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A hybrid Stochastic Approach for Improving Uncertainty Analysis in the Design and Development of a Wind Turbine

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Abstract

This paper presents an analysis of potential technological advancements for a 1.5 MW wind turbine using a hybrid stochastic method to improve uncertainty estimates of embodied energy and embodied carbon. The analysis is specifically aimed at embodied energy and embodied carbon results due to the fact that life cycle assessment (LCA) based design decision making is most important at the concept design stage. The development of efficient and cleaner energy technologies and the use of renewable and new energy sources will play a significant role in the sustainable development of a future energy strategy. Thus, it is highlighted in International Energy Agency that the development of cleaner and more efficient energy systems and promotion of renewable energy sources are a high priority for (i) economic and social cohesion, (ii) diversification and security of energy supply, and (iii) environmental protection. Electricity generation using wind turbines is generally regarded as key in addressing some of the resource and environmental concerns of today. In the presented case studies, better results for the baseline turbine were observed compared to turbines with the proposed technological advancements. Embodied carbon and embodied energy results for the baseline turbine show an about 85% probability that the turbine manufacturer may have lost the chance to reduce carbon emissions, and 50% probability that the turbine manufacturer may have lost the chance to reduce the primary energy consumed during its manufacture. Conclusively, the presented approach is a feasible alternative when more reliable results are desired for decision making in LCA.

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Keywords: Embodied energy; Embodied carbon; Technology Improvement Opportunities; Uncertainty; 1.5 MW wind turbine

1. Introduction

Wind and other renewable energy systems are often assumed to be environmentally friendly and sustainable energy sources in mainstream debate. All energy systems for converting energy into usable forms however have environmental impacts associated with them [1-3]. The production of renewable energy sources, like every other production process, involves the consumption of natural resources and energy as well as the release of pollutants [4]. Life cycle assessment (LCA) is a popular way of measuring the energy performance and environmental impacts of wind energy [1, 5]. Oebels et al. [6] states that estimation of embodied carbon and energy is a significant part of life cycle assessments. Hammond and Jones [7] defined embodied carbon (energy) of a material as the total carbon released (primary energy consumed) over its life cycle. This would normally encompass extraction, manufacturing and transportation. It has however become common practice to specify the embodied carbon (energy) as 'Cradle-to-Gate', which includes all carbon (energy – in primary form) until the product leaves the factory gate [7].

Embodied carbon and energy are traditionally estimated deterministically using single fixed point values to generate single fixed point results [8]. Lack of detailed production data and differences in production processes result in substantial variations in emission factor (EF) and embodied energy coefficient (EEC) values among different life cycle inventory (LCI) databases [9, 10]. Hammond and Jones [7] notes that a comparison of selected values in these inventories would show a lot of similarities but also several differences. These

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variations termed as "data uncertainty" which significantly affects the results of embodied carbon and embodied energy LCA [11]. Uncertainty is unfortunately part of embodied carbon and energy analysis and even data that is very reliable carries a natural level of uncertainty [7, 12]. Decision makers have different attitudes towards uncertainty or risk therefore information on uncertainty in LCA is highly desired [9, 11]. The analysis of data uncertainty is therefore a significant improvement to the deterministic approach because it provides more information for decision making [12, 13].

A number of generally accepted and well understood methods such as stochastic modelling, analytical uncertainty propagation, interval calculations, fuzzy data sets and scenario modelling are normally used to propagate uncertainty in LCA studies [10]. Stochastic and scenario modelling methods were used to propagate uncertainty in the wind energy LCA studies surveyed.

The Monte Carlo analysis method used by Kabir et al. [12], Fleck and Huot [14] and Khan et al. [15] performs well for cases when reliability of the uncertainty estimate is not of utmost importance. This method has a drawback when applied, as due to its "rule of thumb" nature it may lead to inaccurate results. For more reliable results, Lloyd and Ries [8] highlights that the determination of significant contributors to uncertainty, selection of appropriate distributions and maintaining correlation between parameters are areas requiring better understanding. In this study, a method for improving uncertainty estimates is presented and discussed. The method employs the same basics as the Monte Carlo analysis but has a key distinction, aiming at removing the drawback of the Monte Carlo analysis method by employing a stochastic pre-screening process to determine the influence of parameter contributions. The overall aim of this study is to present an analysis of potential technological advancements for a 1.5 MW wind turbine using a hybrid stochastic method to improve uncertainty estimates of embodied energy and embodied carbon. This approach can be a valuable tool for design scheme selection aiming to find an embodied energy and embodied carbon saving design when information on uncertainty is needed for LCA based design decision making. The organisation of the content of this paper is as follows: Section 2 explains the fundamentals of the methodology. Section 3 contains a description of the case studies and results. Section 4 and 5 are the discussions and conclusion.

Nomenclature

CDF: Cumulative distribution function
CFRP: Carbon Fibre Reinforced Plastic
CV: Coefficient of Variation
DQI: Data Quality Indicator
EEC: Embodied energy coefficient
EF: Emission Factor
HDS: Hybrid Data Quality Indicator and Statistical
LCA: Life Cycle Assessment
MCS: Monte Carlo Simulation
M_{DQI}: Mean of DQI result
M_{HDS}: Mean of HDS result
MRE: Mean Magnitude of Relative Error
MW: Megawatt
N_M: Least number of data points required
N_{MD}: Least number of required data points for individual parameter distribution estimation
N_P:Number of parameters involved
NREL: National Renewable Energy Laboratory
PDF: Probability distribution function
TIO: Technology Improvement Opportunities

2. Methodology

The stochastic results are calculated by MCS algorithm, according to the input and output relationships, using the intricately estimated probability distributions for the parameters as the inputs. Figure 1 shows the procedure for the hybrid data quality indicator and statistical (HDS) approach.

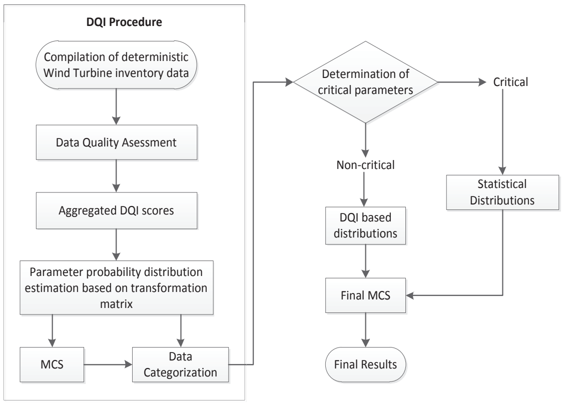

Fig. 1. Procedure of HDS approach [9].

To validate the HDS approach, comparisons are made between the pure data quality indicator (DQI), statistical and HDS methods. The measurements Mean Magnitude of Relative Error (MRE) (Eq. (1)) and Coefficient of Variation (CV) (Eq. (2)) are used to measure the differences in the results of the pure DQI and HDS. CV is an indicator that shows the degree of uncertainty and measures the spread of a probability distribution. A large CV value indicates a wide distribution spread. The data requirements are also used to compare the HDS with the statistical method, as large enough sample size needs to be satisfied during parameter distribution estimation. The least number of data points necessary for estimating parameter distributions in each method is calculated (Eq. (3)) and compared.

$$MRE = \frac{(M_{HDS} \quad M_{DQI})}{M_{HDS}} x100\% \qquad (1)$$

Where M_{DQI} is the mean of the DQI results and M_{HDS} is the mean of the HDS results.

$$CV = \frac{SD}{M} \qquad (2)$$

Where M is the mean and SD is the standard deviation

$$N_M = N_{MD} \times N_P \qquad (3)$$

Where N_M is the least number of data points required; N_{MD} is the least number of required data points for individual parameter distribution estimation; N_P is the number of parameters involved.

3. Case study and result analysis

3.1. Background of the case study

Projections of future technological designs as a result of research and scientific developments, based on National Renewable Energy Laboratory (NREL) [16] 1.5 MW wind turbine technology forecasting studies and further elaborated by Cohen et al., [17] and Lantz et al., [18] provided the basis for modelling future inventory changes for this study. Embodied energy and embodied carbon are considered as a measure of environmental impact measurement.

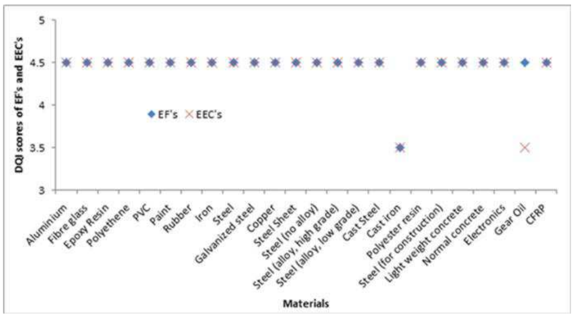

Fig. 2. Aggregated DQI scores for Emission Factors and Embodied Energy Coefficients.

3.2. Quantitative DQI transformation

To appropriately transform the qualitative assessment results to the equivalent quantitative probability density functions, Wang and Shen [10] suggests that the aggregated DQI scores be approximated to the nearest nominal value so as to use the transformation matrix. Figure 2 shows the obtained aggregated DQI scores. The quantitative DQI procedure was then used to transform the scores into Beta distributions. Most of the data used in the study are of good quality and were taken from the same data source and hence showed identical transformed Beta function parameters (α = 4, β = 4), the same DQI score of 4.5 and range end points of 15%. The exceptions were Cast iron EF, Cast iron EEC and Gear oil EEC showing DQI scores of 3.5, transformed Beta function parameters of (α = 2, β = 2) and range end points of 25% making them more uncertain.

3.3. Parameter Categorization and Probability Distributions Estimation

Results of the influence analysis (10,000 iterations MCS) showing the two parameters contributing the most to the resulting uncertainty is presented in Table 1. Two parameters, Steel and CFRP, demonstrated the largest influence on the final resulting uncertainty of embodied energy and embodied carbon across all case studies. For the parameters with a lesser contribution to the final resulting uncertainty, there were variations across all case studies. Normal concrete and Carbon fibre reinforced plastic (CFRP) show the lesser contribution for embodied carbon, while Steel (no alloy), CFRP and Cast iron show the lesser contribution for embodied energy across all case studies. Combining these results, further analysis was conducted on the two identified parameters for each test case using the statistical method, while the values for the remaining parameters were obtained from the quantitative DQI. Probability distributions were thus fitted to data points collected manually from literature. Results of the estimated probability distributions for the different parameters are presented in Table 2.

Table 1. Influence Analysis.

	Embodied Carbon	Influence (%)	Embodied Energy	Influence (%)
Baseline Turbine	Steel EF	78	Steel EEC	62
	Normal concrete EF	9	Steel (no alloy) EEC	9
TIO 1	Steel EF	66	Steel EEC	47
	CFRP EF	17	CFRP EEC	22
TIO 2	CFRP EF	99	CFRP EEC	97
	Normal concrete EF	0.3	Steel (no alloy) EEC	0.7
TIO 3	Steel EF	81	Steel EEC	66
	Normal concrete EF	8	Cast iron EEC	9
TIO 4	CFRP EF	98	CFRP EEC	97
	Normal concrete EF	0.6	Steel (no alloy) EEC	0.5

Table 2: Probability distribution estimation for the different parameters.

Parameter	Probability Distribution	Mean	Data points collected
Steel EF	Beta (1.24, 4.47)	1.73 $tonCO_2/ton$	30
Steel EEC	Beta (2.96, 4.16)	25.87 GJ/ton	31
Normal concrete EF	Beta (20.8, 87.7)	0.11 $tonCO_2/ton$	31
Steel (no alloy) EEC	Beta (48.6, 62.3)	25.57 GJ/ton	31
CFRP EF	Beta (3.16, 2.2)	52.4 $tonCO_2/ton$	31
CFRP EEC	Beta (2.13, 6.23)	191.3 GJ/ton	31
Cast iron EEC	Beta (36.6, 75.2)	35.4 GJ/ton	31

3.4. Stochastic Results Comparison of DQI and HDS Approaches for the Different Case Studies

Embodied carbon and embodied energy stochastic results (10,000 iterations MCS) using the pure DQI and HDS methods were obtained for the baseline turbine and TIO's 1 - 4 the results of which are presented in this section. Results for each case study are presented graphically through probability distribution functions (PDF's) and cumulative distribution functions (CDF's) in Figures 3 and 4 (these only show a few samples of the full results). In addition to these figures, MRE and CV values were also calculated. A summary of the relevant information is provided in Table 3.

Probability distributions were fitted to the stochastic results according to K-S test. From the PDF's (Figures 3a and 4a), it can be seen that the mean value and standard deviation for the pure DQI and HDS results show rather different dispersion across all the case studies. The CV values of the HDS results are on average about 6 times larger than the CV values of the pure DQI results. In terms of MRE, the difference observed between the HDS and pure DQI results indicate that the HDS method captures more possible outcomes compared to the pure DQI. The differences between the deterministic, pure DQI and HDS results can be inferred from the CDF's (Figures 3b and 4b). Figure 3b for example shows that for the HDS result, about 85% of the likely resulting values are smaller than the deterministic result obtained while for the DQI result, 50% of the possible results are smaller than the deterministic result. Figure 3d also shows that for the HDS result about 15% of the likely results are smaller than the deterministic result while for the DQI result, half of the possible resulting values are lesser than the deterministic result. A comprehensive analysis of the implications of these results is presented in the discussion section.

3.5. Comparison of Statistical and HDS Methods in terms of Data Requirements

It can be seen that from the procedure of the HDS approach which categorizes critical parameters and uses the statistical method to estimate their probability distributions, the reliability of the HDS results are not greatly jeopardized. According to Wang and Shen [10], the statistical method requires at least 30 data points to estimate one parameter distribution. Hence in this study, 46 parameter distributions are required to be estimated for each case study with the exception of TIO 1 which has 48 parameter distributions for estimation. If the statistical method was implemented, at least 1380 data points would have been required for the estimation for each case study. That would mean 6900 data points across all the case studies. This would have been very time consuming even if all the data points were available. The HDS requires only 120 data points for each case study (600 data points across all the case studies) thus reducing the data requirements by approximately 91%.

This avoids the issue associated with lack of data, and saves cost and time without seriously compromising the reliability of the HDS results as the critical parameters identified explain the majority (at least 69%) of the overall uncertainty across all the case studies.

Table 3: Pure DQI and HDS results for the different case studies.

	Embodied Carbon		Embodied Energy	
	DQI	HDS	DQI	HDS
Baseline Turbine	Beta distribution (4.5, 5.3) μ = 932 $tonCO_2$ σ = 22 $tonCO_2$ CV = 0.02	Beta distribution (1.8, 5.1) μ = 733 $tonCO_2$ σ = 183 $tonCO_2$ CV = 0.25 MRE = 27%	Normal distribution μ = 11909 GJ σ =218 GJ CV = 0.02	Beta distribution (4.4, 4.7) μ = 11831 GJ σ = 1424 GJ CV = 0.12 MRE = 1%
TIO 1	Normal distribution μ =1070 $tonCO_2$ σ = 24 $tonCO_2$ CV = 0.02	Beta distribution (2.3, 5.2) μ =1269 $tonCO_2$ σ =188 $tonCO_2$ CV = 0.15 MRE = 16%	Normal distribution μ = 13735 GJ σ = 244 GJ CV = 0.02	Beta distribution (3.8, 4.7) μ = 13276 GJ σ = 1469 GJ CV = 0.11 MRE = 3.5%
TIO 2	Beta distribution (5, 5.3) μ = 2475 $tonCO_2$ σ = 96 $tonCO_2$ CV = 0.04	Beta distribution (5.8, 4.1) μ = 5521 $tonCO_2$ σ = 1654 $tonCO_2$ CV = 0.3 MRE = 55%	Beta distribution (4.1, 4.8) μ = 31822 GJ σ = 1166 GJ CV = 0.04	Beta distribution (2.4, 4.7) μ =24687 GJ σ = 7608 GJ CV = 0.3 MRE = 29%
TIO 3	Beta distribution (5.3, 5.7) μ = 849 $tonCO_2$ σ = 22 $tonCO_2$ CV = 0.03	Beta distribution (1.6, 4.6) μ = 647 $tonCO_2$ σ =185 $tonCO_2$ CV = 0.29 MRE = 31%	Normal distribution μ =10722 GJ σ =211 GJ CV = 0.02	Beta distribution (3.8, 4.8) μ =11249 GJ σ = 1474 GJ CV = 0.13 MRE = 5%
TIO 4	Gamma distribution (529, 4.8) μ = 2529 $tonCO_2$ σ = 108 $tonCO_2$ CV = 0.04	Weibull distribution (3.96, 6621) μ = 5988 $tonCO_2$ σ = 1746 $tonCO_2$ CV = 0.29 MRE = 58%	Beta distribution (4.7, 4.5) μ = 32503 GJ σ = 1304 GJ CV = 0.04	Beta distribution (2.1, 4.6) μ = 24299 GJ σ = 8419 GJ CV = 0.35 MRE = 33%

4. Discussion

This study uses the HDS approach to provide insight into potential technological advancements for a 1.5 MW wind turbine and makes evident how variability of input parameters results in differing embodied energy and embodied carbon results. Analysing the parameter categorization revealed that EF's and EEC's for Steel, Normal concrete, Steel (no alloy), CFRP and Cast iron accounted for the majority of output uncertainty in embodied energy and embodied carbon results. Steel is the main material component of the baseline wind turbine, followed by normal concrete. The large contribution of steel is probably attributed to the wide EF and EEC distributions assigned to steel in the probability distribution estimations. Therefore any uncertainty in steel EF's and EEC's is magnified by the sheer mass of steel. Interestingly although the mass of concrete (575 tons) is greater than the mass of steel (144 tons), steel EF's and EEC's contribute more to the overall uncertainty of embodied energy and embodied carbon. For example, the EF's of steel ranges from 0.01 – 5.93 tonCO2/ton steel, whereas values for concrete range from 0.02 – 0.28 tonCO2/ton. Likewise, the EEC's for steel range from 8.6 – 51 GJ/ton steel, whereas values for steel (no alloy) range from 8.3 – 50.7 GJ/ton. Concrete generally is much less emission intensive than steel for CO2 and hence, is a lesser contributor to the sensitivity of embodied carbon. It can also be observed that while normal concrete EF and steel (no alloy) EEC contribute 9% each, steel EF and steel EEC contribute 78% and 62% respectively to the resulting uncertainty.

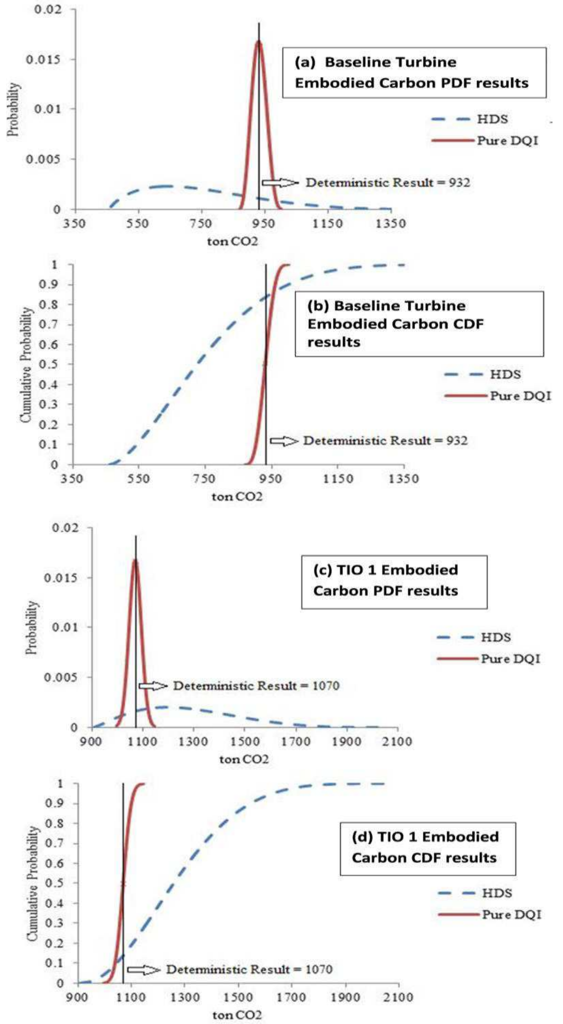

Fig 3. Sample results 1.

This highlights the influence of the wider distribution range of steel (no alloy) EEC compared to normal concrete EF. Due to the wide distribution ranges and mass of steel, variations in steel EF's and EEC's have significantly more impact on the embodied energy and embodied carbon uncertainty even though there is normally more concrete than steel.

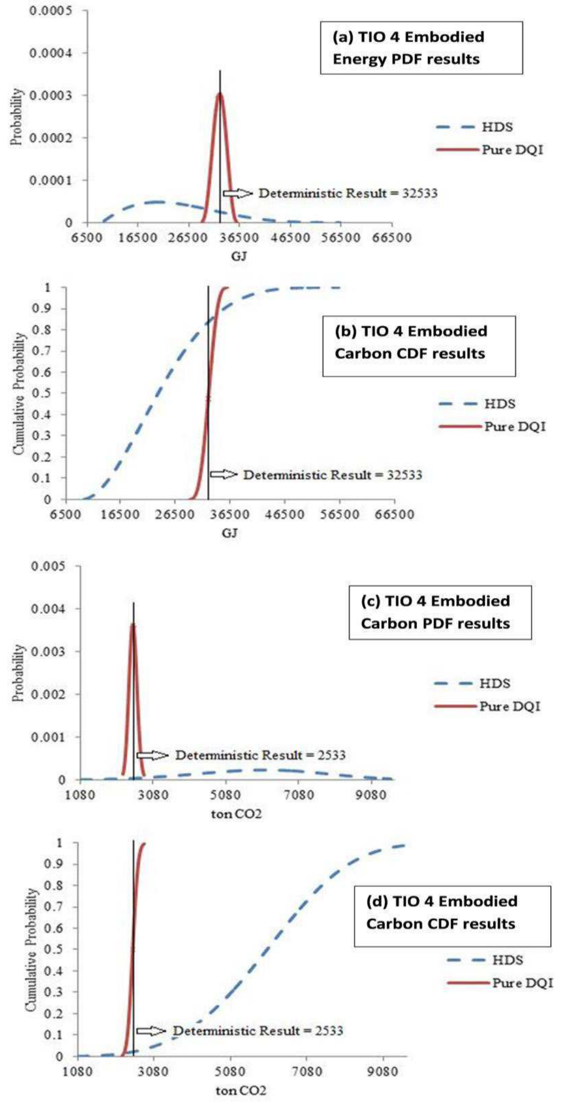

Fig 4. Sample results 2.

5. Conclusions

In this paper the competence of the HDS method in estimating data uncertainty in deterministic embodied carbon and embodied energy LCA results and its application to decision making is examined through case studies. In order to evaluate the reliability of the HDS method, first, embodied carbon and embodied energy results were estimated deterministically. Then for each case study, using DQI and HDS methods, the effect on uncertainty estimates for embodied energy and embodied carbon are investigated. In performing the uncertainty analysis, the reliability measures MRE and CV are considered. Using the results obtained the following conclusions are drawn.

Firstly, with respect to the use of both methods, the HDS approach demonstrated its effectiveness in evaluating deterministic 1.5 MW wind turbine embodied carbon and embodied energy results. MRE and CV results show the HDS far outperforms the DQI. In other words, a strong argument could be made to advocate for the use of the HDS over DQI when accuracy of the uncertainty estimate is paramount. Secondly, for the class of the problem at hand, similar conclusions can be drawn in terms of embodied energy and embodied carbon for all case studies. Uncertainty in the results largely depends on distribution ranges of the input parameters. This is magnified by the mass of the materials which result in the overall contributions to the uncertainty. Hence, it is shown that a strong relationship exists between material mass and input parameter distribution ranges. Thirdly, when comparing the different turbine designs based on the studied cases, the results were quite clear. With the performance improvements incorporated using the TIO's, the baseline turbine had the best embodied carbon and embodied energy performance. Therefore, when all the criteria are considered, the potential investor must decide whether the environmental benefits for a particular design are worth the investment.

It is important to note that the NREL baseline turbine design represents a composite of wind turbine technology available in 2002. Clearly, technology has changed since 2002 and these changes are not incorporated into the current analysis. Future studies may conduct uncertainty analysis using the HDS approach to analyse these technological changes in the development of newer wind turbines and other renewable technologies. This would be another excellent application for the HDS methodology.

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