Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 56 (2016) 19 – 24

www.elsevier.com/locate/procedia

9th International Conference on Digital Enterprise Technology - DET 2016 – "Intelligent Manufacturing in the Knowledge Economy Era

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

Matthew Ozoemena, Wai M. Cheung*, Reaz Hasan, Haitem Fargani

Northumbria University, City Campus, Wynne Jones Building, Newcastle Upon Tyne, NE1 8ST, United Kingdom

* Corresponding author. Tel.: +44 (0)191-243-7584; *E-mail address:* wai.m.cheung@northumbria.ac.uk

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.

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production

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

Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production
doi:10.1016/j.procir.2016.10.009

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.

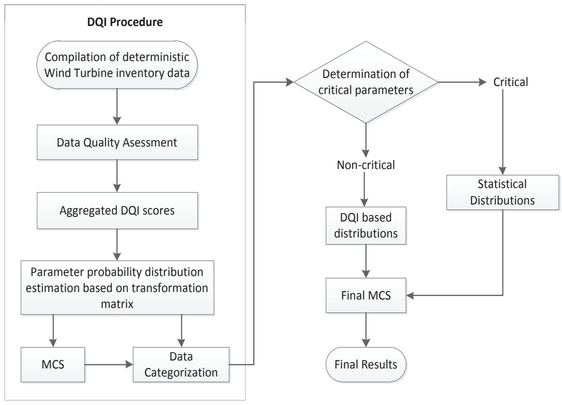

Fig. 1. Procedure of HDS approach [9].

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

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