said column adds 0, 0, 0, 0, 0.0462, and 0.0717 to yield 0.1179. Notwithstanding, the next column, which contains,  $\pi^{(a,b)}$  is obtained using Equation (11). But since the sum of the weights is 1, the obtained value of 0.1179 is retained  $\pi^{(a,b)}$ . The following computation phase is the determination of leaving and entering outranking flows. The leaving (positive) flow for the  $a^{th}$  alternative is given by Equation (13), while Equation (14) provides the entry with the (negative) flow for the  $a^{th}$  alternative. Table 6 contains twelve values of  $w_jP(R_i-R_j)$ , summarized in Table 7, that eventually form the outranking flow table. Now consider

the third row of Table 6, where the last column contains 0.1179. This value is placed in Table 7 along the row containing A but under a B column since it describes  $w_jP(R_1-R_2)$ . The next row in Table 6 is  $w_jP(R_1-R_2)$ , where the corresponding value on the last column of the same table is 0.2765. Notice that in Table 7, this value is placed along with row A and column C. By following this procedure, all the twelve values corresponding to  $w_jP(R_1-R_2)$  to  $w_jP(R_4-R_3)$  are filled in Table 7.

When filling these values in Table 7, the next step is to determine the data's leaving flow (positive) and entering flow (negative) items. The leaving flow is the last column of Table 7, the average along the row. For instance, for A, the value for the leaving flow is the average of 0.1179, 0.2765, and 0.4583, which yields 0.2843. This procedure is used to obtain the leaving flow belonging to B, C and D. However, E has no value, which means that it is not an essential element in the goal achievement for the problem studied. The entering flow (negative) is also computed similarly by finding the averages along the columns. For instance, only three entries are available for column A to calculate the entry flow (negative) values, which are 0.5042, 0.1946, and 0.3378. The average is 0.3455. By following this approach, all the entering flow values (negative) under B, C, and D are obtained as 0.0777, 0.3149, and 0.2661, respectively. The next phase in the computation is to obtain the net outranking flow is subtracts the entering flow (negative) from the positive flow (positive) (Table 8). For this computation, Equation (15) is relevant.

$$\phi(a) = \phi^+(a) - \phi^-(a)$$

Here, the summation of weight,

$$\sum w_j = 0.2 + 0.2 + 0.2 + 0.2 + 0.2 = 1$$

Table 8 shows the net outranking values of the problem. Interestingly, PROMETHEE II is regarded as an outranking method, which is competent to determine whether or not an alternative has a higher rank than the other. This means that in the perspective of considering the signal-to-noise ratios, an alternative may be more important than the other. In the PROMETHEE method used, two components of the outranking flow are

considered: the positive outranking flow and the negative outranking flow. The balance of the two outranking flows, i.e., positive and negative, makes up the net outranking flows. But an alternative with a higher net flow is superior to a lower net flow, Table 8. Table 8 contains  $\phi^+(a)$  the second column, which represents a positive outranking flow and reveals to what degree each of the alternatives B, C, and D outrank all others. For instance, alternative B outranks C and D are determined by this positive outranking symbol. It is known that higher  $\phi^+(a)$  is the superior option. The symbol  $\phi^+(a)$  represents a's power, which is its outranking character (Deshmukh, 2013).

Furthermore, the negative outranking flow reveals to what degree others outrank the alternatives B, C, and D. (Deshmukh, 2013). For the symbol  $\phi^-(a)$ , smaller values are preferred (Deshmukh, 2013). This situation  $\phi^-(a)$  shows power, which means its outranked attribute (Deshmukh, 2013). Thus, the positive, negative, and net outranking values are shown in the second, third, and fourth columns of Table 8. The net outranking values shows the highest value of 0.2802 for alternative B, followed by -0.0612 for alternative A and then -0.0748 for alternative D and -0.0983 for alternative C. Therefore, they are ranked as 1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>, and 4<sup>th</sup> accordingly. Therefore, the final weight parameter is the best, and the length parameter is the worst. This information is useful for decision-making.

#### 4.2. Validation of the results

In this article, five parameters, namely the initial weight, final weight, length, thickness, and time were considered as the experimental data utilized by Ajibade et al. (2019) and used to test the DEA-PROMETHEE method for the hull of ship composite parametric analysis. However, the DEA-PROMETHEE method may be presented in a new case study on selecting acetylation parameters in a water absorption experiment for bamboo, which could serve as reinforcement for composites of a ship's hull. Thus, the results of the present article may be validated using this new case study that considers decision

Table 9a. Analysis on net outranking – composite parameters

Alternative	$\phi^+(a)$	$\phi^-(a)$	$\phi(a)$	Average of $\phi^+(a)$ and $\phi^-(a)$	Deviation of average from net	Rank	Comment
A (Initial weight)	0.2843	0.3455	-0.0612	0.3149	6.1454	2	High
B (Final weight)	0.3579	0.0777	0.2802	0.2178	0.2227	1	Very low
C (Length)	0.2166	0.3149	-0.0983	0.2658	3.7035	4	High
D (Thickness)	0.1913	0.2661	-0.0748	0.2287	4.0575	3	High

Table 9b. Analysis on net outranking – acetylation parameters

Alternative	$\phi^+(a)$	$\phi^-(a)$	$\phi(a)$	Average of $\phi^+(a)$ and $\phi^-(a)$	Deviation of average from net	Rank	Comment
Q (Time soaked in acetic anhydride)	0.4980	0.4996	-0.0016	0.4988	312.7500	1	Very high
R (Difference in % water absorption)	0	1.4946	-1.4946	0.7473	1.5000	2	High

criteria as  $M$ ,  $N$ ,  $P$ ,  $Q$ , and  $R$ . The results of the comparison are shown in Tables 9a and 9b. The average of  $\phi^+(a)$  and  $\phi^-(a)$  was determined for each alternative. The deviation of this value from the net outranking value  $\phi(a)$  evaluated.

Accordingly, the deviation for the alternatives of composites reveals the least value of 0.0223 for the final weight alternative to the highest value of 6.1454 for the initial weight alternative. The observation is that the deviation was high for most of the alternatives and very low for only one alternative. For the acetylation alternatives, the least deviation was 1.5000, obtained for the different % water absorption, while the highest was for the time soaked in acetic anhydride, which yielded 312.7500. This value is the most significant deviation in the results from the composite analysis and that of the acetylation alternatives. The results show that the analysis from the composites is the better option considering the deviation of the average of the entering flow and leaving flow from the net outranking flow. In addition, the net outranking values from both the composite experimental analysis and the acetylation experiment were subjected to a correlation test. The findings revealed a perfect negative correlation coefficient of -1, indicating a perfect negative relationship between the outcomes of the two datasets. This suggests that the two datasets work well with the DEA-PROMETHEE method used to analyze the workability of selecting factors from multiple alternatives.

## 5. CONCLUSIONS

In this article, the efficiency of alternatives in composite parameters for a ship's hull was assessed and concurrently selected the best parameter. Consequently, an attempt to use the DEA method was made. However, its shortfall in poor discrimination power, which disallows a total ranking of the alternatives, prompts the adoption of the PROMETHEE method in a combined form to correct this weakness of the DEA method. Thus, the article established the efficiency of composite water absorption parameters for the ship's hull and instituted a total ranking of the alternatives. The institution of the hull of a ship case study using a DEA-PROMETHEE method on the Taguchi SN ratio response table platform is a novel study rarely discussed in the literature. Furthermore, the water absorption parameters will benefit the related practices, i.e., ship manufacturers or the shipping industry. Based on the research findings, the following conclusions are made:

- The DEA-PROMETHEE method reveals that only the initial weight, final weight, length, and thickness are the essential parameters that should be considered during the design and development of the hull form for the ship. However, time is not an important parameter.
- The proposed method ranks final weight as the 1<sup>st</sup> (net outranking value of 0.2802), initial weight as 2<sup>nd</sup> (net outranking value of -0.0612), thickness as 3<sup>rd</sup> (net outranking value of -0.0748), and length as 4<sup>th</sup> (net outranking value of -0.0983).
- A DEA-PROMETHEE method is a valid approach to evaluating the efficiency of alternatives and ranking them for composite development in the hull of a ship's case.

Evidence also abounds for the illustrative example on optimization and selection acetylation parameters.

- In developing composites for a ship's hull, final weight should be given the utmost importance. Thus, the ship manufacturers can improve the hull's performance of a composite ship by considering composites with water resistance.

In the light of advancements in decision-making in engineering, particularly on the development and improvement of composites for the hull of a shipbuilding practice, the DEA-PROMETHEE demonstrates the potential to optimize the parameters of the water absorption parameters effectively. While many existing algorithms need substantial information to properly function (i.e., linear programming), many engineering problems in shipbuilding may offer limited information. The DEA-PROMETHEE method will still function effectively despite this limitation of a paucity of data. In the future, the investment of efforts to integrate the Box Behnken Design into the framework, which will concurrently optimize and select parameters, could be beneficial to the ship manufacturer.

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