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Analysis of technology improvement opportunities for a 1.5 MW wind turbine using a hybrid stochastic approach in life cycle assessment

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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 these two quantities due to the fact that LCA based design decision making is of utmost importance at the concept design stage. 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 that there is about 85% probability that the turbine manufacturers may have lost the chance to reduce carbon emissions, and 50% probability that they may have lost the chance to reduce the primary energy consumed during its manufacture. The paper also highlights that the adopted methodology can be used to support design decision making and hence is more feasible for LCA studies.

1. Introduction

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 [20,63]. It is highlighted in International Energy Agency (2013) 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. According to the World Wind Energy Association [64] wind energy technology has steadily improved and costs have declined. This technological progress is obvious in the movement to better wind conditions and shift to higher nominal power of wind turbines [60,62]. However, all renewable systems for converting energy into usable forms such as electricity have environmental impacts associated with them [11,31] and is an important issue in mainstream debate. Further, as pointed out by Chen et al. [8] and Yang et al. [65]; it is essential that the long term sustainability of such systems are scrutinized to support the astonishing growth (actual plus planned) of wind farms as well as to allow policy makers to take robust decisions to mitigate climate change through the implementation of this technology at the design stage.

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 [2]. Life cycle assessment (LCA) is a popular way of measuring the energy performance and environmental impacts of wind energy [11,40]. Hammond and Jones [23] defined embodied energy of a material as the total amount of primary energy consumed over its life cycle. This would normally encompass extraction, manufacturing and transportation and the terminology has been in use for over four decades [10]. In a similar fashion embodied carbon refers to the life cycle greenhouse gas emissions (expressed as carbon dioxide equivalents − CO_2e) that occur during the manufacture and transport of a material [8]. Embodied energy and embodied carbon assessments are considered a subset of LCA studies.

Embodied energy and embodied carbon are traditionally estimated deterministically using single fixed point input values to

List of symbols and abbreviations: LCA, life cycle assessment; EEC, embodied energy coefficient; EF, emission factor; DQI, data quality indicator; HDS, hybrid data quality INDICATOR and Statistical; MCS, Monte Carlo simulation; K−S, Kolmogorov−Smirnov; MRE, mean magnitude of relative error; M_{HDS}, mean of HDS result; M_{DQI}, mean of DQI result; CV, coefficient of variation; σ, standard deviation; μ, mean; 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; MW, megawatt; TIO, technology improvement opportunities; CFRP, carbon fibre reinforced plastic; PDF, probability distribution function; CDF, cumulative distribution function.

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generate single fixed point results [38]. 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 [53,59]. Hammond and Jones [23] note that a comparison of selected values in these inventories would show a lot of similarities but also several differences. These variations termed as “data uncertainty” in Huijbregts [28] significantly affect the results of embodied energy and embodied carbon LCA studies. Uncertainty is unfortunately part of embodied carbon and energy analysis and even data that is very reliable carries a natural level of uncertainty [23,30]. Hence, the analysis of data uncertainty is a significant improvement to the deterministic approach because it provides more information for decision making [59,30,53,54].

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 analysis. In a survey of approaches used to incorporate uncertainty in LCA studies, Lloyd and Ries [38] have found that the majority of the published work employed scenario modelling to propagate uncertainty on LCA outcomes [40,21,22,12,56,57,66,19,67,43,45,3,39], while only three [30,18,32], have employed stochastic modelling to propagate uncertainty. Of the twelve studies using scenario modelling, all assessed scenarios using sensitivity analysis, while for the studies employing stochastic modelling, all used Monte Carlo simulation with random sampling. The Monte Carlo analysis method used by Kabir et al. [30], Fleck and Huot [18] and Khan et al. [32] 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 [38] 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 methodology (termed as HDS) for improving uncertainty estimate 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 very reliable statistical method is then used to estimate probability distributions for the identified critical parameters. By applying the HDS method to a baseline 1.5 MW wind turbine and four Technology Improvement Opportunity variants [9,34], the uncertainty estimates of embodied energy and embodied carbon are examined. This methodology can be a very valuable tool for making informed decisions at the design stage in order to make savings on embodied energy and embodied carbon by taking into consideration the uncertainty estimates of these quantities. The overall contribution 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. 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 their background theory. In Section 4 the results are analysed and discussed. Finally, in Section 5, conclusion and future work are presented.

2. Methodology

Statistical and Data quality indicator (DQI) methods are used to estimate data uncertainty in LCA with different limitations and advantages [38,59]. The statistical method uses a goodness of fit test to fit data samples characterizing data range with probabilistic distributions if sufficient data samples are available [59]. On the other hand, the DQI method estimates data uncertainty and reliability based on expert knowledge and descriptive metadata e.g. source of data, geographical correlation of data etc. It is used quantitatively [38] and qualitatively [29,38]. Compared to the statistical method the DQI costs less, although it is less accurate than the statistical method [54,59]. The statistical method is preferred when high accuracy is required, though its implementation cost is high [53,59]. The DQI method is generally applied when the accuracy of the uncertainty estimate is not paramount, or the size of the data sample is not sufficient enough for significant statistical analysis [59].

Considering the trade-off between cost of implementation and accuracy, Wang and Shen [59] presented an alternative stochastic solution using a hybrid DQI-statistical (HDS) approach to reduce the cost of the statistical method while improving the quality of the pure DQI method in whole-building embodied energy LCA. The study focused on the reliability of the HDS approach compared to the pure DQI without considering the effect of either approach on the decision making process. An application test case to the analysis of embodied energy and embodied carbon of potential 1.5 MW wind turbine technological advancements and the effect of these approaches on decision making is presented here to validate the methodology.

2.1. Embodied energy and embodied carbon estimation

This study considers embodied energy and embodied carbon as the primary environmental impacts to be investigated Wang and Sun [60] and Ortiz et al. [44] express embodied carbon and embodied energy mathematically as follows:

$$Embodied\ Carbon = \sum_{i=1}^{n} Q_i \times EF_i \tag{1}$$

$$Embodied\ Energy = \sum_{i=1}^{n} Q_i \times EEC_i \tag{2}$$

Where

Q_i = Quantity of material i
EEC_i = Embodied energy coefficient of material i
EF_i = Emission factor of material i

Since the purpose of the different wind turbine designs is electricity production, the functional unit is defined as ‘generation of 1 KWh of electricity’. The scope of the study for all the wind turbine design options considered is from ‘cradle to gate’.

2.2. Qualitative DQI method

Qualitative DQI uses descriptive indicators, often arranged as a Data Quality Indicator (DQI) matrix (Table 1), to characterize data quality. Rows in the matrix represent a quality scale, ranging from 1 to 5. Columns represent data quality indicators such as age of the data, reliability of the data source etc. General quality for a data is specified by an aggregated number that takes into account all the indicators. For example if three indicators are assigned scores of (1, 3, 5) respectively for a given parameter, and the indicators are equally weighted, the parameter's aggregated DQI score is $P = 1 \times 1/3 + 3 \times 1/3 + 5 \times 1/3 = 3$.