**Devarajan Ramanujan**
School of Mechanical Engineering,
Purdue University,
West Lafayette, IN 47907
e-mail: dramanuj@purdue.edu

**William Z. Bernstein**
School of Mechanical Engineering,
Purdue University,
West Lafayette, IN 47907

**Jun-Ki Choi**
Department of Mechanical and
Aerospace Engineering,
University of Dayton,
Dayton, OH 45469

**Mikko Koho**
Department of Production Engineering,
Tampere University of Technology,
Tampere FI-33720, Finland

**Fu Zhao**
School of Mechanical Engineering,
Purdue University,
West Lafayette, IN 47909

**Karthik Ramani**
School of Mechanical Engineering,
Purdue University,
West Lafayette, IN 47907

# Prioritizing Design for Environment Strategies Using a Stochastic Analytic Hierarchy Process

*This paper describes a framework for applying design for environment (DfE) within an industry setting. Our aim is to couple implicit design knowledge such as redesign/process constraints with quantitative measures of environmental performance to enable informed decision making. We do so by integrating life cycle assessment (LCA) and multicriteria decision analysis (MCDA). Specifically, the analytic hierarchy process (AHP) is used for prioritizing various levels of DfE strategies. The AHP network is formulated so as to improve the environmental performance of a product while considering business-related performance. Moreover, in a realistic industry setting, the onus of decision making often rests with a group, rather than an individual decision maker (DM). While conducting independent evaluations, experts often do not perfectly agree and no individual expert can be considered representative of the ground truth. Hence, we integrate a stochastic simulation module within the MCDA for assessing the variability in preferences among DMs. This variability in judgments is used as a metric for quantifying judgment reliability. A sensitivity analysis is also incorporated to explore the dependence of decisions on specific input preferences. Finally, the paper discusses the results of applying the proposed framework in a real-world case.* [DOI: 10.1115/1.4025701]

*Keywords: design for environment, analytic hierarchy process, stochastic simulation*

## 1 Introduction

DfE involves the systematic evaluation of design performance with respect to environmental, health, and safety objectives over the entire product life cycle. Establishing appropriate DfE strategies is critical for improving the environmental aspects of a product [1]. The process of establishing such strategies requires simultaneous consideration of environmental as well as business concerns using the concept of MCDA for selecting relevant DfE strategies [2]. However, product designers often lack access to reliable data regarding the environmental impacts of products and processes, which are essential for making decisions involving complex trade-offs between competing objectives [3]. Although data gathered for life cycle impact assessment offers one way to bridge this knowledge gap, problems are often compounded by unfamiliarity with environmental issues among product development personnel. Arguably so, the process of product design, development and management, usually incorporates environmental considerations as a regulation/compliance issue which leads to a failure in proactively adopting DfE practices. In order to instill a proactive approach among designers, an MCDA framework should be based on quantitative measurements of a product's environmental performance obtained from a validated sustainability assessment tool.

On a coarse scale, tools that assess the environmental sustainability of a product or process can be categorized into various levels based on the nature of assessment, i.e., (a) qualitative/quantitative, (b) on temporal/spatial scales, and (c) on their integration of environmental, economic and social systems. From a systems perspective, an ecologically sustainable society is defined as that state (condition) of society in which nature is not subject to systematically increasing (a) concentrations of substances extracted from the Earth's crust, (b) concentrations of substances produced by the society, (c) degradation by physical means, and (d) society needs [4]. However, in regards to product design, the system boundaries for assessing a product's environmental sustainability must be objectively defined and are usually much smaller in scope.

A few earlier studies [5,6] have reviewed approaches for environmentally sustainable product design. Masui [7] developed the QFD for environment by incorporating environmental aspects into quality function deployment (QFD) to handle environmental and traditional product quality requirements simultaneously. Brezet and Hemel [8] developed the life cycle design strategy wheel method and considered the impacts of a product or service across different levels: product component, product structure, and product system. Keoleian et al. [9] suggest a method to identify all design requirements in the form of a matrix that allows the designer to decide so-called *must requirements* and *want requirements*. However, these studies do not incorporate quantitative models in the product development process. Also, checklist type design guidelines may overwhelm product designers. There have been some frameworks that have proposed solving design problems with mathematical modeling [10–12]. However, these techniques have not been extended to specifically address the environmental aspects of product design. For doing so, the key environmental design drivers of a product must be identified quantitatively and correlated with corresponding traditional design drivers (i.e., from a bottom-line perspective). Some useful approaches have been studied in reference to the mentioned framework in related domains. Thurston and Srinivasan [13] present a framework for employing mathematical decision modeling

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via a constrained optimization approach as applicable to green engineering. Michalek et al. [14] propose a methodology to solve multi-objective formulations involved in marketing, manufacturing, and engineering design decisions with concurrent engineering strategies. Skerlos and Zhao [15] apply optimization algorithms for assessing the economics of metalworking fluids recycling. However, in most of these studies quantitative LCA studies are not conducted for identifying environmental hotspots (problem areas) within a product system. The widespread use of easy-to-use, computer-based commercial LCA packages makes it possible for DfE practitioners to analyze the environmental impacts of a product without necessarily having an in-depth understanding of LCA methodologies [16].

Most of the applications of decision analysis in conjunction with LCA have been confined to the weighting of inventory data issues [17–22]. Few papers, discuss the integration of LCA and MCDA either for ranking alternative processes or for prioritizing strategies that enable environmentally sustainable product design (ESPD) [23–27]. This is primarily due to the fact that LCA has been developed without an explicit link to a specific decision analysis framework. Weil et al. [28] and Xiong et al. [29] address integrating MCDA within the LCA framework while considering uncertainties in the input data, for robust selection among given alternatives. The focus of these papers is not on facilitating decisions in regards to environmentally sustainable product design. Moreover, the expressed preferences in these MCDAs are implicitly assumed to be deterministic as scenarios with independent evaluations by a group of experts are not accounted for. Huang et al. [30] discuss a framework for material selection in environmentally conscious design using an MCDA similar to the TOPSIS method. They also consider uncertainties in inventory data as well as a judgment criterion using an entropy based approach. A review in regards to the applications of different MCDA methods towards environmental decision making can be found in Ref. [31]. Methods for addressing uncertainty related to product design are discussed in Refs. [32–34], but issues related to ESPD are not considered. Duncan et al. [35] extensively discusses modeling uncertainties for environmentally benign decision making using the information gap decision theory (IGDT). Uncertainties in life cycle inventory and those that arise in the process of applying IGDT for design decision making are considered. Whenever multiple decision makers are involved, additional analyses regarding the combined consistency of the group's evaluations and the relative importance of the each specific judgment is required [36]. Additionally, conducting a sensitivity analysis on the alternatives may help the decision makers refine their judgments.

In this paper, a framework for integrating LCA with a stochastic MCDA is illustrated in order to facilitate rational decision making with regards to aiding ESPD. Sometimes, a deterministic single score may mislead the designer, especially when competing DfE criteria have similar scores as indicated in the author's previous study [37]. Therefore, uncertainty and sensitivity analyses are incorporated through a Monte Carlo simulation (MCS) within the decision making process to provide a spread of feasible decision criteria. Although different companies have different strategies and criteria, a general framework will allow companies to systematically prioritize DfE strategies enabling more robust decisions for ESPD. The remainder of this paper proceeds as follows. Section 2 describes the proposed methodology, including an LCA module, a DfE module, and an MCDA module with uncertainty analysis. Section 3 describes the process of applying the proposed framework to a real world case study. This case study involves prioritizing DfE strategies for the redesign of a surface drilling rig within leading mining equipment manufacturer based in Finland. Section 4 summarizes the results and discusses the statistical testing methods necessary for making statistically sound decisions with the resulting stochastic data. Section 5 concludes the paper and sets the direction for future research.

## 2 Methodology

The general framework for eliciting expert preferences and prioritizing corresponding DfE strategies using the AHP from an individual DM has been presented in the author's previous work [37]. The proposed framework involves conducting an LCA of a product to identify environmental hotspots throughout the product's entire life cycle. The results from the LCA provide information about the most significant life cycle stages in terms of specific environmental impacts. Then, various levels of DfE strategies involved in the specific life cycle stage are prioritized using an AHP to assist the designer in identifying the relative importance of environmental and business-related performances within that product. The current paper aims at extending the earlier framework by (1) including the case of independent evaluations by multiple DMs (2) incorporating uncertainty and statistical testing methods in the prior methodology to aid better decision making. Uncertainties resulting from DM's preferences in the AHP are characterized using Bootstrap re-sampling. (3) And finally, this paper validates the overall methodology by applying it within a real-world industry setting.

The process diagram of the general framework used for prioritizing DfE strategies is shown in Fig. 1. First, the LCA module identifies the environmental impact of the specified product system. There are various types of LCA: traditional SETAC LCA or a process based LCA [38], economic I/O (input/output) based LCA [39,40], and a hybrid LCA [41]. Each LCA has a scope that defines the system boundaries. SETAC LCA provides the most accurate result in the finest level within limited system boundaries while an economic I/O based LCA provides the most comprehensive result on an aggregated economic sector level perspective. A hybrid LCA combines these two types to mitigate the weaknesses of each methodology. Since the proposed framework is intended for application in a business setting, there are severe constraints on available resources and time which require the set system boundaries to be relatively fine. Therefore, a SETAC LCA is preferred. Also, the use of existing life cycle inventory databases greatly simplifies the life cycle inventory analysis.

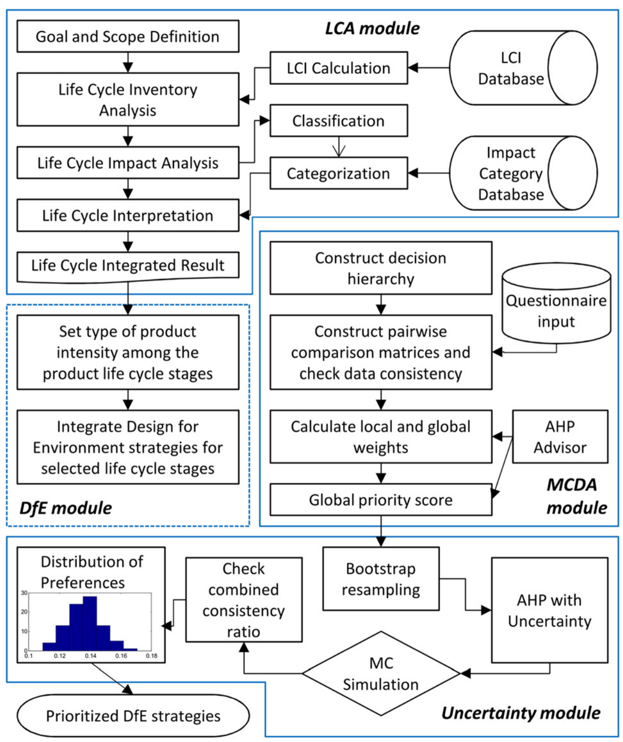


**Fig. 1 Schematic diagram of the proposed framework for integrating an sAHP based MCDA with a traditional LCA**

Although life cycle inventory analysis provides insight regarding the environmental hotspots of the product system, it cannot be applied directly to judge the environmental performance of a product system due to the lack of specific judgment criteria. Therefore, life cycle impact assessment is conducted to convert the inventory results to normalized environmental impact results. Once the inventory parameters are classified into impact categories, the relative contribution of each inventory parameter to a given impact category is quantified using a characterization factor [42]. The next step in the methodology is life cycle interpretation where key issues such as the activities, processes, materials, components, and life cycle stages are identified [43]. Each life cycle stage has a set of associated DfE strategies each contain various sub-criteria for improving the environmental aspect of a product system as shown in Fig. 2. Within a DfE module, the DMs analyze the LCA results to determine how the corresponding sub-criteria should be prioritized. The AHP is used in this study for prioritizing DfE strategies. AHP, developed by [44], is a flexible MCDA tool for complex problems where both qualitative and quantitative aspects are considered. It helps the analyst organize the critical aspects of a problem into a hierarchical structure similar to a family tree. Key elements in traditional AHP are shown in the following equations. Equation (1) calculates the consistency index (CI) between decision criteria and provides a confidence level of the decisions provided by the subjective experts and Eq. (2) calculates its consistency ratio (CR). Equation (3) calculates the global weight of each sub-criteria and Eq. (4) captures the global priority score which provides a deterministic, single value of the relative importance of each DfE strategy.

$$C.I = (\Psi_{\max} - N)/(N-1) \tag{1}$$

$$\mathrm{C.R} = \mathrm{C.I}/\mathrm{R.I}_N \tag{2}$$

$$\mathrm{GW}_j = \mathrm{LW}_i \times \mathrm{LW}_j \tag{3}$$

$$\mathrm{GPS}_k = \sum (\mathrm{GW}_j \times \mathrm{RS}_{j,k}) \tag{4}$$

People lacking experience in the fundamentals of AHP might encounter difficulties when directly inputting ambiguous judgments into the preference matrix. Questionnaires provide a more systematic approach for constructing the AHP matrix. Structuring a questionnaire includes defining the main elements of the hierarchy at each level and eliciting their importance through specific questions. It is important to avoid possible misunderstandings with the respondent, as the phrasing of the questions and recording of the answers could influence the final result. The perceived direction of the objectives (i.e., positive or negative) plays an important role within the design of the questionnaire. All the objectives on a common level should share a common perceived direction. For example, objectives such as *improved use of recycled material* for the raw material criteria and *enhanced supplier relationship* need to have a positive direction with respect to the external driver. In this study, the following items are included along with the questionnaire: a cover letter expressing the purpose of the survey, brief instructions for filling out the survey, a graphical representation of the decision hierarchy and a copy of the report on the LCA of the product. The main contents of the survey contain comparison-based questions regarding each criterion in each level of the decision hierarchy. Subjective data from the questionnaires is used for the construction of pair-wise comparison matrices and then eigenvalue problems are solved to provide the CI and CR of each pair-wise comparison for each criterion.

| LC Stage | DfE strategies | Sub-criteria |
|---|---|---|
| Raw materials | Material use Optimization | **Design for resource conservation**<br>• Reduction of used material<br>• Use renewable material<br>• Use recycled material<br>**Design for low impact material**<br>• Avoid toxics<br>• Use material with lower energy content |
| Manuf-acturing | Clean manufacturing | **Design for cleaner production**<br>• Minimize material variety<br>• Avoid material waste<br>• Select low impact materials and processes |
| Distribution | Efficient distribution | **Design for efficient distribution**<br>• Reduce product weight<br>• Reduce packaging weight<br>• Use of reusable/recyclable packaging<br>• Ensure efficient distribution |
| Product Use | Clean use/ operation | **Design for energy efficiency**<br>**Design for material conservation**<br>**Design for minimal consumption**<br>**Avoidance of waste**<br>**Design for low-impact use/operation**<br>**Design for durability** |
| End of Life | End of Life optimization | **Design for re-use**<br>**Design for re-manufacturing**<br>**Design for disassembly**<br>**Design for recycling**<br>**Design for safe disposal** |

**Fig. 2 List of DfE strategies in a typical product life cycle [8]**

Although a traditional AHP can be a useful tool, it requires DMs to translate ambiguous judgments into a deterministic preference values for estimating pairwise comparisons of objectives and decision alternatives. The accuracy of the comparisons of all pairs of criteria and the resulting decision alternatives may be significantly influenced by the information available to the DMs, their understanding of the problem under consideration, as well as their previous perceptions [45]. These issues are especially a concern when dealing with a complex, global issue such as DfE. Misconceptions based on media outlets and specific design experiences can greatly affect decisions within sustainable product development [46]. Moreover, design decisions within an organization are taken by a group of DMs. It is reasonable to assume that each DM in a group has a different value scheme that may significantly deviate from the value scheme held by another DM in the group. This assumption is especially true when considering decision groups for DfE which are usually formed from people belonging to diverse work groups i.e. product designers, financial managers, environmental engineers, suppliers etc. By adopting a deterministic weighting scheme in the AHP, any resulting uncertainties or valuable information about individual preferences of the team cannot be analyzed. Therefore, for robust decision making, the AHP should incorporate means for statistical testing or significance comparison among alternatives. The priority ranking of alternatives resulting from the AHP should also be analyzed for variation with respect to uncertain input data.

As constructing a closed-form analytic model to represent output uncertainties as an explicit function of input uncertainties entails significant complexities previous research has approached this problem by incorporating methods such as probabilistic judgments, interval analysis and fuzzy theory within the AHP. The methods described above aid DMs in reaching a statistically significant conclusion regarding their decisions. However, the above methods are limited by the fact that they need a large sample size of decision weights and consequently DMs. An additional problem when dealing with purely probabilistic judgments is the fact that the small sample size of input data prevents accurate parameterization of this data by a statistical distribution [47]. The modified analytic hierarchy process (MAHP) developed by Ref. [48] tries to address the above issues and also considers management related factors in decision making. The MAHP makes use of a MCS through random sampling of an estimated statistical distribution of input preferences. Uncertainties associated with the model are propagated through the decision making framework. It should be noted that an MCS based approach can be considered the most effective quantification method for uncertainties and variability among the tools available for environmental system analysis [49]. However, the MAHP is limited by the fact that it forces the DMs to parameterize decision weights using a triangular distribution. Although the assumption of a triangular distribution for decision weights works well when they converge to a unique modal value, this assumption may not be valid in cases where they are uniformly distributed across a range or multimodal. The process of surveying a small sample of DMs can be considered as polling a subset of expert DMs from the available population. Using a triangular parameterization prevents DMs from making inferences about the population as a whole. To overcome the above limitations, the proposed MCDA framework incorporates a stochastic analytic hierarchy process (sAHP) that uses Bootstrap re-sampled decision weights. Bootstrap re-sampling is applied in this case as it (1) is nonparametric in nature (i.e., it does not assume that the data is representative of a specific statistical distribution) and (2) allows for measuring the variability of input data by independent and identically distributed (i.i.d) sampling. Also, the resulting bootstrap distribution is centered on the expected value of the true distribution and thus, the performed sAHP analysis will be centered on an AHP analysis conducted by averaging individual preferences.

In a sAHP, instead of deterministic preference values of a traditional AHP, an (i.i.d) sample $(\beta_{ij}(\mathrm{m}))$ is drawn from a set of preference values. The expected value of these preference values $(b_{ij})$ from all the parameters are plugged into a pair-wise comparison matrix, producing a possible prioritization of the alternatives under consideration. Repeated calculations ("N" times) produce a distribution of the predicted output values reflecting combined parameter uncertainties. Thus, this process is akin to performing a MCS with bootstrap re-sampling. It should be noted that uncertainties in the LCA can influence the results of the sAHP. Even though our proposed framework does not explicitly model uncertainties in LCA, a highly uncertain LCA will cause a large variance in priority weights which will, in turn, result in overlapping preference values.

Figure 3 illustrates the difference between the deterministic and the stochastic AHP. In a traditional AHP, the pairwise comparison matrix contains deterministic values that indicate how much more important the *i*th criteria is than the *j*th criteria. On the other hand, the pairwise matrix of a sAHP contains one of the many possible expected values of that criteria weight. The sAHP leads to the construction of a set of priority vectors corresponding to each possible evaluation of importance criteria. Consequently, the sAHP generates a statistical distribution of prioritized alternatives and their consistency ratios (CR). While conducting an MCDA involving independent assessments by a group of DMs, it is also essential to identify the decision variables that can significantly affect the final outcome. In the present study, this is achieved by performing a sensitivity analysis on the model. A sensitivity analysis reduces the evaluation space, and thus, the amount of time necessary to refine evaluations. In the context of this paper, the term sensitivity can be defined as the degree of correlation between the renormalized DfE preference values and the input criterion of the sAHP.

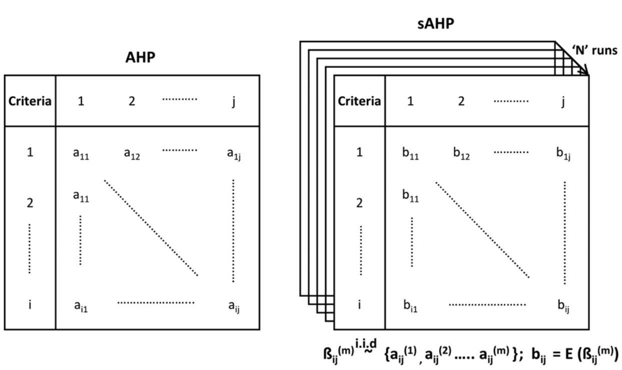


**Fig. 3 Structure of the pairwise comparison matrix of a deterministic AHP and the proposed sAHP**

The specific steps for incorporating an sAHP with regards to DfE are detailed below:

(1) Conduct a LCA of the product to discover life cycle stages, design decisions, and specific parts/operations that have significant environmental impact. Using the above data, construct a set of recommendations that enable redesign for environmental sustainability
(2) Develop a list of specific DfE strategies using [8]. The selected set of DfE strategies will be evaluated for feasibility of implementation using the sAHP framework
(3) Construct the corresponding AHP hierarchy, where prioritization of a particular DfE strategy from the prementioned DfE list is placed on the first level of the hierarchy. The second level of the hierarchy provides the local weights of environmental and business-related criteria. Each criterion consists of sub-criteria which represent the desired improvement options and thus provide local weights for sub-criteria. The lowest level of the hierarchy consists of the alternatives, namely the different designs for environmental strategies. Refer Fig. 5 for details
(4) Construct a survey to evaluate pairwise weights relevant to the AHP hierarchy. This survey is then distributed to a group of expert DMs that have sufficient knowledge of the life cycle of the product as well as an understanding of its environmental impacts. It is recommended that individuals are drawn from different organizational divisions such as design, management, maintenance etc.
(5) Set up the sAHP process where each pairwise weight is an i.i.d sample drawn from the set of all such pairwise weights obtained from the survey. Evaluate priority vectors and principal eigenvalues and screen out runs which do not meet the desired consistency ratio. Generate a set of global priority scores obtained from multiple runs of the above.
(6) Generate a ranking scheme for the DfE strategies using confidence bounds of the normalized preference for each DfE strategy.
(7) Perform a sensitivity analysis to evaluate the variance of the ranking scheme with respect to variation in input data.

A detailed explanation of the above in addition to the method for performing sensitivity analysis is explained in the context of the case study in Sec. 3.

## 3 Case Study

The proposed methodology was applied within a leading manufacturer of mining equipment (henceforth titled "Company A") based in Finland. "Company A" manufactures a wide variety of drilling rigs among which a hydraulic, surface drilling rig (henceforth titled "Product 1" for confidentiality) was earmarked for environmental assessment based on the principles of life cycle assessment. It should be understood that "Product 1" is an assembly of over 5000 individual parts and conducting an extensive LCA requires accessing material and design specifications from highly confidential inventory data. Therefore, the present study is based on a prior LCA conducted internally by the company on "Product 1". The authors were directly involved in interpreting the results of the conducted LCA and designing the DfE and the MCDA module as per the company requirements.

**3.1 LCA Module.** The LCA on "Product 1" was conducted according to the ISO14040 and 14044 standards on environmental management. The LCA includes the following stages of the life cycle: raw material acquisition, part manufacturing and assembly, transportation, use phase, maintenance, and the product's end-of-life. The end-of-life phase examines scenarios of remanufacturing, reuse, disassembly, recycling, and disposal. It should be noted that the review of post-use phase is largely based on qualitative inputs due to nonavailability of real world data.

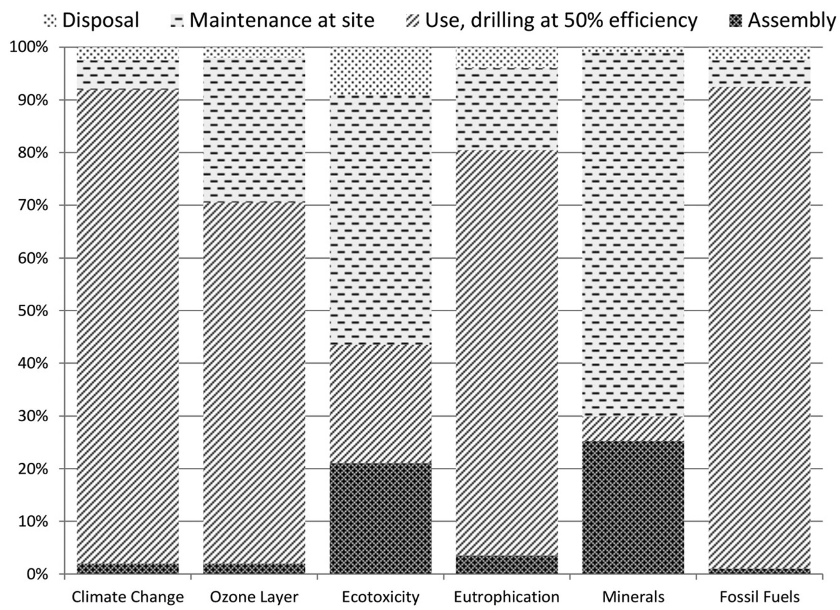


**Fig. 4 Figure outlining the significance of use and maintenance phase in the LCA of "Product 1"**

Listed below are the definitions of the conducted life cycle assessment.

(1) Goal and Scope: The LCA in the present case is an exploratory study of the life cycle resource consumptions and emissions of "Product 1". The primary goal of the LCA is to develop and implement practical guidelines that minimize impacts resulting from the production processes as well as the product itself. The intention is to use this method to identify business-related risks and strategies from an environmental point-of-view to aid future purchasing decisions and incorporate recommended design changes or improvements. The short term goal is to improve the life cycle resource efficiency of "Product 1" and to implement cleaner, less expensive, and smarter solutions in the business process. This involves discovering the factors of environmental impact which are not only the most significant but also exhibit economically feasible redesign opportunities. The long term goal is to gain useful information for future product planning to make all products more eco-friendly. A special point of interest within the LCA is evaluating the feasibility of a selective take back program and a systematic disassembly scheme.
(2) Functional Unit: The functional unit is defined as the production, use and disposal of one drill rig which fulfills the functional requirements set to its life time service and which is constructed with inputs (material and energy) of as low environmental impact as possible. Expected service life is taken into account. The product's lifetime under normal conditions of utilization and maintenance is expected to be 25 yr.
(3) Reference Flow: The reference flow of this LCA study is the manufacture of one "Product 1" drill rig containing mainly steel and hydraulic parts.
(4) Impact Categories Selected and LCIA Methodology: The used impact categories are climate change, acidification, eutrophication, toxic effects on humans and ecosystems, ozone formation, depletion of fossil fuels, and minerals. The used LCA methodology is comprehensive and follows standards of LCA using the EcoInvent database for inventory analysis [50] and the EI99 scheme provided by SimaPro™[51]
(5) Allocation Procedures/Boundaries in Relation to Other Life Cycles: Allocation is avoided by splitting the process in specific separate processes. The manufacturing process does not include any clear co-processes or co-products
(6) Intended Audiences: The LCA of "Product 1" is to be used for internal purposes.
(7) Report Generation: The report of the LCA follows the requirements of ISO 14048 LCA data documentation format. The documented report contains LCA data, tables, and figures.

**3.2 LCA Results.** The results of the conducted life cycle assessment revealed the following significant details:

(1) The most significant life cycle phase from an environmental perspective is maintenance and use. Close to 95% of the life cycle impact of "Product 1" is due to high diesel fuel consumption and resulting emissions. Figure 4 outlines the normalized LCA result outlining the impact contribution of this stage.
(2) Oil consumption along with maintenance of change rods and crowns also contribute toward significant use phase impacts.
(3) There is a strong potential for reducing end-of-life environmental impacts by pursuing strategies related to substitution with recyclable materials and elimination of toxic materials.
(4) Planning for disassembly is a key criterion for enabling better management of the end of life of "Product 1". This process should be coupled with consumer awareness programs.
(5) Design for durability can greatly aid in reducing use phase impact by reducing the frequency of oil and part changes.
(6) Reducing material flow and waste at the assembly plant could lead to significant savings.

Based on the results of the LCA the following specific recommendations were made in order to reduce the life cycle impact of "Product 1":

(1) Reduce use phase oil consumption.
(2) Reduce the percentage of Nickel and Chromium in the steel mixture of "Product 1".

(3) Increase part reliability to minimize the number of part replacements over the lifetime of the product.
(4) Incorporate a recycling program for minimizing the end-of-life impacts of the product.
(5) Reduce consumption of drilling consumables.
(6) Reduce part count of the product one through design for manufacturing strategies.
(7) Reduce assembly phase consumables in the plant, including electricity and water.
(8) Reduce use phase noise pollution.

Although the above recommendations would greatly help in reducing the life cycle impact of "Product 1", the feasibility of implementing these strategies or their effect on the business performance of the company were not analyzed within the life cycle assessment.

**3.3 DfE and MCDM Module.** Figure 5 illustrates the overall hierarchy structure of MCDA conducted within "Company A". In this case, the AHP hierarchy is constructed as per the procedure detailed in the methodology section. For this case study, the list of DfE strategies is chosen from an exhaustive list compiled by Ref. [8] as shown in Fig. 2. However, conducting an AHP based on the entire set of strategies is time and resource intensive (n DfE strategies with m assessment criteria will require $n^2m/2$ evaluations). Thus a pre-assessment of DfE strategies is performed for narrowing the selection before incorporating them within the AHP hierarchy. Within this case study, product managers from the company ranked the criteria as per their relevance to the project and its applicability. Two product managers of "Product 1" independently ranked the DfE criterion on a Likert scale ranging from very important (9), to least important (1). The top eight DfE criteria were chosen for detailed analysis based on the sAHP. It should be noted that the number of DfE strategies selected for final evaluation is a function of available project resources (time, applicability of the DfE strategies in the context of the product, relevance of DfE strategies to company goals, etc.) and the outcome of the rankings. Although the pre-assessment of DfE strategies reduces the scope of the final evaluation, strategies that are of most interest to the company with regards to feasibility of implementation pass through the pre-assessment stage. If these strategies do not correspond to specific recommendations made after the LCA, the company can choose to re-evaluate their selection methodology at the pre-assessment stage and re-select better candidate strategies. After performing the DfE pre-assessment module, a pair-wise comparison survey was set to fifteen personnel involved in life cycle planning and environmental assessment for "Product 1". Of these, ten complete responses were returned. Each survey was accompanied with supporting documents as detailed in the methodology section. The survey template was designed on Microsoft Excel® for ease of distribution and data extraction. The respondents were required to allocate pair-wise weights within the survey based on the LCA results and their inherent knowledge about the feasibility of the design process. These sets of ten unique pair-wise weights for a specific comparison factor were used for data re-sampling through the sAHP. For conducting the sAHP, a custom simulation tool was created using Visual Basic for applications in Microsoft Excel®.

## 4 Results

Figure 6 illustrates an example of the results of the simulation ($n = 1500$) run of the sAHP. A frequency distribution of the normalized preference of the DfE strategy *ensure efficient distribution* is plotted on the left and the overall consistency ratio of the sAHP is plotted on the right. Each bar on the plot of the overall consistency ratio is analogous to the likelihood of having a given consistency ratio. The spread of the overall consistency ratio's is between 0.035 and 0.07, which is well below the acceptable score of 0.1 as defined by Saaty. The variance of the normalized preference values represents the variability in the input preference weights combined with the errors resulting from bootstrap re-sampling. Similar results can also be obtained for all the other DfE strategies. Figure 6 also visualizes all the DfE strategies plotted on the same scale by smoothing the resulting histograms using a normal kernel density estimate. The kernel density estimate is a probability density estimate of the sample, based on a normal kernel function evaluated at 100 equally spaced points that cover the range of the data. As all the DfE preferences are plotted on a normalized scale, the magnitude of the expected value of each DfE distribution gives a measure of its overall preference. For example, from Fig. 6 it is evident that *minimize consumption* and *efficient distribution* are the most and least preferred DfE strategies, respectively.

Figure 7 compares the results of the sAHP with the preference values obtained by conducting a deterministic AHP by averaging the pairwise comparisons provided by the ten DMs. As seen, the mean value of normalized preferences in the sAHP is

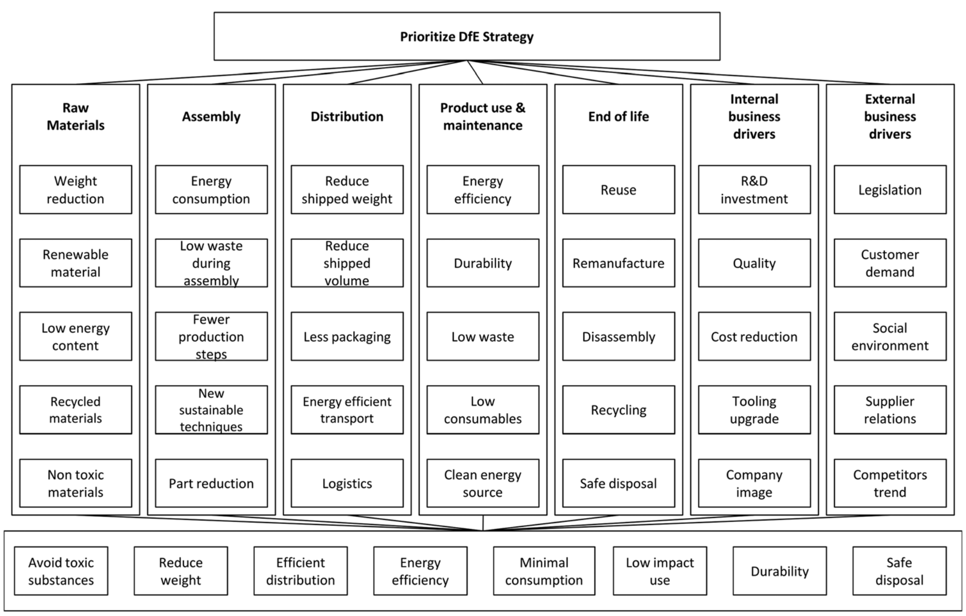


**Fig. 5 Structure of the overall AHP network used for prioritization of DfE strategies**

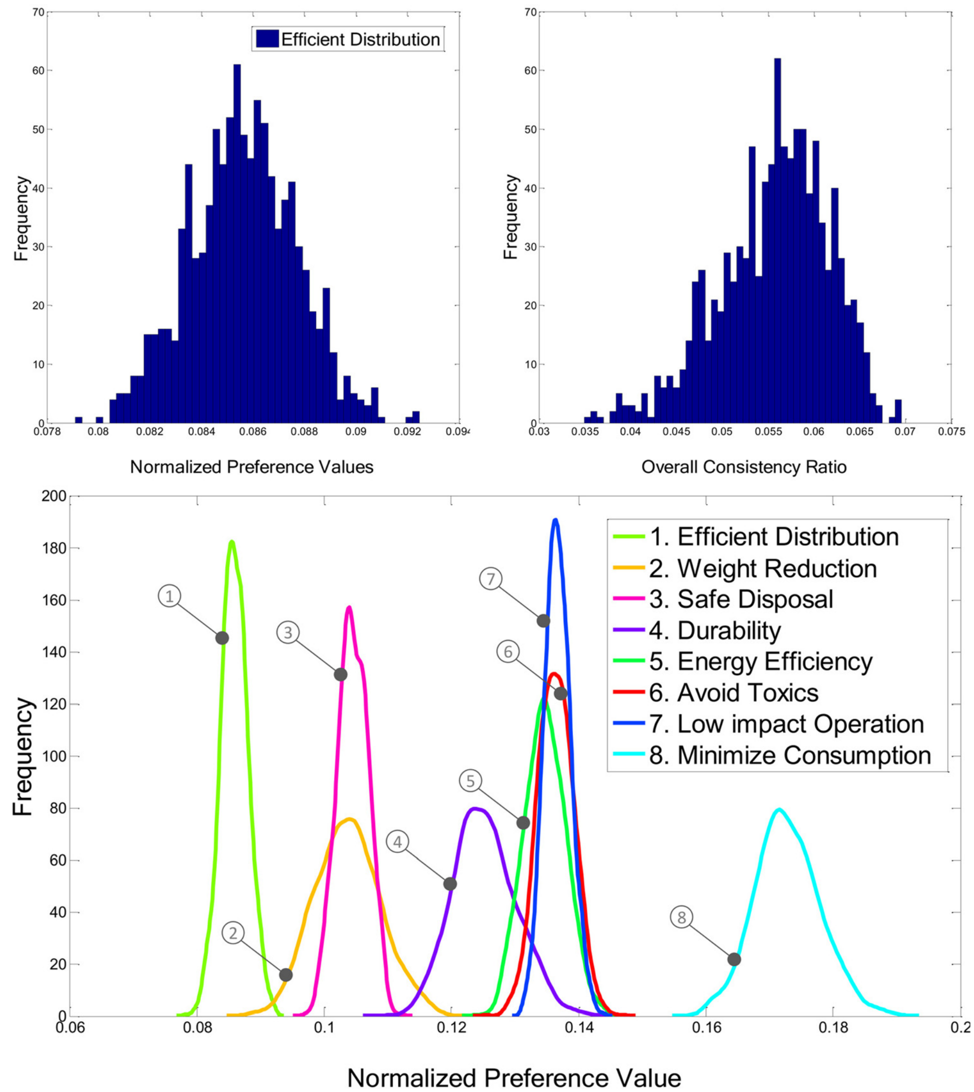


**Fig. 6 A snapshot of example results from the sAHP framework**

approximately equal to the former, the difference resulting from errors in the process of bootstrap re-sampling. The sAHP framework allows for estimating the variability in the resulting preference values due to differences in pairwise comparisons by multiple DMs. On the other hand, this information is lost while averaging the weights a priori for the sake of conducting a deterministic AHP.

To ensure that the decisions made based on the results of the sAHP are statistically valid, (1) a measure of confidence bounds for characterizing the error due to bootstrap re-sampling is incorporated, and (2) the difference in the normalized preference values of the DfE alternatives is verified to test statistical significance ($p = 0.05$). For characterizing the error in bootstrap re-sampling, a 95% bootstrap percentile confidence interval (i.e., the interval between the 2.5% and 97.5% percentiles) of the statistic is generally used. However, when the resulting bootstrap distribution has a small bias and approximates a Gaussian distribution, the confidence interval can be approximated as shown below [52].

$$[\mathrm{BCI}_h, \mathrm{BCI}_l] = \mu + t^* S \tag{5}$$

In the given case, a Lilliefors test is performed to confirm the normality of the resulting bootstrap data. The Lilliefors test is a two sided goodness of fit test that tests the hypothesis that the sample data comes from a distribution in the Gaussian family against the possibility that the sample data does not come from a Gaussian distribution [53]. To compute whether the means of the preference values are statistically significant, the differences in the means of DfE alternatives are computed and as shown in Eq. (6), i.e., inspecting whether this difference is greater than the maximum value of bootstrap standard error.

$$\mu_1 - \mu_2 > t^*(S_1 + S_2) \tag{6}$$

This analysis is performed for each of the DfE alternatives with respect to all the other seven DfE alternatives. The results of this analysis are displayed in matrix form within Fig. 8 where a "1" indicates that the null hypothesis, $\mu_1 \le \mu_2$ can be rejected at a significance level of 5%. Figure 8 also shows that the DfE principle of *minimizing consumption* has the highest mean, and thus, is the most preferred alternative. *Efficient distribution* is the least preferred alternative.

Although, the above analysis is sufficient for ranking the alternatives in the sAHP, it is important to characterize the sensitivity between the various alternatives with respect to the input data in the sAHP model. More specifically, the Spearman's rank correlation coefficient, a non-parametric measure of the statistical dependence, is used. The null hypothesis is that the rank of the normalized preference value of the DfE alternative does not co-vary with the rank of the values of a particular sAHP input. A high value of the Spearman coefficient along with a p-value of less than 0.05 rejects the null hypothesis. The DfE alternatives in

| | sAHP mean | AHP |
|---|---|---|
| **Avoid toxics** | 0.13638 | 0.13533 |
| **Weight reduction** | 0.10370 | 0.10601 |
| **Efficient distribution** | 0.08593 | 0.08630 |
| **Energy efficiency** | 0.13470 | 0.13625 |
| **Minimize consumption** | 0.17283 | 0.17230 |
| **Low impact operation** | 0.13668 | 0.13590 |
| **Durability** | 0.12528 | 0.12345 |
| **Safe Disposal** | 0.10450 | 0.10446 |

**Fig. 7 Comparison of the normalized preference values of the sAHP with the deterministic AHP**

| | AT | WR | ED | EE | MC | LIC | DY | SD |
|---|---|---|---|---|---|---|---|---|
| **AT** | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **WR** | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| **ED** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **EE** | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **MC** | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |
| **LIC** | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| **DY** | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **SD** | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

| DfE Strategy | Rank |
|---|---|
| Minimize Consumption | 1 |
| Low Impact Operation | 2 |
| Durability | 3 |
| Avoid Toxics | 3 |
| Energy Efficiency | 3 |
| Weight Reduction | 4 |
| Safe Disposal | 4 |
| Efficient Distribution | 5 |

**Fig. 8 Results of the hypothesis testing**

the present case study are the most sensitive to the input weight of *low production waste*. Figure 9, visualizes the sensitivity plot. Therefore, the DM team may wish to investigate this criterion further in the hopes of reducing its uncertainty involved in con-

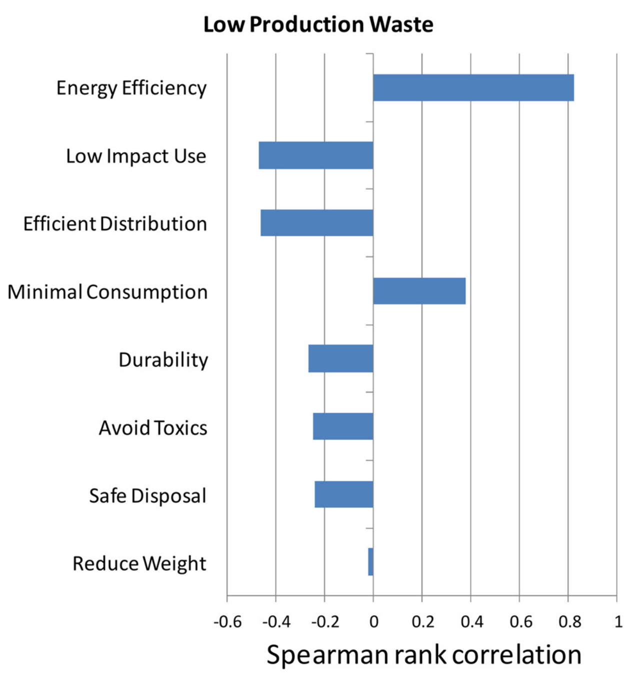


**Fig. 9 Sensitivity of alternatives for an example sAHP input**

| Recommendation based on LCA | Corresponding DfE strategy with rank |
|---|---|
| Reduce use phase oil consumption | Low impact operation (2) |
| Reduce % of Nickel and Chromium in steel mixture | Avoid Toxics (3) |
| Increase part reliability to minimize no. of replacements | Durability (3) |
| Incorporate recycling program for Product 1 | Safe Disposal (4) |
| Reduce consumption of drilling consumables | Energy Efficiency (3), Low impact operation (2) |
| Reduce part count of Product 1 | Weight Reduction (4), Efficient Distribution (5) |
| Reduce assembly phase consumables (electricity, water, etc…) | Minimize Consumption (1) |
| Reduce use phase noise pollution | Low impact operation (2) |

**Fig. 10 Recommendations for adopting LCA strategies based on DfE rankings**

structing a pairwise comparison matrix. A similar analysis can be performed for all the factors present in the sAHP.

The final recommendations made to "Company A" based on the results of the LCA with MCDA pipeline proposed in this paper are shown in Fig. 10. The feasibility of adopting a particular recommendation made using the results of the LCA are rated according to the rankings of the corresponding design for environment strategies as per the sAHP. The results show that *minimizing consumption* of assembly phase consumables and *teducing use phase oil/noise consumption* are the most feasible recommendations. However, they account for a minor fraction of the overall life cycle impact for "Product 1". Conversely, use phase impacts (including operation and maintenance) amount to nearly 95% of the total impact. The corresponding DfE strategies i.e., *designing for energy efficiency* and *low impact operation* are viewed by "Company A" as mid-level feasible. Therefore, it was suggested that "Company A" immediately address the issue of reducing assembly phase impacts and develop a long term strategy to redesign "Product 1" for lower operation phase impacts. Upcoming European Union energy regulations such as the energy using products (EuP) further strengthen the cause for such a long term goal. Reflecting on the least favored strategies namely ensure efficient distribution and safe disposal, it can be hypothesized that "Company A" has little or no control over the sustainability practices of its suppliers and end users. Since drilling rigs operate in remote areas, product recovery is a formidable task. Furthermore, these two stages do not significantly contribute to the overall life cycle impact of 'Product 1'. The primary motivation for pursuing one of these strategies would be to comply with possible regulations in the domain. The above discussion makes a case for adoption of the presented decision framework within the industry to abate environmental impact of their products in cognizance of the company's goals, business needs, and resource constraints.

## 5 Conclusions and Future Work

An MCDA based tool that allows designers' to balance business decisions, process feasibility, and environmental considerations is likely to enhance the willingness of decision makers to pursue ESPD. Although there are numerous business vendors within design and engineering solutions/services that package individual modules such as LCA, AHP, and Monte Carlo simulation, the real challenge is to develop an easy-to-use, holistic platform which integrates all these modules in order to facilitate systematic decision making for ESPD. This paper details a framework for addressing the above, with the primary goal of improving the environmental aspect of the product through DfE whilst integrating business and feasibility parameters. The proposed framework integrates the qualitative and quantitative aspects of decision making by correlating LCA with an AHP based stochastic analysis. It is a qualitative method in the sense that it utilizes subjective data collected from experts through a developed questionnaire. At the same time, it is a quantitative method since it calculates the global priority scores (GPS) and estimates the eigenvalue/eigenvectors for each decision criteria which are based on a LCA of the product. Furthermore, the process for solving eigenvalues and eigenvectors of each pairwise comparison matrix evaluates that the data provided by the design team is logically consistent, facilitating a rational decision making process. One of the major contributions of this paper is the integration of an uncertainty analysis module within this integrated framework through the use of a stochastic AHP with bootstrap re-sampling. Additionally, statistical significance testing and a sensitivity analysis enable decision makers in taking robust decisions as well as refining the accuracy of the analysis.

Methods for designing the questionnaire, constructing the pairwise comparison matrix, and calculating GPS are also illustrated in order to understand the proposed methodology. Finally, the implementation of the methodology within "Company A" verifies its ease of applicability in a real-world industry setting.

Although an integrated framework that incorporates environmental and business considerations was presented, it should be understood that the method only identifies management level strategies to support ESPD. Decisions that support ESPD activities need to consider product information from both a company level as well as the product component level perspective. Future research will focus on extending this framework so as to translate the presented DfE strategies to the product component level with the goal of generating specific redesign instructions.

## 6 Supporting Information

For the sake of brevity, supporting information, including the original dataset from the ten surveys and the Microsoft Excel® based survey, is not comprehensively described in the paper. Interested readers can download this content from the following webpage.[1]


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## Nomenclature

$\mathrm{BCI}_h$ = upper bound of the bootstrap confidence interval
$\mathrm{BCI}_l$ = lower bound of the bootstrap confidence interval
C.I = Saaty's consistency index
C.R = consistency ratio of the pair-wise comparison matrix
$\mathrm{GPS}_k$ = global priority score of $k$th DfE strategy
$\mathrm{GW}_j$ = global weight of $j$th criteria
$i$ = type of criteria $i \in 1, 2, ..., I$
$j$ = type of sub-criteria $j \in 1, 2, ..., J$
$k$ = type of DfE strategy $k \in 1, 2, ..., K$
$\mathrm{LW}_i$ = local weight of $i$th criteria
$\mathrm{LW}_j$ = local weight of $j$th criteria
$N$ = number of activities/size of the pair-wise comparison matrix
$\mathrm{R.I}_N$ = random consistency index for the pair-wise comparison matrix of size $N$
$\mathrm{RSj}_{,k}$ = rating of $k$th DfE strategy with respect to $j$th sub-criteria
$S$ = sootstrap standard error
$t^*$ = critical value of the $t(n-1)$ distribution at a $p$ value of 0.05
$\mu$ = expected value of the bootstrap distribution
$\Psi_{\max}$ = max eigenvalue of the pair-wise comparison matrix of size $N$

[1] http://goo.gl/C4HIE

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