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A Treatise on Reconnoitering the Suitability of Fuzzy MARCOS for Assessment of Conceptual Designs

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Abstract: The development of an equipment starts from an effective design activity. The concept selection process is an activity that is entailed in the design stage, and its relevance in the design process cannot be overemphasized because it informs the choice of optimal conceptual design from a set of alternative designs. Hence, there is a need to accrue efforts to the concept selection process because of its importance. This article presents the identification of optimal conceptual design as a multicriteria decision-making model by assessing the suitability of fuzzy Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS). The fuzzy MARCOS model was developed to access four alternative conceptual designs of briquetting machines considering eight design features with several sub-features. The results obtained from the decision analysis showed that the fuzzy MARCOS model was able to rank the designs based on their performance and the final values of the overall utility function. The overall utility function is based on the utility degree of the conceptual design alternatives in terms of the best and worst designs identified by the model. The utility degree created a platform for comparison on how the design alternatives varied from the best and worst designs. The results obtained from the MARCOS method were validated using the TOPSIS method and modified TOPSIS method, and the results obtained showed that the MARCOS method is in conformity with the validation results.

Keywords: design concept selection; fuzzy MARCOS; design process; multi-criteria decision making; briquetting machine

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1. Introduction

Achieving the goal of developing a product with all-embracing design features starts from brainstorming activities in the design phase of the product when several conceptual design concepts have been established. An important task at this stage is decision making on identification of the optimal conceptual design. Decision making in the preliminary design phase and extensive design concept selection from several conceptual designs can be accrued to the robust design of a product [1,2]. The number of design features that are embedded in the optimal design concept is also important because they depict the multifarious functions that the product can perform. A good way to develop a product with several design features is to examine the features of different conceptual designs during the concept selection phase. Selecting an optimal design implies that the design has a satisfactory performance considering all the design features [3,4]. Also, an optimal design can be developed so that the design features from other conceptual designs can be added to the design. This makes the decision process important, and the efforts put into it cannot be overemphasized. Design engineers provide several design solutions in the developmental stage before a detailed analysis is carried out [5]. Provision of several design solutions is necessary because the management of a manufacturing firm wants to reduce the cost of fabrication and produce an extensive product that will have a high demand in a competitive market and extended useful life. Also, the firm may be interested in selecting a design that is realistic in terms of completion time and utilization of existing technologies of fabrication. In essence, selecting an optimal design concept from a set of alternative designs becomes inevitable considering the fact that all the design solutions have several benefits and shortcomings [2].

Research has shown that an excellent way to arrive at an optimal solution in the decision-making process in this scenario is to introduce the Multi-Criteria Decision Model (MCDM) [6,7]. In the preliminary phase of an equipment or a product, the design features and sub-features are identified alongside various design alternatives in order to allow for decision making on the optimal design concept to be modelled as an MCDM. Basically, MCDMs can be broadly divided into two categories, which are the Multi-Attribute Decision Model (MADM) and Multi-Objective Decision Model (MODM) [8,9]. The MADM is applicable in cases that involves making a choice from a set of alternatives in a discrete or well-defined solution space. The MODM is applied to solve decision problems with several goals where there are no discrete sets of explicitly defined alternatives. Also, the MODM also applies to scenarios where the alternatives are to be ranked based on several criteria. In this case, the decision process is performed at different times in order to satisfy the various objectives of the decision criteria [9,10]. Several MADMs have been introduced to solve real-life decision-making problems, but there is a need to investigate the suitability of these models in the design process. Among the MADMs used in decision-making processes are the Multi-Attribute Utility Theories (MAUTs). MAUTs include the Analytic Hierarchy Process (AHP), Weighted Decision Matrix (WDM), Analytic Network Process (ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and Elimination and Choice Translating Reality (ELECTRE), among others [11].

Several efforts have been made by researchers to apply these MADMs in the selection of an optimal design from a set of alternative conceptual designs. Considering the fact that the design features that are usually applied as criteria in the decision process are different dimensions and units, researches have introduced the theory of fuzzy membership functions and rough numbers into the MADMs. The introduction of the fuzzy and rough number theories is to cater to the multifarious units and dimensions of the design features and ensure that the decision process is unprejudiced and there is no allocation of a crisp value to weights of the design features of different units and dimensions or performance of the design concepts in the decision matrix [12]. Depending on the nature and objectives of the decision process and the complexity of the design features, the Triangular Fuzzy Number (TFN) and Trapezoidal Fuzzy Number (TrFN) have been applied as membership functions in different MADM models in order to proffer solutions in the decision process of selecting an optimal conceptual design [1].

Further, since the introduction of the Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) in the year 2020 [13], it has gained attention by researchers and its application has been extended to several fields of applications for decision making. Examples of the areas of application include supplier selection [14–18], logistics [19,20], infrastructure and technology assessment [21–30] and management decisions [31]. At inception, it was applied to assess sustainable supplier selection in the medical industry, which is a very important task in the medical firm that must be strategically addressed because of the quality expected from medical supplies. Considering eight suppliers and twenty-one decision criteria, the MARCOS method was able to define the relationship between the suppliers and the reference values in order to obtain the utility functions of the suppliers and rank them in relation to the reference values [13]. Further, the MARCOS method was applied to determine the response of insurance companies in terms of healthcare services to the COVID-19 pandemic considering its ability to consider a large set of alternatives, decision criteria and sub-criteria without compromising on the stability and computational integrity of the decision process [31]. In order to avoid a vague decision process, the intuitionistic fuzzy membership function was introduced to evaluate ten insurance companies considering five expert opinions and seven decision criteria. The decision process was able to identify payback period, premium price and network as the substantial criteria for evaluating healthcare insurance companies.

Also, considering the importance of effective supply chain management to the growth of industries and business and the fact that a sustainable supply chain is essential in running the day-to-day activities of the company, several articles have provided explicit information on the application of the MARCOS method in supplier selection and its integration with other multi-attribute models. An example of this application is the integration of extended VIKOR and MARCOS for sustainable supplier selection in organ transplantation networks for healthcare devices using an interval-valued intuitionistic fuzzy model [32]. Ayşegül and Adali [14] integrated the fuzzy MARCOS model with fuzzy SWARA (Stepwise Weight Assessment Ratio Analysis) in green supply chain management in order to identify the best supplier from alternative suppliers in a textile industry where green and environmentally friendly textile dyes are needed to be supplied in the industries. The implementation of this integrated fuzzy MARCOS with fuzzy SWARA for green supplier selection has also been verified by Tas et al. [33]. The integration of SWARA and MARCOS also finds application in decision making in the logistics field, where a decision was made on inventory classification. The decision process involved the evaluation of fifty products to be stored considering the quantity of the products purchased, their unit price and annual value of purchase [34]. Another important area of application of the MARCOS model is the field of manufacturing. The MARCOS method was applied in the process for powder-mixed electrical discharge machining of cylindrical-shaped parts using a chromium silicon steel tool, and the result obtained was compared with TOPSIS and MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis). The results obtained showed that the three methods selected the same alternative as the optimal alternative from the eighteen alternatives considered in the decision process [35]. Similarly, the MARCOS method was also compared with MAIRCA, TOPSIS and EAMR (Evaluation by an Area-based Method of Ranking) considering the turning process. The cutting speed, feed and depth of cut were the input parameters in the cutting process in order to determine the material removal rate and surface roughness of the workpiece. The results obtained from the application showed that the four models are in conformity, as they identified the same alternative as the optimal process from the sixteen alternatives considered in the decision process [36]. The result was similar to the application and comparison of MARCOS to EDAS (Evaluation based on Distance from Average Solution), TOPSIS, MOORA (Multi-Objective Optimization on the basis of Ratio Analysis) and PIV (Proximity Indexed Value) in the milling decision-making process [37]. Further, the MARCOS method was applied in the grinding, turning and milling processes in order to determine the optimum material removal rate and effective surface finish considering nine trials with different machining parameters [38].

Considering the applications of the MARCOS model in different areas of application, it can be observed that the model finds more application in infrastructure and technology assessment, it is suitable for handling several numbers of alternatives and it also has a consideration for the ideal and anti-ideal scenarios in the formation of the decision matrix. This makes it possible for the model to capture the variations of the alternatives from the ideal and anti-ideal solutions considering the utility degree and functions of all the alternatives in order to confirm the optimal alternative. Also, considering the application areas of the MARCOS model, it is necessary to investigate its suitability to decision making on the identification of optimal design concept considering several conceptual design alternatives. Hence, this article attempts to extend the application of the fuzzy MARCOS model to the identification of an optimal design concept considering four conceptual designs of a briquette making machine. The decision process considered eight design features, with each of the design features having several sub-features. The importance of considering several design features is to ensure that the decision process is robust and all-encompassing in order to ascertain the computational integrity of the fuzzy MARCOS model.

2. Methodology

There is a need to develop a preliminary decision matrix that contains the weights of the design features and the performance weights of the design concepts relative to each design feature in the decision process. The task involved in the development of the preliminary decision matrix can be divided into two. First, the relative contributions of the sub-features to the design features are aggregated considering the opinions of several design experts in order to determine the weights of the design features and sub-features. Second, the availability of the sub-features in the design alternatives are also evaluated by design experts in order to obtain sub-aggregates for the design concepts. The sub-aggregate for the design concepts for each of the design features form the elements of the decision matrix together with the weights of the design features. In order to avoid apportioning of crisp values in the development of the preliminary decision matrix, linguistic terms are used to represent the Triangular Fuzzy Numbers (TFNs).

2.1. TFN and Membership Functions

Considering the multi-dimensional nature and different units of measurements and quantification of the design features and their sub-features, apportioning the crisp number will allow ambiguous and prejudice in the decision process. Hence, a fuzzy number with the triangular membership function is applied by using a linguistic scale to represent the membership functions as presented in Table 1. The linguistic scale was applied for aggregating the relative contributions of the sub-features to the design features and the availability of the sub-features in the design alternatives. For ease of analysis, consider a TFN 'M', of which membership function '$\mu_m(y)$' is contained in [0 1] as defined in Equation (1) [39].

$$\mu_m(y) = \begin{cases} \frac{1}{b-a}y - \frac{a}{b-a} & y \in [a \ \ b] \\ \frac{1}{b-c}y - \frac{c}{b-c} & y \in [b \ \ c] \\ 0 & \text{Otherwise} \end{cases} \tag{1}$$

Table 1. Linguistic terms and membership functions for the decision process.

Relative Contributions of Sub-Features to Design Feature	Relative Availability of Sub-Features in the Design Alternatives	Triangular Fuzzy Numbers and Membership Function
Indeterminate Contribution (**IDC**)	Extremely Poor Availability (**ELA**)	1 1 1
Indeterminate-Moderate Contribution (**IMC**)	Very Low Availability (**VLA**)	$1\ \frac{3}{2}\ 2$
Moderate Contribution (**MDC**)	Low Availability (**LOA**)	$\frac{3}{2}\ 2\ \frac{5}{2}$
Moderate-High Contribution (**MHC**)	Medium Low Availability (**MLA**)	$2\ \frac{5}{2}\ 3$
High Contribution (**HGC**)	Medium Availability (**MEA**)	$\frac{5}{2}\ 3\ \frac{7}{2}$
High-Very High Contribution (**HVC**)	Medium High Availability (**MHA**)	$3\ \frac{7}{2}\ 4$
Very High Contribution (**VHC**)	High Availability (**HGA**)	$\frac{7}{2}\ 4\ \frac{9}{2}$
Very High-Extreme Contribution (**VEC**)	Very High Availability (**VHA**)	$4\ \frac{9}{2}\ 5$
Extreme Contribution (**EXC**)	Extremely High Availability (**EHA**)	$\frac{9}{2}\ 5\ \frac{11}{2}$

In Equation (1), a, b and c represent the lower, modal and upper values of M, respectively, such that $a \leq b \leq c$. The TFN (M) described in Equation (1) can be defuzzified to obtain a crisp value 'M_{crisp}', which is the best non-fuzzy performance value, as presented in Equation (2) [40].

$$M_{crisp} = \frac{a + 4b + c}{6} \tag{2}$$

2.2. Preliminary Decision Matrix

Consider a scenario where there are 'n' number of alternative conceptual designs (C_{dn}) that are to be assessed before commencement of detailed design and prototyping. If the assessment is done with 'm' number of design features, then it is possible to develop a preliminary decision matrix. In order to determine the weights of the design features and their sub-features, the ratings of design experts' decisions are developed in a sub-decision matrix as presented in Equation (3). Also, the availability of sub-features in the design concepts can also be presented in a fuzzified sub-decision matrix using 'k' number of design experts as described in Equation (4). The matrices described in Equations (3) and (4) are developed based on the linguistic scale presented in Table 1. The weights of the design features and sub-features are instrumental in the determination of aggregate TFNs for the design concepts.

$$d_{fm} \quad \begin{array}{ccccccccc} & d_{sf}^{m1} & d_{sf}^{m2} & d_{sf}^{m3} & \cdots & d_{sf}^{mi} & Cu_k^m & \widetilde{W}d_{fm} \\ DE_1 & d\widetilde{E}_1^{m,1} & d\widetilde{E}_1^{m,2} & d\widetilde{E}_1^{m,3} & \cdots & d\widetilde{E}_1^{m,i} & \cdots & \\ DE_2 & d\widetilde{E}_2^{m,1} & d\widetilde{E}_2^{m,2} & d\widetilde{E}_2^{m,3} & \cdots & d\widetilde{E}_2^{m,i} & \cdots & \\ \vdots & \vdots & \vdots & \vdots & & \vdots & & \cdots \\ DE_k & d\widetilde{E}_k^{m,1} & d\widetilde{E}_k^{m,2} & d\widetilde{E}_k^{m,2} & \cdots & d\widetilde{E}_k^{m,i} & \cdots & \\ \widetilde{W}d_{sf}^{m} & \widetilde{W}d_{sf}^{m1} & \widetilde{W}d_{sf}^{m2} & \widetilde{W}d_{sf}^{m3} & \cdots & \widetilde{W}d_{sf}^{mi} & & \end{array} \tag{3}$$

In Equation (3), $d\widetilde{E}_k^{m,i}$ represents the decision of design expert 'k' for the relative contribution of the ith sub-feature (d_{sf}^{mi}) corresponding to design feature m (d_{fm}). Cu_k^m is the cumulative weight of the decisions of the kth design expert, which is obtainable from Equation (5). Also, $\widetilde{W}d_{sf}^{mi}$ and $\widetilde{W}d_{fm}$ are the weights of the ith sub-feature and design feature m, respectively. $\widetilde{W}d_{sf}^{mi}$ and $\widetilde{W}d_{fm}$ can also be obtained from Equations (6) and (7), respectively.

$$\begin{array}{cccccccccccccc} & & & Cd_1 & & & Cd_2 & & \cdots & & Cd_n & \\ d_{fm} & d_{sf} & DE_1 & \rightarrow & DE_k & DE_1 & \rightarrow & DE_k & \cdots & DE_1 & \rightarrow & DE_k \\ & \widetilde{W}d_{sf}^{m1} & d\widetilde{E}_1^1\Big|_m^1 & \cdots & d\widetilde{E}_1^1\Big|_m^k & d\widetilde{E}_2^1\Big|_m^1 & \cdots & d\widetilde{E}_2^1\Big|_m^k & \cdots & d\widetilde{E}_n^1\Big|_m^1 & \cdots & d\widetilde{E}_n^1\Big|_m^k \\ & \widetilde{W}d_{sf}^{m2} & d\widetilde{E}_1^2\Big|_m^1 & \cdots & d\widetilde{E}_1^2\Big|_m^k & d\widetilde{E}_2^2\Big|_m^1 & \cdots & d\widetilde{E}_2^2\Big|_m^k & \cdots & d\widetilde{E}_n^2\Big|_m^1 & \cdots & d\widetilde{E}_n^2\Big|_m^k \\ \widetilde{W}d_{fm} & \widetilde{W}d_{sf}^{m3} & d\widetilde{E}_1^3\Big|_m^1 & & d\widetilde{E}_1^2\Big|_m^k & d\widetilde{E}_2^3\Big|_m^1 & & d\widetilde{E}_2^3\Big|_m^k & & d\widetilde{E}_n^3\Big|_m^1 & & d\widetilde{E}_n^3\Big|_m^k \\ & \vdots & \vdots & & \vdots & \vdots & & \vdots & & \vdots & & \vdots \\ & \widetilde{W}d_{sf}^{mi} & d\widetilde{E}_1^i\Big|_m^1 & \cdots & d\widetilde{E}_1^i\Big|_m^k & d\widetilde{E}_2^i\Big|_m^1 & \cdots & d\widetilde{E}_2^i\Big|_m^k & \cdots & d\widetilde{E}_n^i\Big|_m^1 & \cdots & d\widetilde{E}_n^i\Big|_m^k \\ & \left[\widetilde{A}_{gg}\right]_n^k & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots \\ & \left[\widetilde{A}\right]_n^m & & \cdots & & & \cdots & & & & \cdots & \end{array} \tag{4}$$

$$Cu_k^m = \sum_{i=1}^{i=i}\left[d\widetilde{E}_k^{m,i}\right]\Bigg|_{\forall\, k=1,\,2\,.....\,k}^{\forall\, m=1,\,2,\,3\,.....\,m} \tag{5}$$

$$\widetilde{W}d_{sf}^{mi} = \frac{\sum\limits_{k=1}^{k=k}\left[d\widetilde{E}_k^{m,i}\right]}{\sum k}\Bigg|_{\forall\, i=1,\,2,\,3\,.....\,i}^{\forall\, m=1,\,2,\,3\,.....\,m} \tag{6}$$

$$\widetilde{W}d_{fm} = \frac{\sum\limits_{k=1}^{k=k} Cu_k^m}{\sum k} = \sum_{i=1}^{i=i}\left[\frac{\sum\limits_{k=1}^{k=k}\left[d\widetilde{E}_k^{m,i}\right]}{\sum k}\right]\Bigg|\forall\, m = 1,\,2,\,3\ldots..\,m \tag{7}$$

In Equation (4), $d\widetilde{E}_n^i\Big|_m^k$ is the decision of design expert 'k' on the availability of sub-feature 'i' in design concept 'n' corresponding to design feature 'm'. Also, $\left[\widetilde{A}_{gg}\right]_n^k$ denotes the aggregate TFN for the nth design concept corresponding to the decision of the kth design expert, and $\left[\widetilde{A}\right]_n^m$ is the overall TFN for the nth design concept considering design feature 'm'. $\left[\widetilde{A}_{gg}\right]_n^k$ and $\left[\widetilde{A}\right]_n^m$ can be obtained from Equations (8) and (9), respectively.

$$\left[\widetilde{A}_{gg}\right]_n^k = \frac{\sum_{i=1}^{i=i}\left[\widetilde{W}d_{sf}^{mi} * d\widetilde{E}_n^i\Big|_m^k\right]}{\sum i}\Bigg|_{\forall\, n=1,\,2,\,3\,.....\,n}^{\forall\, k=1,\,2\,.....\,k} \tag{8}$$

$$\left[\widetilde{A}\right]_n^m = \frac{\sum_{i=1}^{i=i}\left[\widetilde{W}d_{sf}^{mi} * d\widetilde{E}_n^i\Big|_m^k\right]}{\sum i \sum k}\Bigg|_{\forall\, n=1,\,2,\,3\,.....\,n}^{\forall\, m=1,\,2,\,3\,.....\,k} \tag{9}$$

The weight of the design features and the overall TFN obtained from Equation (9) for all the design concepts corresponding to the design features will be harnessed to develop a decision matrix as presented in Equation (10). This matrix will be used for decision making in the fuzzy MARCOS process.

$$\begin{array}{c|ccccc} & \widetilde{W}d_{f1} & \widetilde{W}d_{f2} & \widetilde{W}d_{f3} & \cdots & \widetilde{W}d_{fm} \\ Cd_1 & \left[\widetilde{A}\right]_1^1 & \left[\widetilde{A}\right]_1^2 & \left[\widetilde{A}\right]_1^3 & \cdots & \left[\widetilde{A}\right]_1^m \\ Cd_2 & \left[\widetilde{A}\right]_2^1 & \left[\widetilde{A}\right]_2^2 & \left[\widetilde{A}\right]_2^3 & \cdots & \left[\widetilde{A}\right]_2^m \\ Cd_3 & \left[\widetilde{A}\right]_3^1 & \left[\widetilde{A}\right]_3^2 & \left[\widetilde{A}\right]_3^3 & \cdots & \left[\widetilde{A}\right]_3^m \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ Cd_n & \left[\widetilde{A}\right]_n^1 & \left[\widetilde{A}\right]_n^2 & \left[\widetilde{A}\right]_n^3 & \cdots & \left[\widetilde{A}\right]_n^m \end{array} \tag{10}$$

2.3. Fuzzy MARCOS

In order to implement the fuzzy MARCOS model, the first step is to create an extended fuzzy matrix containing the best (Cd^b) and worst (Cd^w) design concepts based on the beneficial (B_{df}) and cost (C_{df}) categories of design features. The best and worst design concepts created in this case will represent the ideal and anti-ideal design concepts, respectively. The best and worst design concepts can be obtained from Equations (11) and (12), respectively. The matrix containing the best and worst design concepts can be obtained by rewriting Equation (10) as presented in Equation (13).

$$Cd^b = \begin{cases} \underset{n}{Min}\left[\widetilde{A}\right]_n^m \;\forall\, m \in B_{df} \\ \\ \underset{n}{Max}\left[\widetilde{A}\right]_n^m \;\forall\, m \in C_{df} \end{cases} \tag{11}$$

$$Cd^w = \begin{cases} \underset{n}{Max}\left[\widetilde{A}\right]_n^m \;\forall\, m \in B_{df} \\ \\ \underset{n}{Min}\left[\widetilde{A}\right]_n^m \;\forall\, m \in C_{df} \end{cases} \tag{12}$$

$$
\begin{array}{lccccccc}
 & & \widetilde{W}d_{f1} & \widetilde{W}d_{f2} & \widetilde{W}d_{f3} & \cdots & \widetilde{W}d_{fm} \\
\text{Best Design} & Cd^{b} & \left[\widetilde{A}\right]_{b}^{1} & \left[\widetilde{A}\right]_{b}^{2} & \left[\widetilde{A}\right]_{b}^{3} & \cdots & \left[\widetilde{A}\right]_{b}^{m} \\
 & Cd_{1} & \left[\widetilde{A}\right]_{1}^{1} & \left[\widetilde{A}\right]_{1}^{2} & \left[\widetilde{A}\right]_{1}^{3} & \cdots & \left[\widetilde{A}\right]_{1}^{m} \\
 & Cd_{2} & \left[\widetilde{A}\right]_{2}^{1} & \left[\widetilde{A}\right]_{2}^{2} & \left[\widetilde{A}\right]_{2}^{3} & & \left[\widetilde{A}\right]_{2}^{m} \\
 & Cd_{3} & \left[\widetilde{A}\right]_{3}^{1} & \left[\widetilde{A}\right]_{3}^{2} & \left[\widetilde{A}\right]_{3}^{3} & & \left[\widetilde{A}\right]_{3}^{m} \\
 & \vdots & \vdots & \vdots & \vdots & & \vdots \\
 & Cd_{n} & \left[\widetilde{A}\right]_{n}^{1} & \left[\widetilde{A}\right]_{n}^{2} & \left[\widetilde{A}\right]_{n}^{3} & & \left[\widetilde{A}\right]_{n}^{m} \\
\text{Worst Design} & Cd^{w} & \left[\widetilde{A}\right]_{w}^{1} & \left[\widetilde{A}\right]_{w}^{2} & \left[\widetilde{A}\right]_{w}^{3} & \cdots & \left[\widetilde{A}\right]_{w}^{m}
\end{array} \tag{13}
$$

Further, the elements of the extended fuzzy decision matrix in Equation (13) can be normalized using Equation (14) for the beneficial (B_{df}) and cost (C_{df}) features considering the notations for the lower, modal and upper values of the TFN defined in Equation (1).

$$
\left[\widetilde{A}\right]_{w}^{m}\Big|_{N} = [a\ b\ c]_{w}^{m}\Big|_{N} = \begin{cases} \dfrac{[\widetilde{A}]_{w}^{m}\big|^{a}}{[\widetilde{A}]_{n}^{m}\big|^{c}}\ \dfrac{[\widetilde{A}]_{w}^{m}\big|^{a}}{[\widetilde{A}]_{n}^{m}\big|^{b}}\ \dfrac{[\widetilde{A}]_{w}^{m}\big|^{a}}{[\widetilde{A}]_{n}^{m}\big|^{a}} & \forall m \in C_{df} \\ \\ \dfrac{[\widetilde{A}]_{n}^{m}\big|^{a}}{[\widetilde{A}]_{w}^{m}\big|^{c}}\ \dfrac{[\widetilde{A}]_{n}^{m}\big|^{b}}{[\widetilde{A}]_{w}^{m}\big|^{c}}\ \dfrac{[\widetilde{A}]_{n}^{m}\big|^{c}}{[\widetilde{A}]_{w}^{m}\big|^{c}} & \forall m \in B_{df} \end{cases} \tag{14}
$$

In Equation (14), $\left[\widetilde{A}\right]_{n}^{m}\Big|^{a} \left[\widetilde{A}\right]_{n}^{m}\Big|^{b} \left[\widetilde{A}\right]_{n}^{m}\Big|^{c}$ represents the lower, modal and upper values of the elements of the extended fuzzy decision matrix while $\left[\widetilde{A}\right]_{w}^{m}\Big|^{a} \left[\widetilde{A}\right]_{w}^{m}\Big|^{b} \left[\widetilde{A}\right]_{w}^{m}\Big|^{c}$ represents the lower, modal and upper values of the elements of the worst design. The next step is to compute the weighted normalized fuzzy decision matrix $[\widetilde{v}]_{n}^{m}$ as presented in Equation (15). This is obtainable by multiplying the weights of the design features with the normalized elements of the decision matrix. Hence, the weighted and normalized version of Equation (13) can be expressed in Equation (16).

$$
[\widetilde{v}]_{n}^{m} = \left[\widetilde{A}\right]_{n}^{m}\Big|_{N} * \widetilde{W}d_{fm} \tag{15}
$$

$$
\begin{array}{lcccccc}
\text{Best Design} & Cd^{b} & \left[\widetilde{A}\right]_{b}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{b}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{b}^{3}\Big|_{N} * \widetilde{W}d_{f3} & \cdots & \left[\widetilde{A}\right]_{b}^{m}\Big|_{N} * \widetilde{W}d_{fm} \\
 & Cd_{1} & \left[\widetilde{A}\right]_{1}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{1}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{1}^{3}\Big|_{N} * \widetilde{W}d_{f3} & \cdots & \left[\widetilde{A}\right]_{1}^{m}\Big|_{N} * \widetilde{W}d_{fm} \\
 & Cd_{2} & \left[\widetilde{A}\right]_{2}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{2}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{2}^{3}\Big|_{N} * \widetilde{W}d_{f3} & & \left[\widetilde{A}\right]_{2}^{m}\Big|_{N} * \widetilde{W}d_{fm} \\
 & Cd_{3} & \left[\widetilde{A}\right]_{3}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{3}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{3}^{3}\Big|_{N} * \widetilde{W}d_{f3} & & \left[\widetilde{A}\right]_{3}^{m}\Big|_{N} * \widetilde{W}d_{fm} \\
 & \vdots & \vdots & \vdots & \vdots & & \vdots \\
 & Cd_{n} & \left[\widetilde{A}\right]_{n}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{n}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{n}^{3}\Big|_{N} * \widetilde{W}d_{f3} & & \left[\widetilde{A}\right]_{n}^{m}\Big|_{N} * \widetilde{W}d_{fm} \\
\text{Worst Design} & Cd^{w} & \left[\widetilde{A}\right]_{w}^{1}\Big|_{N} * \widetilde{W}d_{f1} & \left[\widetilde{A}\right]_{w}^{2}\Big|_{N} * \widetilde{W}d_{f2} & \left[\widetilde{A}\right]_{w}^{3}\Big|_{N} * \widetilde{W}d_{f3} & \cdots & \left[\widetilde{A}\right]_{w}^{m}\Big|_{N} * \widetilde{W}d_{fm}
\end{array} \tag{16}
$$

The cumulative fuzzy matrix ($\widetilde{C}_I$) can be obtained by summing the elements of the weighted matrix. This is obtainable from Equation (17). The cumulative fuzzy matrix is necessary for estimating the utility degree of the design alternatives $\left[\widetilde{U}_d^I\right]_n$. The utility degree of the design alternatives is a function of the cumulative matrices of the best and worst design. Hence, the utility degree can be expressed in terms of best $\left[\widetilde{U}_d^I\right]_n^+$ and worst $\left[\widetilde{U}_d^I\right]_n^-$ design scenarios as presented in Equations (18) and (19), respectively. The next step is to compute the fuzzy utility matrix $\left[\widetilde{T}\right]_n$. The fuzzy utility matrix is a summation of the utility degrees for the best and worst scenario of the design concepts as presented in Equation (20). Further, the fuzzy utility matrix is necessary for determining a new fuzzy number $\left[\widetilde{T}\right]_n^{new}$, which is the maximum of the utility matrix as presented in Equation (21). This new fuzzy number will be defuzzified using Equation (2) in order to compute the utility functions in relation to the best $F\left[\widetilde{U}_d^I\right]_n^+$ and worst $F\left[\widetilde{U}_d^I\right]_n^-$ design alternatives as presented in Equations (22) and (23), respectively. The next step is to defuzzify the TFNs for the best and worst utility degree scenarios and the best and worst utility functions. This is necessary for the determination of a crisp value for the overall utility function for the design concepts, as presented in Equation (24).

$$\widetilde{C}_I = \sum_{m=1}^{m=m} [\widetilde{v}]_n^m \tag{17}$$

$$\left[\widetilde{U}_d^I\right]_n^+ = \frac{\widetilde{C}_I}{\widetilde{C}_I^b} \tag{18}$$

$$\left[\widetilde{U}_d^I\right]_n^- = \frac{\widetilde{C}_I}{\widetilde{C}_I^w} \tag{19}$$

In Equations (18) and (19), $\widetilde{C}_I^b$ and $\widetilde{C}_I^w$ are the cumulative fuzzy matrix for the best and worst designs, respectively.

$$\left[\widetilde{T}\right]_n = \left[\widetilde{U}_d^I\right]_n^+ \oplus \left[\widetilde{U}_d^I\right]_n^- \tag{20}$$

$$\left[\widetilde{T}\right]_n^{new} = \underset{n}{Max}\left[\widetilde{T}\right]_n \tag{21}$$

$$F\left[\widetilde{U}_d^I\right]_n^+ = \frac{\left[\widetilde{U}_d^I\right]_n^+}{\left.\left[\widetilde{T}\right]_n^{new}\right|_{crisp}} \tag{22}$$

$$F\left[\widetilde{U}_d^I\right]_n^- = \frac{\left[\widetilde{U}_d^I\right]_n^-}{\left.\left[\widetilde{T}\right]_n^{new}\right|_{crisp}} \tag{23}$$

$$F\left[U_d^I\right]_n = \frac{\left[U_d^I\right]_n^+ + \left[U_d^I\right]_n^-}{1 + \frac{1-F\left[U_d^I\right]_n^+}{F\left[U_d^I\right]_n^+} + \frac{1-F\left[U_d^I\right]_n^-}{F\left[U_d^I\right]_n^-}} \tag{24}$$

In Equation (24), $\left[U_d^I\right]_n^+$, $\left[U_d^I\right]_n^-$, $F\left[U_d^I\right]_n^+$ and $F\left[U_d^I\right]_n^-$ represent the crisp values for $\left[\widetilde{U}_d^I\right]_n^+$, $\left[\widetilde{U}_d^I\right]_n^-$, $F\left[\widetilde{U}_d^I\right]_n^+$ and $F\left[\widetilde{U}_d^I\right]_n^-$, respectively. The design concepts are ranked according to the values of the overall utility functions such that the design with the highest value is the optimal design.

3. Implementation

In order to investigate the suitability of the methodology, it is necessary to implement its application in the conceptual design of a product. In this article, four conceptual designs of a briquette making machine are considered for evaluation using the design for X features. A framework for application of the methodology to conceptual designs of briquetting making machines is presented in Figure 1. It is worthwhile to know that all the sub-features allotted to the design for X features are performance indicators for effective operation of the briquette making machine. For simplification of analysis, a framework for application of the fuzzy MARCOS is presented in Figure 2. Firstly, sub-matrices for aggregating the relative contributions of the sub-features to the design features are developed as presented in Tables A1–A8 in Appendix A following Equation (3) and using the linguistic terms presented in Table 1. Also, sub-matrices for aggregating the relative availability of the sub-features in the design concepts are developed as presented in Tables A9–A16 in Appendix A using the weights obtained for the sub-features.

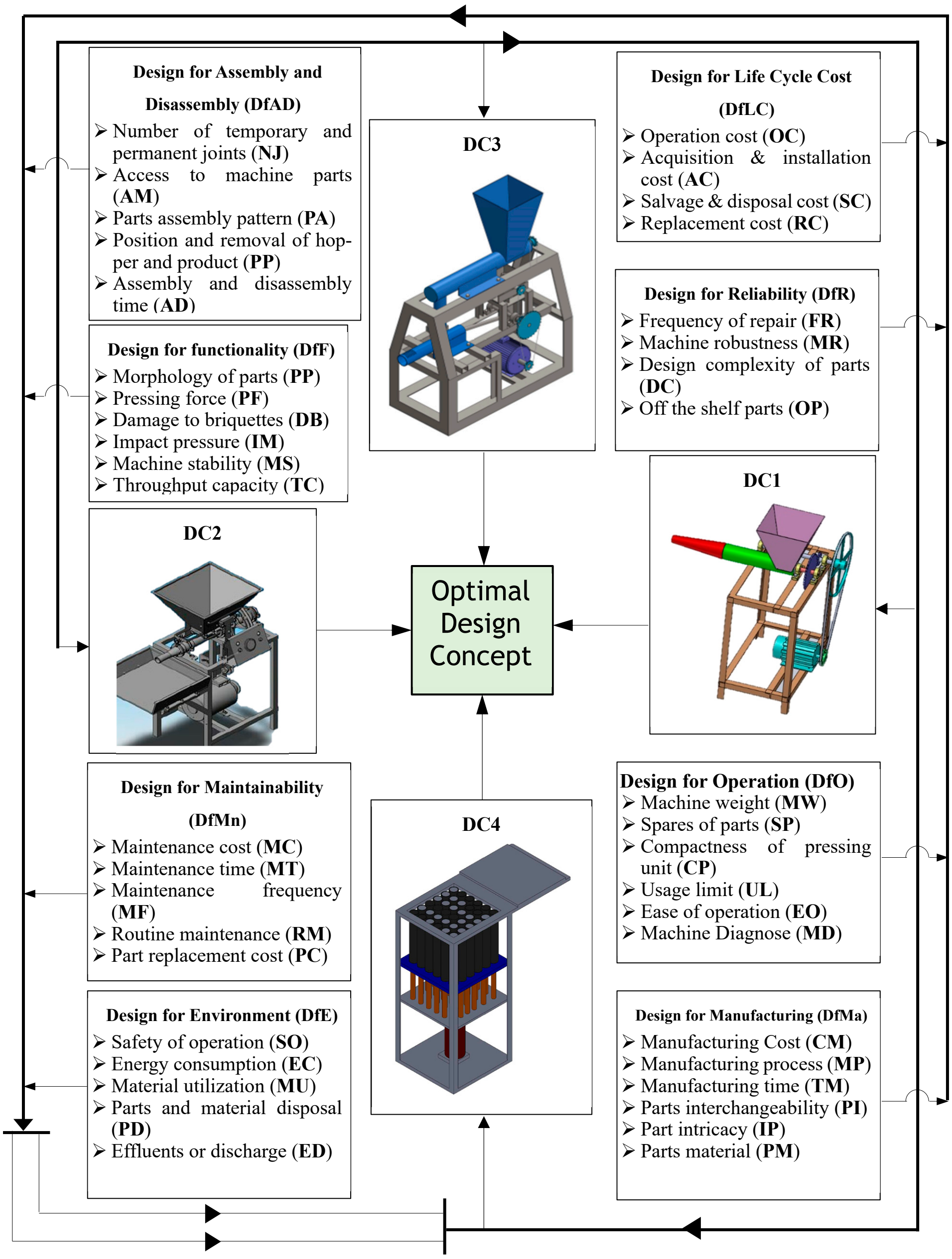

Figure 1. Application to preliminary conceptual designs of briquette making machines.

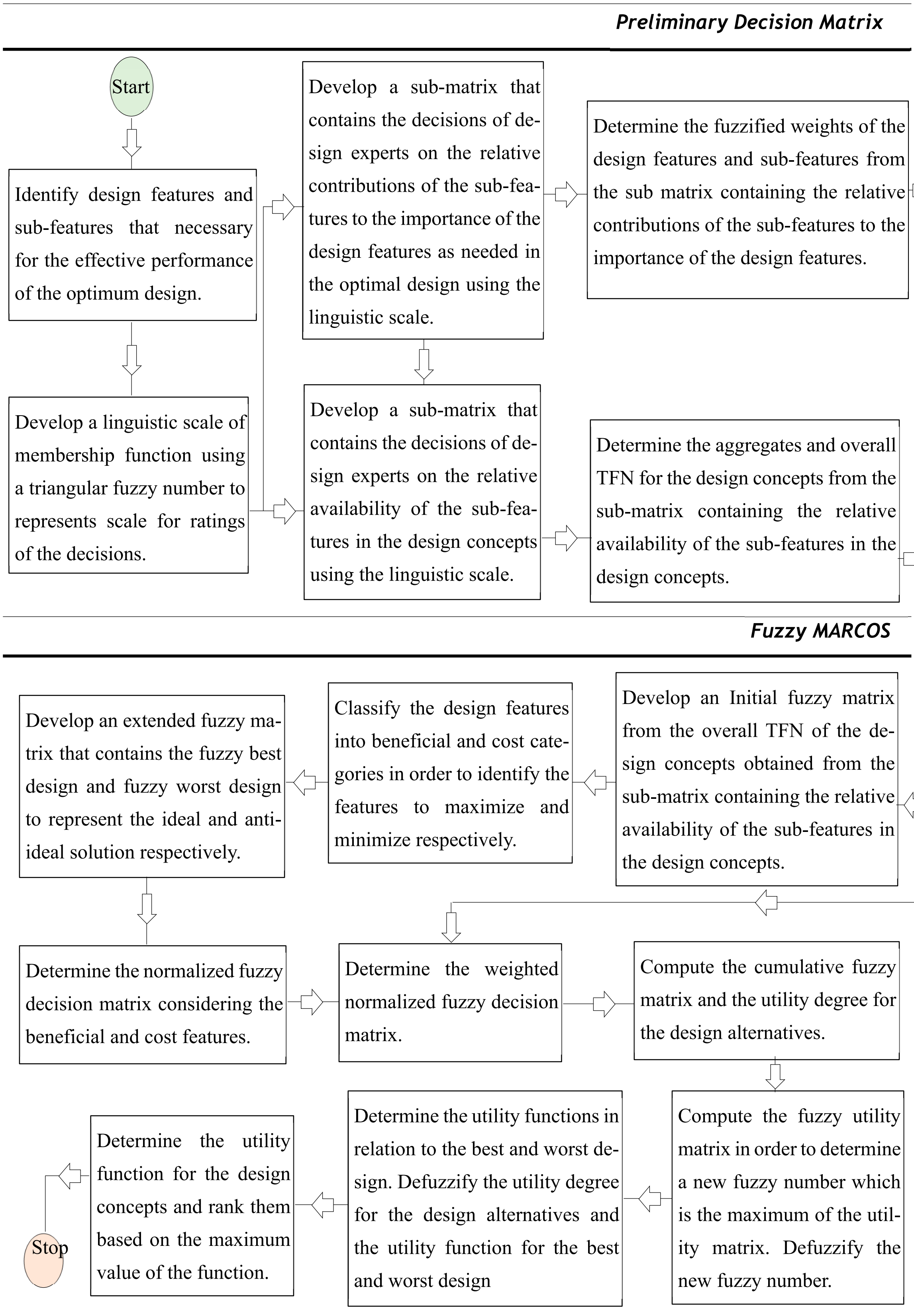

Figure 2. Framework for the application of fuzzy MARCOS.

4. Results and Discussion

4.1. Results

The aggregate TFNs for the design concepts in Tables A9–A16 are harnessed alongside the weights of the design features obtained from Tables A1–A8 in order to arrive at a preliminary decision matrix as presented in Table 2. It is necessary to normalize the elements of the decision matrix in order to consider the beneficial and cost features. the normalized decision matrix is presented in Table 3. The cumulative matrix, utility degree in relation to the best and worst designs, utility matrix and utility functions in relation to the best and worst designs can be obtained from Equations (17)–(23) considering the weighted normalized decision matrix in Table 4. Table 5 shows the computations of the cumulative matrix, utility degree in relation to the best and worst designs, utility matrix and utility functions in relation to the best and worst designs. In order to obtain the utility functions for the design alternatives considering Equation (24), the utility function and utility degree in relation to best and worst designs are defuzzified using Equation (2) as presented in Table 6. The design concepts are ranked according to the values of their utility functions.

Table 2. Fuzzified decision matrix with the best and worst designs and weight of design features.

Design Features (DF)	Best Design	Design Concepts				Worst Design
		DC1	DC2	DC3	DC4	
DfAD $16\frac{2}{3}\ 19\frac{1}{6}\ 21\frac{2}{3}$	$12\frac{19}{20}\ 16\frac{49}{60}\ 21\frac{11}{60}$	$9\frac{1}{36}\ 12\frac{5}{17}\ 16\frac{3}{49}$	$10\frac{51}{67}\ 14\frac{14}{45}\ 18\frac{13}{36}$	$12\frac{19}{20}\ 16\frac{49}{60}\ 21\frac{11}{60}$	$8\frac{17}{30}\ 11\frac{23}{30}\ 15\frac{7}{15}$	$8\frac{17}{30}\ 11\frac{23}{30}\ 15\frac{7}{15}$
DfO 19 22 25	$11\frac{3}{10}\ 14\frac{25}{27}\ 19\frac{3}{59}$	$7\frac{16}{27}\ 10\frac{26}{41}\ 14\frac{16}{91}$	$10\frac{16}{91}\ 13\frac{18}{29}\ 17\frac{48}{85}$	$11\frac{3}{10}\ 14\frac{25}{27}\ 19\frac{3}{59}$	$8\frac{62}{65}\ 12\frac{11}{54}\ 15\frac{41}{43}$	$7\frac{16}{27}\ 10\frac{26}{41}\ 14\frac{16}{91}$
DfE 15 $17\frac{1}{2}$ 20	$9\frac{35}{36}\ 13\frac{16}{45}\ 17\frac{16}{67}$	$9\frac{35}{36}\ 13\frac{16}{45}\ 17\frac{16}{67}$	$8\frac{34}{45}\ 11\frac{43}{45}\ 15\frac{59}{90}$	$8\frac{38}{45}\ 12\frac{3}{49}\ 15\frac{7}{9}$	$9\frac{17}{90}\ 12\frac{41}{90}\ 16\frac{2}{9}$	$8\frac{34}{45}\ 11\frac{43}{45}\ 15\frac{59}{90}$
DfR $10\frac{1}{2}\ 12\frac{1}{2}\ 14\frac{1}{2}$	$9\frac{5}{6}\ 13\frac{13}{48}\ 17\frac{5}{24}$	$7\frac{31}{36}\ 10\frac{12}{13}\ 14\frac{35}{72}$	$8\frac{35}{36}\ 12\frac{9}{37}\ 16\frac{1}{72}$	$7\frac{5}{6}\ 10\frac{43}{48}\ 14\frac{11}{24}$	$9\frac{5}{6}\ 13\frac{13}{48}\ 17\frac{5}{24}$	$7\frac{5}{6}\ 10\frac{43}{48}\ 14\frac{11}{24}$
DfLc 11 13 15	$8\frac{9}{37}\ 11\frac{25}{72}\ 14\frac{39}{41}$	$8\frac{61}{72}\ 12\frac{1}{18}\ 15\frac{55}{72}$	$8\frac{9}{37}\ 11\frac{25}{72}\ 14\frac{39}{41}$	$8\frac{9}{16}\ 11\frac{3}{4}\ 15\frac{7}{16}$	$8\frac{14}{31}\ 11\frac{23}{36}\ 15\frac{16}{49}$	$8\frac{61}{72}\ 12\frac{1}{18}\ 15\frac{55}{72}$
DfFu $19\frac{5}{6}\ 22\frac{5}{6}\ 25\frac{5}{6}$	$12\frac{10}{83}\ 15\frac{6}{7}\ 20\frac{5}{54}$	$10\frac{1}{2}\ 14\ 17\frac{42}{43}$	$11\frac{13}{36}\ 14\frac{71}{72}\ 19\frac{1}{9}$	$12\frac{10}{83}\ 15\frac{6}{7}\ 20\frac{5}{54}$	$10\frac{26}{53}\ 13\frac{42}{43}\ 17\frac{26}{27}$	$10\frac{26}{53}\ 13\frac{42}{43}\ 17\frac{26}{27}$
DfMa $18\frac{1}{6}\ 21\frac{1}{6}\ 24\frac{1}{6}$	$8\frac{42}{43}\ 12\frac{13}{54}\ 16$	$10\frac{7}{72}\ 13\frac{19}{36}\ 17\frac{11}{24}$	$8\frac{42}{43}\ 12\frac{13}{54}\ 16$	$9\frac{24}{73}\ 12\frac{26}{41}\ 16\frac{11}{25}$	$9\frac{58}{67}\ 13\frac{14}{55}\ 17\frac{1}{7}$	$10\frac{7}{72}\ 13\frac{19}{36}\ 17\frac{11}{24}$
DfMn $15\frac{1}{6}\ 17\frac{2}{3}\ 20\frac{1}{6}$	$10\frac{13}{30}\ 13\frac{9}{10}\ 17\frac{13}{15}$	$9\frac{19}{30}\ 12\frac{59}{60}\ 16\frac{5}{6}$	$10\frac{1}{18}\ 13\frac{41}{90}\ 17\frac{16}{45}$	$10\frac{13}{30}\ 13\frac{9}{10}\ 17\frac{13}{15}$	$9\frac{7}{20}\ 12\frac{2}{3}\ 16\frac{29}{60}$	$9\frac{7}{20}\ 12\frac{2}{3}\ 16\frac{29}{60}$

Table 3. Normalized fuzzy decision matrix with the best and worst designs and weight of design features.

Design Features (DF)	Best Design	Design Concepts				Worst Design
		DC1	DC2	DC3	DC4	
DfAD $16\frac{2}{3}\ 19\frac{1}{6}\ 21\frac{2}{3}$	$\frac{11}{18}\ \frac{27}{34}\ 1$	$\frac{26}{61}\ \frac{18}{31}\ \frac{61}{91}$	$\frac{31}{61}\ \frac{25}{37}\ \frac{13}{15}$	$\frac{11}{18}\ \frac{27}{34}\ 1$	$\frac{36}{89}\ \frac{5}{9}\ \frac{46}{63}$	$\frac{36}{89}\ \frac{5}{9}\ \frac{46}{63}$
DfO 19 22 25	$\frac{35}{59}\ \frac{76}{97}\ 1$	$\frac{2}{5}\ \frac{24}{43}\ \frac{32}{43}$	$\frac{47}{88}\ \frac{5}{7}\ \frac{71}{77}$	$\frac{35}{59}\ \frac{76}{97}\ 1$	$\frac{39}{83}\ \frac{41}{64}\ \frac{67}{80}$	$\frac{2}{5}\ \frac{24}{43}\ \frac{32}{43}$
DfE 15 $17\frac{1}{2}$ 20	$\frac{11}{19}\ \frac{55}{71}\ 1$	$\frac{11}{19}\ \frac{55}{71}\ 1$	$\frac{32}{63}\ \frac{43}{62}\ \frac{89}{98}$	$\frac{39}{76}\ \frac{7}{10}\ \frac{54}{59}$	$\frac{8}{15}\ \frac{13}{18}\ \frac{16}{17}$	$\frac{32}{63}\ \frac{43}{62}\ \frac{89}{98}$
DfR $10\frac{1}{2}\ 12\frac{1}{2}\ 14\frac{1}{2}$	$\frac{4}{7}\ \frac{27}{35}\ 1$	$\frac{37}{81}\ \frac{40}{63}\ \frac{16}{19}$	$\frac{12}{23}\ \frac{37}{52}\ \frac{67}{72}$	$\frac{5}{11}\ \frac{19}{30}\ \frac{21}{25}$	$\frac{4}{7}\ \frac{27}{35}\ 1$	$\frac{5}{11}\ \frac{19}{30}\ \frac{21}{25}$
DfLc 11 13 15	$\frac{43}{78}\ \frac{8}{11}\ 1$	$\frac{23}{44}\ \frac{13}{19}\ \frac{41}{44}$	$\frac{43}{78}\ \frac{8}{11}\ 1$	$\frac{8}{15}\ \frac{47}{67}\ \frac{26}{27}$	$\frac{7}{13}\ \frac{17}{24}\ \frac{79}{81}$	$\frac{23}{44}\ \frac{13}{19}\ \frac{41}{44}$
DfFu $19\frac{5}{6}\ 22\frac{5}{6}\ 25\frac{5}{6}$	$\frac{38}{63}\ \frac{15}{19}\ 1$	$\frac{23}{44}\ \frac{39}{56}\ \frac{17}{19}$	$\frac{13}{23}\ \frac{44}{59}\ \frac{39}{41}$	$\frac{38}{63}\ \frac{15}{19}\ 1$	$\frac{12}{23}\ \frac{16}{23}\ \frac{59}{66}$	$\frac{12}{23}\ \frac{16}{23}\ \frac{59}{66}$
DfMa $18\frac{1}{6}\ 21\frac{1}{6}\ 24\frac{1}{6}$	$\frac{23}{41}\ \frac{11}{15}\ 1$	$\frac{18}{35}\ \frac{2}{3}\ \frac{8}{9}$	$\frac{23}{41}\ \frac{11}{15}\ 1$	$\frac{6}{11}\ \frac{27}{38}\ \frac{51}{53}$	$\frac{11}{21}\ \frac{21}{31}\ \frac{10}{11}$	$\frac{18}{35}\ \frac{2}{3}\ \frac{8}{9}$
DfMn $15\frac{1}{6}\ 17\frac{2}{3}\ 20\frac{1}{6}$	$\frac{7}{12}\ \frac{7}{9}\ 1$	$\frac{7}{13}\ \frac{8}{11}\ \frac{49}{52}$	$\frac{9}{16}\ \frac{61}{81}\ \frac{34}{35}$	$\frac{7}{12}\ \frac{7}{9}\ 1$	$\frac{45}{86}\ \frac{56}{79}\ \frac{12}{13}$	$\frac{45}{86}\ \frac{56}{79}\ \frac{12}{13}$

Table 4. Weighted normalized fuzzy decision matrix with the best and worst designs.

DF	Best Design	Design Concepts				Worst Design
		DC1	DC2	DC3	DC4	
DfAD	$10\frac{4}{21}\ 15\frac{17}{78}\ 21\frac{2}{3}$	$7\frac{8}{77}\ 11\frac{1}{8}\ 16\frac{3}{7}$	$8\frac{29}{62}\ 12\frac{77}{81}\ 18\frac{18}{23}$	$10\frac{4}{21}\ 15\frac{17}{78}\ 21\frac{2}{3}$	$6\frac{20}{27}\ 10\frac{46}{71}\ 15\frac{60}{73}$	$6\frac{20}{27}\ 10\frac{46}{71}\ 15\frac{60}{73}$
DfO	$11\frac{13}{48}\ 17\frac{22}{93}\ 25$	$7\frac{4}{7}\ 12\frac{23}{82}\ 18\frac{44}{73}$	$10\frac{7}{47}\ 15\frac{43}{59}\ 23\frac{1}{20}$	$11\frac{13}{48}\ 17\frac{22}{93}\ 25$	$8\frac{53}{57}\ 14\frac{4}{43}\ 20\frac{29}{31}$	$7\frac{4}{7}\ 12\frac{23}{82}\ 18\frac{44}{73}$
DfE	$8\frac{65}{96}\ 13\frac{53}{95}\ 20$	$8\frac{65}{96}\ 13\frac{53}{95}\ 20$	$7\frac{47}{76}\ 12\frac{3}{22}\ 18\frac{8}{49}$	$7\frac{16}{23}\ 12\frac{10}{41}\ 18\frac{25}{82}$	$8\ 12\frac{29}{45}\ 18\frac{32}{39}$	$7\frac{47}{76}\ 12\frac{3}{22}\ 18\frac{8}{49}$
DfR	$6\ 9\frac{16}{25}\ 14\frac{1}{2}$	$4\frac{47}{59}\ 7\frac{43}{46}\ 12\frac{20}{97}$	$5\frac{28}{59}\ 8\frac{67}{75}\ 13\frac{38}{77}$	$4\frac{46}{59}\ 7\frac{75}{82}\ 12\frac{17}{93}$	$6\ 9\frac{16}{25}\ 14\frac{1}{2}$	$4\frac{46}{59}\ 7\frac{75}{82}\ 12\frac{17}{93}$
DfLc	$6\frac{2}{31}\ 9\frac{4}{9}\ 15$	$5\frac{3}{4}\ 8\frac{8}{9}\ 13\frac{81}{83}$	$6\frac{2}{31}\ 9\frac{4}{9}\ 15$	$5\frac{83}{95}\ 9\frac{3}{25}\ 14\frac{26}{59}$	$5\frac{11}{12}\ 9\frac{17}{82}\ 14\frac{29}{46}$	$5\frac{3}{4}\ 8\frac{8}{9}\ 13\frac{81}{83}$
DfFu	$11\frac{27}{28}\ 18\frac{1}{52}\ 25\frac{5}{6}$	$10\frac{31}{84}\ 15\frac{9}{10}\ 23\frac{6}{53}$	$11\frac{3}{14}\ 17\frac{1}{33}\ 24\frac{4}{7}$	$11\frac{27}{28}\ 18\frac{1}{52}\ 25\frac{5}{6}$	$10\frac{16}{45}\ 15\frac{53}{60}\ 23\frac{2}{21}$	$10\frac{16}{45}\ 15\frac{53}{60}\ 23\frac{2}{21}$
DfMa	$10\frac{18}{95}\ 15\frac{23}{44}\ 40\frac{1}{6}$	$9\frac{15}{44}\ 14\frac{1}{22}\ 35\frac{22}{31}$	$10\frac{18}{95}\ 15\frac{23}{44}\ 40\frac{1}{6}$	$9\frac{23}{25}\ 15\frac{2}{51}\ 38\frac{28}{43}$	$9\frac{41}{80}\ 14\frac{1}{3}\ 36\frac{29}{53}$	$9\frac{15}{44}\ 14\frac{1}{22}\ 35\frac{22}{31}$
DfMn	$8\frac{6}{7}\ 13\frac{67}{90}\ 20\frac{1}{6}$	$8\frac{11}{62}\ 12\frac{31}{37}\ 19$	$8\frac{15}{28}\ 13\frac{25}{82}\ 19\frac{23}{39}$	$8\frac{6}{7}\ 13\frac{67}{90}\ 20\frac{1}{6}$	$7\frac{15}{16}\ 12\frac{21}{40}\ 18\frac{23}{38}$	$7\frac{15}{16}\ 12\frac{21}{40}\ 18\frac{23}{38}$

Table 5. Cumulative matrix, utility degree and functions for the design concepts.

Cumulative for Best Design	$73\frac{11}{52}\ 112\frac{27}{71}\ 182\frac{1}{3}$			
Cumulative for Worst Design	$60\frac{5}{52}\ 94\frac{9}{28}\ 156\frac{2}{13}$			
	DESIGN CONCEPTS			
	DC1	**DC2**	**DC3**	**DC4**
Cumulative matrix $(\widetilde{C}_I)$	$61\frac{15}{19}\ 96\frac{4}{7}\ 159\frac{2}{53}$	$67\frac{5}{7}\ 105\frac{1}{90}\ 172\frac{67}{82}$	$70\frac{49}{89}\ 108\frac{15}{28}\ 176\frac{1}{4}$	$63\frac{19}{49}\ 98\frac{40}{41}\ 162\frac{22}{23}$
Utility degree in relation to best design $\left[\widetilde{U}_d^I\right]_n^+$	$\frac{33}{95}\ \frac{27}{31}\ 2\frac{18}{91}$	$\frac{8}{21}\ \frac{89}{94}\ 2\frac{38}{85}$	$\frac{23}{58}\ \frac{46}{47}\ 2\frac{27}{62}$	$\frac{31}{87}\ \frac{83}{93}\ 2\frac{1}{4}$
Utility degree in relation to worst design $\left[\widetilde{U}_d^I\right]_n^-$	$\frac{19}{48}\ 1\frac{1}{42}\ 2\frac{53}{82}$	$\frac{36}{83}\ 1\frac{6}{53}\ 2\frac{7}{8}$	$\frac{14}{31}\ 1\frac{11}{73}\ 2\frac{14}{15}$	$\frac{28}{69}\ 1\frac{4}{81}\ 2\frac{37}{52}$
Utility matrix $\left[\widetilde{T}\right]_n$	$\frac{26}{35}\ 1\frac{17}{19}\ 4\frac{65}{77}$	$\frac{57}{70}\ 2\frac{5}{83}\ 5\frac{19}{72}$	$\frac{28}{33}\ 2\frac{11}{85}\ 5\frac{7}{19}$	$\frac{16}{21}\ 1\frac{81}{86}\ 4\frac{53}{55}$
Utility function in relation to best design $F\left[\widetilde{U}_d^I\right]_n^+$	$\frac{5}{31}\ \frac{5}{12}\ 1\frac{1}{13}$	$\frac{3}{17}\ \frac{34}{75}\ 1\frac{13}{76}$	$\frac{16}{87}\ \frac{15}{32}\ 1\frac{7}{36}$	$\frac{1}{6}\ \frac{3}{7}\ 1\frac{5}{48}$
Utility function in relation to worst design $F\left[\widetilde{U}_d^I\right]_n^-$	$\frac{14}{99}\ \frac{11}{31}\ \frac{17}{19}$	$\frac{11}{71}\ \frac{32}{83}\ \frac{71}{73}$	$\frac{5}{31}\ \frac{2}{5}\ 1$	$\frac{9}{62}\ \frac{4}{11}\ \frac{11}{12}$

Table 6. Defuzzified utility degrees and functions and ranking of design concepts.

Design Concepts	Utility Degrees and Functions					Rank
	$[U_d^I]_n^+$	$[U_d^I]_n^-$	$F[U_d^I]_n^+$	$F[U_d^I]_n^-$	$F[U_d^I]_n$	
DC1	1	$1\frac{11}{58}$	$\frac{31}{64}$	$\frac{9}{22}$	$\frac{5}{8}(0.625)$	4
DC2	$1\frac{9}{97}$	$1\frac{5}{7}$	$\frac{49}{93}$	$\frac{4}{9}$	$\frac{22}{29}(0.759)$	2
DC3	$1\frac{1}{8}$	$1\frac{1}{3}$	$\frac{45}{83}$	$\frac{38}{83}$	$\frac{30}{37}(0.811)$	1
DC4	$1\frac{1}{34}$	$1\frac{16}{73}$	$\frac{1}{2}$	$\frac{13}{31}$	$\frac{43}{65}(0.662)$	3

4.2. Discussion

Considering the weighted normalized decision matrix in Table 4, a clear picture of the performance of the design alternatives with respect to the design features can be obtained in the form of TFNs. Also, an interesting aspect of the fuzzy MARCOS method is the determination of the best and worst design by selecting the design with the highest upper membership function of the TFNs in all the design features. This implies that the best design will perform well in all the design features, and the worst design will perform poorly in all the design features. Although, in real life, achieving the best design may seem a little bit difficult because a consideration of all the design features in a design may be difficult to achieve. Hence, there will be a trade-off in the design process such that some design features will not be predominantly available in the design. It is worthwhile to note that such design features are also important, but the decision to prioritize the design features has come to play in order to satisfy the features that are necessary for a robust design. Also, when there is a need to prioritize some design features, the alternatives which have the best performance in all these features can easily be identified. In essence, there is a need to classify the design features into cost and beneficial features. The separation of the design features into cost and beneficial features makes it easy to identify the design concepts that will be cost demanding, particularly before fabrication and commercialization. This will go a long way to inform the manufacturer on the logistics that will be involved in the production of the machine before the completion of the design. In this case, design for manufacturing cost and life cycle cost are considered as the cost features. The design for life cycle cost and manufacturing are the cost features as highlighted in Table 4. Considering the upper membership function of the best design concepts in the weighted normalized fuzzy decision matrix in Table 4, it is clear that concept two has the best manufacturing and life cycle costs, but that does not indicate that it is the optimal design concept. However, if the aim of the decision process is to obtain a design with less cost, then design concept two can serve as a best design. Also, it is also clear that the performances of all the design concepts in terms of the beneficial features can be captured in Table 4. This will also help to achieve the identification of design concepts with other beneficial features. Further, considering the upper membership function of the cumulative matrix for the best and worst designs in Table 5, it is obvious that none of the design concepts is closer to the best and worst designs. This is an interesting aspect of the fuzzy MARCOS model because it gives a relative comparison by providing a clear picture of the design alternatives relative to the best and worst designs. The relative position of the design alternatives to the best and worst designs can be depicted in the form of the TFNs, as presented in Figure 3a. This implies that the fuzzy MARCOS method determines a value for the best and worst designs and also provides the values for the design concepts to be assessed. This method is good because it can create a platform for comparison on the distances of the design concept to the best and worst designs. The MARCOS model further determined the optimal design alternative considering the utility degrees, fuzzy utility functions and overall utility function rather than mere defuzzification and comparison with the best and worst designs. Also, considering the comparison in Figure 3a, the model was able to establish the level of performance of the design alternatives relative to the expected performance of the best and worst designs, but a judgment on the optimal design concept cannot be made because the utility degree, which is a function of how each of the designs performs with respect to the best and worst designs, needs to be determined. Hence, in Figure 3b, the design alternatives were ranked based on their scores in the overall utility function. An observation of the final values of the overall utility function showed that there is a closeness in the final values of the design alternatives. This is an indication that the decision process did not apportion values to the design alternatives but rather compared their performances in all the design features.

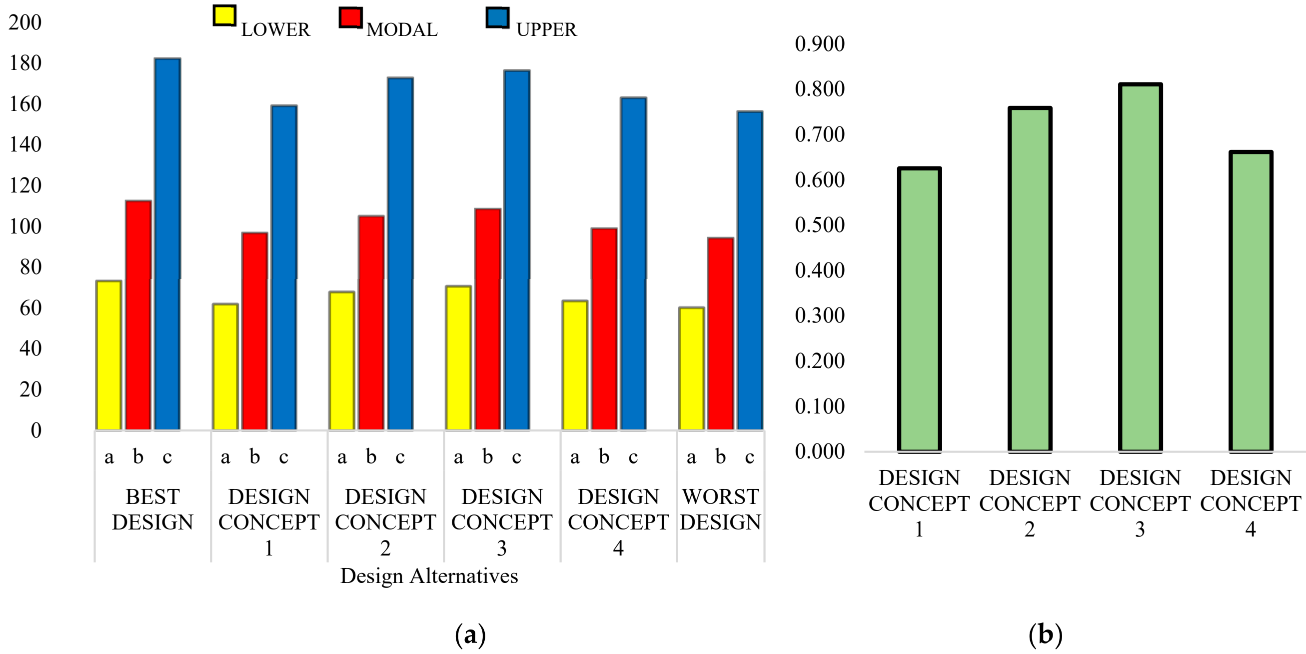

Figure 3. Comparison of design alternatives relative to the best and worst designs and their rankings. (**a**) Comparison of design alternatives. (**b**) Ranking of the design concepts.

5. Results Validation

The results obtained from the implementation of the fuzzy MARCOS on the assessment of the conceptual designs of a briquetting machine is validated via the use of TOPSIS and modified TOPSIS. The TOPSIS method is implemented in order to check for conformity in the results obtained. Considering the weighted normalized fuzzy decision matrix with the best and worst designs in Table 4, it is possible to determine the ideal positive and ideal negative solutions, then the distances to the ideal positive and ideal negative can also be obtained as presented in Table 7. In essence, from Table 7, the ranking of the design concept is also obtained from the closeness coefficient indices, and it can be observed that the TOPSIS method provided the same ranking as the MARCOS method. Further, in order to ascertain the consistency of the MARCOS decision process in terms of the best and worst designs, a modified TOPSIS method is introduced. This method involves the determination of the distances of the design concepts to the best and worst designs. This method is similar to the general TOPSIS method. The only modification is that instead of determining the distances to the positive and negative ideal solution, the distances are determined to the best and worst designs using the vertex method, as described in Equations (25) and (26), respectively.

$$D_n^b = \sqrt{\frac{1}{3}\left((a_n - a_b)^2 + (b_n - b_b)^2 + (c_n - c_b)^2\right)} \tag{25}$$

$$D_n^w = \sqrt{\frac{1}{3}\left((a_n - a_w)^2 + (b_n - b_w)^2 + (c_n - c_w)^2\right)} \tag{26}$$

Table 7. Validation of results by the TOPSIS method.

DF	Ideal Positive Solution	Design Concepts								Ideal Negative Solution
		DC1		DC2		DC3		DC4		
		Distance to Ideal Positive	Distance to Ideal Negative	Distance to Ideal Positive	Distance to Ideal Negative	Distance to Ideal Positive	Distance to Ideal Negative	Distance to Ideal Positive	Distance to Ideal Negative	
DfAD	$21\frac{2}{3}$	$6\frac{1}{7}$	$10\frac{48}{59}$	$7\frac{85}{96}$	$9\frac{2}{7}$	$10\frac{9}{82}$	$7\frac{44}{73}$	$5\frac{29}{41}$	$11\frac{7}{30}$	$6\frac{20}{27}$
DfO	25	$6\frac{61}{66}$	13	$10\frac{17}{81}$	$10\frac{7}{41}$	$11\frac{40}{57}$	$9\frac{7}{66}$	$8\frac{18}{29}$	$11\frac{26}{57}$	$7\frac{4}{7}$
DfE	20	$7\frac{20}{21}$	$7\frac{49}{94}$	$6\frac{48}{77}$	$8\frac{31}{58}$	$6\frac{47}{65}$	$8\frac{5}{11}$	$13\frac{59}{67}$	$8\frac{8}{51}$	$7\frac{47}{76}$
DfR	$14\frac{1}{2}$	$4\frac{27}{41}$	$6\frac{83}{93}$	$5\frac{26}{45}$	$6\frac{11}{68}$	$4\frac{34}{53}$	$6\frac{10}{11}$	$6\frac{27}{86}$	$5\frac{32}{49}$	$4\frac{46}{59}$
DfLc	15	$5\frac{4}{49}$	$6\frac{3}{7}$	$5\frac{3}{4}$	$6\frac{3}{40}$	$5\frac{8}{21}$	$6\frac{13}{47}$	$5\frac{1}{2}$	$6\frac{13}{58}$	$5\frac{83}{95}$
DfFu	$25\frac{5}{6}$	$8\frac{1}{32}$	$10\frac{8}{11}$	$9\frac{3}{37}$	$9\frac{80}{91}$	$10\frac{1}{67}$	$9\frac{4}{21}$	$8\frac{1}{56}$	$10\frac{57}{77}$	$10\frac{31}{84}$
DfMa	$40\frac{1}{6}$	$15\frac{13}{28}$	$23\frac{15}{32}$	$18\frac{3}{19}$	$22\frac{17}{42}$	$17\frac{8}{33}$	$22\frac{59}{82}$	$15\frac{33}{34}$	$23\frac{5}{21}$	$9\frac{15}{44}$
DfMn	$20\frac{1}{6}$	$6\frac{79}{80}$	$8\frac{9}{64}$	$7\frac{27}{65}$	$7\frac{45}{56}$	$7\frac{5}{6}$	$7\frac{28}{55}$	$6\frac{31}{44}$	$8\frac{3}{8}$	$7\frac{15}{16}$
Cumulative Distance		$61\frac{17}{70}$	$86\frac{62}{63}$	$70\frac{26}{37}$	$80\frac{17}{54}$	$73\frac{24}{37}$	$77\frac{10}{13}$	$70\frac{43}{60}$	$85\frac{7}{92}$	
Closeness Coefficient Index (CCI)		$\frac{19}{46}$ (0.413)		$\frac{22}{47}$ (0.468)		$\frac{18}{37}$ (0.486)		$\frac{5}{11}$ (0.454)		
Ranking		4th		2nd		1st		3rd		

In Equations (25) and (26), D_n^b and D_n^w represents the distances to the best and worst designs for n number of design concepts. Also, a_b, b_b, c_b represent the lower, modal and upper TFNs for the best design, while a_w, b_w, c_w represent the lower, modal and upper TFNs for the worst design. Also, a_n, b_n, c_n represent the lower, modal and upper TFNs for the n design concept. Hence, the distances of the design concepts to the best and worst designs are presented in Table 8. Considering Table 8, it is evident that the performance of the design concept in terms of their distances to the best and worst design is depicted in all the design features. Further, the determination of the cumulative distances of the design concepts to the best and worst designs provided the overall performance of the designs before the determination of the closeness coefficient for ranking. The ranking in this case is also in conformity to the MARCOS method, which proves that there is consistency in the MARCOS decision model.

Table 8. Validation of results by modified TOPSIS (distances to best and worst designs).

	Design Concepts							
	DC1		DC2		DC3		DC4	
DF	Distance to Best Design	Distance to Worst Design	Distance to Best Design	Distance to Worst Design	Distance to Best Design	Distance to Worst Design	Distance to Best Design	Distance to Worst Design
DfAD	$4\frac{2}{9}$	$\frac{1}{2}$	$2\frac{1}{3}$	$2\frac{2}{5}$	0	$4\frac{5}{7}$	$4\frac{5}{7}$	0
DfO	$5\frac{1}{7}$	0	$1\frac{4}{7}$	$3\frac{4}{7}$	0	$5\frac{1}{7}$	$3\frac{1}{4}$	$1\frac{7}{8}$
DfE	0	$1\frac{1}{2}$	$1\frac{1}{2}$	0	$1\frac{1}{3}$	$\frac{1}{9}$	1	$\frac{1}{2}$
DfR	$1\frac{4}{5}$	0	$\frac{7}{9}$	1	$1\frac{4}{5}$	0	0	$1\frac{4}{5}$
DfLc	$\frac{2}{3}$	0	0	$\frac{2}{3}$	$\frac{2}{5}$	$\frac{1}{3}$	$\frac{1}{4}$	$\frac{3}{7}$
DfFu	$2\frac{1}{5}$	0	1	$1\frac{1}{5}$	0	$2\frac{1}{5}$	$2\frac{1}{5}$	0
DfMa	$2\frac{3}{4}$	0	0	$2\frac{3}{4}$	1	$1\frac{5}{6}$	$2\frac{1}{4}$	$\frac{1}{2}$
DfMn	1	$\frac{1}{3}$	$\frac{1}{2}$	$\frac{4}{5}$	0	$1\frac{1}{4}$	$1\frac{1}{4}$	0
Cumulative distance to best and worst designs	$17\frac{3}{4}$	$2\frac{1}{3}$	$7\frac{2}{3}$	$12\frac{3}{7}$	$4\frac{1}{2}$	$15\frac{4}{7}$	15	$5\frac{1}{6}$
Closeness Coefficient Index (CCI)	$\frac{1}{9}$(0.116)		$\frac{5}{8}$(0.619)		$\frac{7}{9}$(0.776)		$\frac{1}{4}$(0.254)	
Ranking	4th		2nd		1st		3rd	

6. Conclusions

Conclusively, it is not an overstatement to say that concept selection in the preliminary design phase of a product is very important, and as such, more emphasis and effort needs to be put into the design concept selection in order to have a robust decision process. This is necessary because it provides more information on the design features associated with the optimal design concept. Sometimes, modifications can be made to any of the alternatives or the optimal design in order to accommodate some design features before fabrication commences. Due to the importance that is attached to the concept selection process, this article proposes the adoption of fuzzy MARCOS as a multicriteria decision model as a tool for carrying out the concept selection process. The preliminary decision matrix was developed considering the weights of the design features and sub-features and the availability of the sub-features in each of the design concepts. The essence of considering the availability of the sub-features in the alternative designs is to assists the decision process in obtaining unambiguous values for the performance of the design alternatives in the form of linguistic terms using several experts' opinion. The framework for applying the fuzzy MARCOS model to the selection of the optimal conceptual design was developed based on its application to other subject areas, and the model performed excellently by identifying the optimal design concepts considering its overall utility value relative to the best and worst design. Further work can also be carried out in the aspect of identifying the designs features to be improved on considering the best and worst design concepts identified by the fuzzy MARCOS model.

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Appendix A

Table A1. Contributions of sub-features of design for assembly and disassembly.

Design Experts	Sub-Features of DfAD					Cu_k^m	$\widetilde{W}d_{fm}$
	NJ	AM	PA	PP	AD		
DE1	VEC	VEC	HGC	HGC	EXC	$17\frac{1}{2}$ 20 $22\frac{1}{2}$	$16\frac{2}{3}$ $19\frac{1}{6}$ $21\frac{2}{3}$
DE2	VHC	VEC	VHC	MHC	VHC	$16\frac{1}{2}$ 19 $21\frac{1}{2}$	
DE3	VHC	HVC	HGC	VHC	VHC	16 $18\frac{1}{2}$ 21	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{2}{3}$ $4\frac{1}{6}$ $4\frac{2}{3}$	$3\frac{2}{3}$ $4\frac{1}{6}$ $4\frac{2}{3}$	$2\frac{5}{6}$ $3\frac{1}{3}$ $3\frac{5}{6}$	$2\frac{2}{3}$ $3\frac{1}{6}$ $3\frac{2}{3}$	$3\frac{5}{6}$ $4\frac{1}{3}$ $4\frac{5}{6}$		

Table A2. Contributions of sub-features of design for maintainability.

Design Experts	Sub-Features of DfMn					Cu_k^m	$\widetilde{W}d_{fm}$
	MC	MT	MF	RM	PC		
DE1	EXC	HVC	VHC	HVC	HGC	$16\frac{1}{2}$ 19 $21\frac{1}{2}$	$15\frac{1}{6}$ $17\frac{2}{3}$ $20\frac{1}{6}$
DE2	HGC	MHC	HGC	MHC	VHC	$12\frac{1}{2}$ 15 $17\frac{1}{2}$	
DE3	VEC	VHC	VEC	MHC	HVC	$16\frac{1}{2}$ 19 $21\frac{1}{2}$	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{2}{3}$ $4\frac{1}{6}$ $4\frac{2}{3}$	$2\frac{5}{6}$ $3\frac{1}{3}$ $3\frac{5}{6}$	$3\frac{1}{3}$ $3\frac{5}{6}$ $4\frac{1}{3}$	$2\frac{1}{3}$ $2\frac{5}{6}$ $3\frac{1}{3}$	3 $3\frac{1}{2}$ 4		

Table A3. Contributions of sub-features of design for reliability.

Design Experts	Sub-Features of DfR				Cu_k^m	$\widetilde{W}d_{fm}$
	FR	MR	DC	OP		
DE1	HGC	VHC	MHC	VHC	$11\frac{1}{2}$ $13\frac{1}{2}$ $15\frac{1}{2}$	$10\frac{1}{2}$ $12\frac{1}{2}$ $14\frac{1}{2}$
DE2	VHC	MHC	HVC	MHC	$10\frac{1}{2}$ $12\frac{1}{2}$ $14\frac{1}{2}$	
DE3	HGC	MDC	HVC	HGC	$9\frac{1}{2}$ $11\frac{1}{2}$ $13\frac{1}{2}$	
$\widetilde{W}d_{sf}^{mi}$	$2\frac{5}{6}$ $3\frac{1}{3}$ $3\frac{5}{6}$	$2\frac{1}{3}$ $2\frac{5}{6}$ $3\frac{1}{3}$	$2\frac{2}{3}$ $3\frac{1}{6}$ $3\frac{2}{3}$	$2\frac{2}{3}$ $3\frac{1}{6}$ $3\frac{2}{3}$		

Table A4. Contributions of sub-features of design for life cycle cost.

Design Experts	Sub-Features of DfLC				Cu_k^m	$\widetilde{W}d_{fm}$
	OC	AC	SC	RC		
DE1	VHC	VEC	MDC	VHC	$12\frac{1}{2}$ $14\frac{1}{2}$ $16\frac{1}{2}$	11 13 15
DE2	HGC	HGC	MHC	MDC	$8\frac{1}{2}$ $10\frac{1}{2}$ $12\frac{1}{2}$	
DE3	VHC	HVC	HVC	HGC	12 14 16	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{1}{6}$ $3\frac{2}{3}$ $4\frac{1}{6}$	$3\frac{1}{6}$ $3\frac{2}{3}$ $4\frac{1}{6}$	$2\frac{1}{6}$ $2\frac{2}{3}$ $3\frac{1}{6}$	$2\frac{1}{2}$ 3 $3\frac{1}{2}$		

Table A5. Contributions of sub-features of design for environment.

Design Experts	Sub-Features of DfE					Cu_k^m	$\widetilde{W}d_{fm}$
	SO	EC	MU	PD	ED		
DE1	VHC	VEC	MHC	MDC	VEC	$15\ 17\frac{1}{2}\ 20$	$15\ 17\frac{1}{2}\ 20$
DE2	VEC	HGC	HVC	MHC	HVC	$14\frac{1}{2}\ 17\ 19\frac{1}{2}$	
DE3	HVC	VHC	HVC	VHC	HGC	$15\frac{1}{2}\ 18\ 20\frac{1}{2}$	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{1}{2}\ 4\ 4\frac{1}{2}$	$3\frac{1}{3}\ 3\frac{5}{6}\ 4\frac{1}{3}$	$2\frac{2}{3}\ 3\frac{1}{6}\ 3\frac{2}{3}$	$2\frac{1}{3}\ 2\frac{5}{6}\ 3\frac{1}{3}$	$3\frac{1}{6}\ 3\frac{2}{3}\ 4\frac{1}{6}$		

Table A6. Contributions of sub-features of design for functionality.

Design Experts	Sub-Features of DfF						Cu_k^m	$\widetilde{W}d_{fm}$
	PP	PF	DB	IM	MS	TC		
DE1	MDC	VEC	VEC	VHC	VHC	VEC	$20\frac{1}{2}\ 23\frac{1}{2}\ 26\frac{1}{2}$	$19\frac{5}{6}\ 22\frac{5}{6}\ 25\frac{5}{6}$
DE2	HGC	HVC	HVC	HVC	VHC	EXC	$19\frac{1}{2}\ 22\frac{1}{2}\ 25\frac{1}{2}$	
DE3	MHC	VEC	VHC	HGC	VEC	VHC	$19\frac{1}{2}\ 22\frac{1}{2}\ 25\frac{1}{2}$	
$\widetilde{W}d_{sf}^{mi}$	$2\ 2\frac{1}{2}\ 3$	$3\frac{2}{3}\ 4\frac{1}{6}\ 4\frac{2}{3}$	$3\frac{1}{2}\ 4\ 4\frac{1}{2}$	$3\ 3\frac{1}{2}\ 4$	$3\frac{2}{3}\ 4\frac{1}{6}\ 4\frac{2}{3}$	$4\ 4\frac{1}{2}\ 5$		

Table A7. Contributions of sub-features of design for manufacturing.

Design Experts	Sub-Features of DfMa						Cu_k^m	$\widetilde{W}d_{fm}$
	CM	MP	TM	PI	IP	PM		
DE1	VEC	HGC	HVC	MHC	MDC	VEC	$17\ 20\ 23$	$18\frac{1}{6}\ 21\frac{1}{6}\ 24\frac{1}{6}$
DE2	HVC	VHC	VEC	HGC	HVC	EXC	$20\frac{1}{2}\ 23\frac{1}{2}\ 26\frac{1}{2}$	
DE3	HVC	VHC	HGC	HVC	HGC	HGC	$17\ 20\ 23$	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{1}{3}\ 3\frac{5}{6}\ 4\frac{1}{3}$	$3\frac{1}{6}\ 3\frac{2}{3}\ 4\frac{1}{6}$	$3\frac{1}{6}\ 3\frac{2}{3}\ 4\frac{1}{6}$	$2\frac{1}{2}\ 3\ 3\frac{1}{2}$	$2\frac{1}{3}\ 2\frac{5}{6}\ 3\frac{1}{3}$	$3\frac{2}{3}\ 4\frac{1}{6}\ 4\frac{2}{3}$		

Table A8. Contributions of sub-features of design for operation.

Design Experts	Sub-Features of DfO						Cu_k^m	$\widetilde{W}d_{fm}$
	MW	SP	CP	UL	EO	MD		
DE1	VEC	HVC	VEC	VHC	VEC	MDC	$20\ 23\ 26$	$19\ 22\ 25$
DE2	HVC	HGC	VEC	VHC	EXC	MHC	$19\frac{1}{2}\ 22\frac{1}{2}\ 25\frac{1}{2}$	
DE3	VHC	HGC	HGC	HVC	HVC	HVC	$17\frac{1}{2}\ 20\frac{1}{2}\ 23\frac{1}{2}$	
$\widetilde{W}d_{sf}^{mi}$	$3\frac{1}{2}\ 4\ 4\frac{1}{2}$	$2\frac{2}{3}\ 3\frac{1}{6}\ 3\frac{2}{3}$	$3\frac{1}{2}\ 4\ 4\frac{1}{2}$	$3\frac{1}{3}\ 3\frac{5}{6}\ 4\frac{1}{3}$	$3\frac{5}{6}\ 4\frac{1}{3}\ 4\frac{5}{6}$	$2\frac{1}{6}\ 2\frac{2}{3}\ 3\frac{1}{6}$		

Table A9. Availability of sub-features of assembly and disassembly in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	DE2	DE3	DE1	DE2	DE3	DE1	DE2	DE3	DE1	DE2	DE3
NJ $3\frac{2}{3}\ 4\frac{1}{6}\ 4\frac{2}{3}$	MEA	HGA	MHA	HGA	MHA	VHA	VHA	HGA	VHA	MEA	MHA	MHA
AM $3\frac{2}{3}\ 4\frac{1}{6}\ 4\frac{2}{3}$	HGA	MEA	MEA	HGA	HGA	VHA	MHA	VHA	EHA	MLA	MHA	MHA
PA $2\frac{5}{6}\ 3\frac{1}{3}\ 3\frac{5}{6}$	MLA	MLA	MHA	HGA	HGA	MHA	VHA	VHA	MHA	MEA	MEA	MLA
PP $2\frac{2}{3}\ 3\frac{1}{6}\ 3\frac{2}{3}$	MHA	HGA	MLA	VHA	MHA	MHA	VHA	EHA	EHA	MLA	HGA	MEA
AD $3\frac{5}{6}\ 4\frac{1}{3}\ 4\frac{5}{6}$	MHA	MLA	MEA	MLA	MLA	MEA	VHA	HGA	VHA	MEA	MLA	MEA
Sub-DM	$9\frac{1}{36}\ 12\frac{5}{17}\ 16\frac{3}{49}$			$10\frac{51}{67}\ 14\frac{14}{45}\ 18\frac{13}{36}$			$12\frac{19}{20}\ 16\frac{49}{60}\ 21\frac{11}{60}$			$8\frac{17}{30}\ 11\frac{23}{30}\ 15\frac{7}{15}$		

Table A10. Availability of sub-features of operation in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
MW $3\frac{1}{2}4\ \ 4\frac{1}{2}$	MLA	MEA	VLA	MHA	MLA	MEA	MEA	MEA	MHA	MLA	MLA	MEA
SP $2\frac{2}{3}3\frac{1}{6}\ \ 3\frac{2}{3}$	MEA	MHA	MLA	HGA	VHA	MHA	VHA	VHA	MHA	MEA	MEA	MHA
CP $3\frac{1}{2}4\ \ 4\frac{1}{2}$	VLA	LOA	MEA	VHA	HGA	VHA	VHA	EHA	VHA	HGA	HGA	MHA
UL $3\frac{1}{3}3\frac{5}{6}\ \ 4\frac{1}{3}$	MHA	MEA	HGA	HGA	MHA	MHA	MHA	HGA	HGA	MHA	HGA	MEA
EO $3\frac{5}{6}\ \ 4\frac{1}{3}4\frac{5}{6}$	MLA	MHA	HGA	VHA	MHA	MEA	HGA	VHA	VHA	HGA	MLA	MHA
MD $2\frac{1}{6}2\frac{2}{3}3\frac{1}{6}$	MEA	MLA	HGA	HGA	MHA	MHA	VHA	HGA	VHA	MHA	HGA	MEA
Sub-DM	$7\frac{16}{27}10\frac{26}{41}\ 14\frac{16}{91}$			$10\frac{16}{91}13\frac{18}{29}\ 17\frac{48}{85}$			$11\frac{3}{10}14\frac{25}{27}\ 19\frac{3}{59}$			$8\frac{62}{65}12\frac{11}{54}\ 15\frac{41}{43}$		

Table A11. Availability of sub-features of environmental in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
SO $3\frac{1}{2}4\ \ 4\frac{1}{2}$	VHA	MHA	VHA	MLA	MLA	MHA	MEA	MEA	MLA	HGA	MHA	MHA
EC $3\frac{1}{3}\ 3\frac{5}{6}\ \ 4\frac{1}{3}$	MHA	MHA	HGA	HGA	HGA	VHA	MHA	HGA	VHA	HGA	VHA	VHA
MU $2\frac{2}{3}\ 3\frac{1}{6}\ \ 3\frac{2}{3}$	HGA	HGA	MHA	MEA	MLA	MEA	MEA	MLA	MLA	MLA	MEA	LOA
PD $2\frac{1}{3}\ 2\frac{5}{6}\ \ 3\frac{1}{3}$	MLA	MEA	MEA	MHA	HGA	MLA	HGA	MHA	MEA	HGA	HGA	MHA
ED $3\frac{1}{6}\ 3\frac{2}{3}\ \ 4\frac{1}{6}$	VHA	VHA	HGA	HGA	MHA	HGA	HGA	HGA	VHA	MHA	MHA	MEA
Sub-DM	$9\frac{35}{36}13\frac{16}{45}\ 17\frac{16}{67}$			$8\frac{34}{45}11\frac{43}{45}\ 15\frac{59}{90}$			$8\frac{38}{45}12\frac{3}{49}\ 15\frac{7}{9}$			$9\frac{17}{90}12\frac{41}{90}\ 16\frac{2}{9}$		

Table A12. Availability of sub-features of reliability in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
FR $2\frac{5}{6}\ 3\frac{1}{3}\ \ 3\frac{5}{6}$	MHA	MEA	HGA	HGA	VHA	HGA	MHA	MHA	MLA	HGA	HGA	VHA
MR $2\frac{1}{3}\ 2\frac{5}{6}\ \ 3\frac{1}{3}$	HGA	MHA	MHA	MHA	HGA	VHA	HGA	HGA	MHA	HGA	VHA	VHA
DC $2\frac{2}{3}\ 3\frac{1}{6}\ \ 3\frac{2}{3}$	MHA	HGA	HGA	VHA	MHA	HGA	MHA	HGA	HGA	VHA	HGA	VHA
OP $2\frac{2}{3}\ 3\frac{1}{6}\ \ 3\frac{2}{3}$	MEA	MEA	MLA	HGA	MHA	MEA	MEA	MLA	HGA	HGA	VHA	HGA
Sub-DM	$7\frac{31}{36}10\frac{12}{13}\ 14\frac{35}{72}$			$8\frac{35}{36}12\frac{9}{37}\ 16\frac{1}{72}$			$7\frac{5}{6}10\frac{43}{48}\ 14\frac{11}{24}$			$9\frac{5}{6}13\frac{13}{48}\ 17\frac{5}{24}$		

Table A13. Availability of sub-features of life cycle cost in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
OC $3\frac{1}{6}\ 3\frac{2}{3}\ \ 4\frac{1}{6}$	MHA	VHA	MHA	MHA	MHA	HGA	MHA	HGA	HGA	MLA	MEA	MHA
AC $3\frac{1}{6}\ 3\frac{2}{3}\ \ 4\frac{1}{6}$	HGA	MHA	VHA	MHA	HGA	HGA	MHA	MEA	MHA	MHA	HGA	MEA
SC $2\frac{1}{6}\ 2\frac{2}{3}\ \ 3\frac{1}{6}$	MHA	MEA	MLA	MEA	MHA	MHA	HGA	HGA	MHA	HGA	HGA	MHA
RC $2\frac{1}{2}3\ \ 3\frac{1}{2}$	HGA	MHA	HGA	MHA	MEA	MLA	MHA	HGA	MEA	HGA	VHA	HGA
Sub-DM	$8\frac{61}{72}12\frac{1}{18}\ 15\frac{55}{72}$			$8\frac{9}{37}11\frac{25}{72}\ 14\frac{39}{41}$			$8\frac{9}{16}11\frac{3}{4}\ 15\frac{7}{16}$			$8\frac{14}{31}11\frac{23}{36}\ 15\frac{16}{49}$		

Table A14. Availability of sub-features of functionality in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
PP $2\ 2\frac{1}{2}3$	HGA	MHA	MHA	HGA	VHA	MHA	HGA	HGA	VHA	MHA	MHA	HGA
PF $3\frac{2}{3}\ 4\frac{1}{6}\ \ 4\frac{2}{3}$	MHA	MHA	HGA	MHA	HGA	VHA	VHA	HGA	HGA	HGA	MHA	MEA
DB $3\frac{1}{2}4\ \ 4\frac{1}{2}$	MEA	MEA	HGA	MHA	MEA	HGA	HGA	HGA	MHA	MEA	MEA	MHA
IM $3\ 3\frac{1}{2}\ 4$	MHA	MHA	HGA	HGA	VHA	HGA	VHA	VHA	HGA	HGA	HGA	MHA
MS $3\frac{2}{3}\ 4\frac{1}{6}\ \ 4\frac{2}{3}$	MEA	MEA	VHA	VHA	HGA	MHA	HGA	HGA	VHA	MHA	MHA	HGA
TC $4\ 4\frac{1}{2}\ 5$	HGA	VHA	HGA	HGA	MHA	VHA	VHA	HGA	VHA	HGA	VHA	HGA
Sub-DM	$10\frac{1}{2}14\ 17\frac{42}{43}$			$11\frac{13}{36}14\frac{71}{72}\ 19\frac{1}{9}$			$12\frac{10}{83}15\frac{6}{7}\ \ 20\frac{5}{54}$			$10\frac{26}{53}13\frac{42}{43}\ 17\frac{26}{27}$		

Table A15. Availability of sub-features of manufacturing in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
CM $3\frac{1}{3}\ 3\frac{5}{6}\ \ 4\frac{1}{3}$	VHA	HGA	HGA	MEA	MHA	MHA	MEA	MEA	MHA	MHA	MEA	HGA
MP $3\frac{1}{6}\ 3\frac{2}{3}\ \ 4\frac{1}{6}$	MHA	HGA	VHA	MEA	MEA	HGA	MHA	MHA	HGA	MHA	MHA	VHA
TM $3\frac{1}{6}\ 3\frac{2}{3}\ \ 4\frac{1}{6}$	HGA	VHA	HGA	MHA	HGA	MHA	MHA	HGA	HGA	HGA	VHA	MHA
PI $2\frac{1}{2}3\ \ 3\frac{1}{2}$	MEA	HGA	MHA	MEA	MHA	MHA	MEA	HGA	MHA	HGA	MHA	HGA
IP $2\frac{1}{3}\ 2\frac{5}{6}\ \ 3\frac{1}{3}$	HGA	HGA	MHA	HGA	HGA	VHA	HGA	HGA	MEA	MHA	MEA	HGA
PM $3\frac{2}{3}\ 4\frac{1}{6}\ \ 4\frac{2}{3}$	MHA	MEA	MHA	MHA	MEA	MEA	HGA	MHA	MHA	HGA	HGA	MHA
Sub-DM	$10\frac{7}{72}13\frac{19}{36}\ 17\frac{11}{24}$			$8\frac{42}{43}12\frac{13}{54}\ 16$			$9\frac{24}{73}12\frac{26}{41}\ 16\frac{11}{25}$			$9\frac{58}{67}13\frac{14}{55}\ 17\frac{1}{7}$		

Table A16. Availability of sub-features of maintainability in the design concepts.

Sub-Features	DC1			DC2			DC3			DC4		
	DE1	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**	**DE1**	**DE2**	**DE3**
MC $3\frac{2}{3}\ 4\frac{1}{6}\ \ 4\frac{2}{3}$	MHA	MEA	HGA	HGA	HGA	VHA	VHA	VHA	MHA	HGA	MHA	MHA
MT $2\frac{5}{6}\ 3\frac{1}{3}\ \ 3\frac{5}{6}$	HGA	HGA	MHA	MEA	MHA	HGA	HGA	MHA	MEA	MHA	MHA	MEA
MF $3\frac{1}{3}\ 3\frac{5}{6}\ \ 4\frac{1}{3}$	HGA	MHA	MEA	HGA	MHA	HGA	VHA	HGA	HGA	MEA	MHA	MLA
RM $2\frac{1}{3}\ 2\frac{5}{6}\ \ 3\frac{1}{3}$	MLA	MEA	HGA	MHA	MEA	MEA	HGA	MEA	MHA	MHA	HGA	HGA
PC $3\ 3\frac{1}{2}\ \ 4$	VHA	VHA	HGA	HGA	VHA	HGA	HGA	HGA	VHA	HGA	VHA	HGA
Sub-DM	$9\frac{19}{30}12\frac{59}{60}\ 16\frac{5}{6}$			$10\frac{1}{18}13\frac{41}{90}\ 17\frac{16}{45}$			$10\frac{13}{30}13\frac{9}{10}\ 17\frac{13}{15}$			$9\frac{7}{20}12\frac{2}{3}\ 16\frac{29}{60}$		

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