Toward a framework of social welfare assessment of wind energy systems

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Abstract. Wind energy systems have seen substantial growth over the past decades. It is important to assess the impacts of wind energy systems on the wellbeing of all aspects of life and society. Previous works have been conducting life cycle assessments to evaluate the environmental impacts of wind energy systems; in social research, studies have also been conducted to clarify people’s attitude and perception of wind energy systems. However, to assess social welfare, it is needed to integrate these two approaches and generate indicators on a comparable and objective basis. In this work, we propose such a framework in which community survey designs and data analysis methods are specified. To correct the subjectivity in the answers of individuals, an inverse map of that used in prospect theory is used. Based on the indicators of the five aspects of social welfare evaluated by an individual, the individual utility function can be constructed, which, in turn, can be averaged over the individual’s cluster or group. The cluster averaged individual utility functions will lead to definitions of social welfare function. This work then discusses the effects of cluster weight parameters, social welfare function definitions, as well as the inclusion of the prospect theory concept. The proposed social welfare assessment framework could be valuable for future wind energy system planning and operation.

1. Introduction

With the growing emphasis on energy sustainability, wind is generally viewed as a renewable source of electricity to replace conventional power generation utilizing coal or natural gas. Globally there has been a remarkable increase in wind energy system (WES) capacity installations in the last few decades. In the United States alone, according to the American Wind Energy Association (AWEA) [1], the WES capacity installations steadily increase from 2,502 MW in 2001 to 90,550 MW in 2018. The large-scale, fast-paced WES implementation on the one hand has offered rich empirical data to advance the understanding of it as a complex socio-technical system, and on the other hand poses a pressing need to clarify the wide range of factors involved in WES development and their interactions [2]. This paper presents the conceptual model of an ongoing study that aims to assess WES in terms of social welfare, which includes the wellbeing of the society, the quality of the environment, and other aspects of life [3].

To evaluate the environmental impacts of complex systems, life cycle assessment (LCA) has been a general approach standardized by the International Organization for Standardization (ISO) [4][5]. In the last few decades, LCA has been applied extensively to WESs to examine their viability in terms of...
environmental footprints [6]-[12]. Life cycle sustainability assessment (LCSA) was proposed [13] to extend conventional LCAs which are mainly from the technological point of view to a more balanced consideration on environmental, economic, and social consequences. However, due to lack of relevant database and standard method/tool, this approach has met challenges [14]. On the other hand, in the field of social research (SR), progress has been made to deepen the understanding of public perception and social acceptance of WESs [15]-[18], which supplements WES assessment by adding a community dimension, i.e., characterization of factors related to the individual and collective profiles of the hosting community. These studies highlighted the importance of community engagement and trust building for WES planning but fell short of generating statistical indicators of the community impacts.

Combining the merits of both LCA and SR, this work aims to develop an integrated framework that can guide the assessment of social welfare of a WES. Within this framework, one first conducts the LCA of a WES and obtains environmental indicators including greenhouse gases emission (GHGE), energy payback time (EPBT), and natural resource wastes (NRW). The community members are surveyed on their concerns/perceptions of and attitudes toward the WES, which generates several social indicators. The feedback will contain the weights the community members put on each indicator. A social welfare function (SWF) is then defined and evaluated. In Sec. 2, details of the social welfare assessment outlined above are described. In Sec. 3, based on hypothetical survey scenarios, some representative assessments are demonstrated and discussed. Conclusions and suggestions for future work can be found in Sec. 4.

2. Approach

Fig. 1 illustrates the framework for WES social welfare assessment, which consists of three main steps: LCA, community survey, and data analysis. Each of these steps will be demonstrated in one of the following subsections.

![Figure 1. Block diagram for WES social welfare assessment.](image-url)
2.1. LCA
The analyses in this paper are based on the published literature on LCAs of environmental impacts of WESs compared to traditional power plants (coal and natural gas). The indicators include GHGE, EPBT, and NRW, which will be defined below. Before moving on, it is worthwhile to mention that for a specific WES project, these indicators need to be evaluated using standardized methods. However, it is out of the scope of this work to conduct LCA.

2.1.1. GHGE. The GHGE from power plants are represented by the equivalent grams of CO$_2$ per kWh of energy production. The average amount of GHGE from previous studies are summarized in Table 1.

| Power Plant | Avg. CO$_2$eq (g/kWh) | References |
|-------------|----------------------|------------|
| WES         | 14.90                | [7][8][9][10] |
| Coal        | 1090.94              | [19][20]   |
| Natural Gas | 507.59               | [21][22][23] |

The reduction of GHGE rates that produced by the WES compared to the traditional power plants could be assessed by Eq. (1):

$$I_1 = \frac{GHGE_{trad} - GHGE_{WE}}{GHGE_{trad}}$$

where $I_1 = 98.6\%$ reduction of emissions compared to coal power plants and 97.06% reduction of emissions compared to natural gas power plants.

2.1.2. EPBT. Energy usage and energy efficiency are among the most important aspects of electrical power generation. One of the chief goals in sustainable development is to make the best use of the available resources. In the case of power generation, this means producing the largest amount of electrical energy output for the lowest possible energy input. The EPBT for a WES represents the period of time that the system needs to perform to achieve breakeven in energy investment and payback [24], which is calculated as the ratio of the embedded energy to the annual energy generated by the system. The average EPBT as acquired from [1], [6] and [8] is 0.9 years. The second indicator, the percentage of WES life time that creates net energy profits, is defined by the following equation:

$$I_2 = \frac{WELT - EPBT}{WELT}$$

where the wind energy life time (WELT) is set to be 20 years, resulting in $I_2 = 95.5\%$.

2.1.3. NRW. Less focus has been on the natural resource consumptions in power generation LCAs. Nevertheless, it should still be an important factor for sustainability. Even if a power generation technology is environment friendly and energy efficient, yet it uses up and wastes significant quantities of scarce natural resources, then it may not be considered as a satisfactory solution. The total NRW values for WES is estimated at 46.62 g/kWh according to [7] while the number is 591.42 g/kWh for coal power plants [19]. The reduction of NRW by deploying WES is thus calculated:

$$I_3 = \frac{NRW_{coal} - NRW_{WE}}{NRW_{coal}}$$

The result indicates a $I_3 = 92.11\%$ reduction of NRW in favor of the WES.

2.2. Community survey
The purpose of the community survey is to empirically evaluate the degree to which the WES impact various aspects of people’s wellbeing. As a work in progress, the survey is to be conducted among community members near the Chapman Ranch Wind Farm in Texas (started operation in 2017). Although this is a cross-sectional survey, it can be extended to longitudinal study to see the change in results from the data collected over time. In our survey plan, the data collection will be through telephone and personal interviews. This kind of follow-up study after a WES is built will provide valuable information on the actual impacts experienced by the community.

2.2.1. Population and sample. The population in the study is identified as people whose lives are directly affected by the WES. This includes: (1) residents whose properties overlap with the WES and its peripheral facilities such as power lines and transformer substations, (2) people who have economic and financial relationships with the WES (e.g., investors, employees, and contractors), and (3) those living in the nearby area (e.g., within a 5-mile radius) of the WES. The sampling design is a typical clustering procedure. For each of the 3 clusters identified, we then sample within the names of individuals belonging to the cluster. The clusters may be associated with different weights when constructing the overall social welfare function. Regarding sample size, we have a goal of reaching 50% of cluster (1), 20% of cluster (2), and 10% of cluster (3).

2.2.2. Survey instruments. The survey will ask for the inputs on 5 impacts of a WES as follows: (i) GHGE; (ii) EPBT; (iii) NRW; (iv) non-economic aspects like health and landscape; (v) personal and family economic conditions. As shown in Table 2, for all the aspects (i = 1, ..., 5), each of the surveyed will rate the respective importance $S_i$ on a scale of 0 to 10. For the impacts (iv) and (v), two questions will be asked. The first is about the perceived influence $V_i$ (i = 4,5) on a scale of -2 to 2 representing very negative to very positive. The other question is on the likelihood $P_i$ of the WES being solely responsible for the perceived influences.

The collected data will have a significant portion of subjectivity. Therefore, it is necessary to preprocess the data to facilitate the analysis and interpretation on a relatively objective ground.

### Table 2. Survey instruments used to collect data.

|                | Low     | Medium  | High    |
|----------------|---------|---------|---------|
| Importance     | 0–2     | 3–7     | 8–10    |
| Influence      | -2, -1  | 0 (neutral) | 1, 2   |
| Likelihood     | 0–33%   | 34–67%  | 68–100% |

2.3. Social welfare function

2.3.1. Inspiration from prospect theory. In a ground-breaking paper [25], the authors presented an alternative model to the expected utility theory called prospect theory. It was based on the empirical findings that people underweight outcomes with low probability compared with outcomes with more certainty. According to prospect theory, to assess the prospect for decision making under uncertainty, the probabilities ($P_i$) need to be replaced by decision weights ($W_i$). The latter is higher than the former in low probability ranges and lower otherwise. On the other hand, the value ($V_i$) of each outcome is defined as a function of the deviations ($\Delta_i$) from a reference point and is normally steeper for losses than for gains (i.e., loss aversion). Fig. 2 presents the typical function forms of these conversions.
Now we are proposing to apply prospect theory ideas to the pre-processing the community survey data, which include the decision weights and the value functions. To recover the more “objective” outcome probabilities and deviations, we can simply do an inverse operation of that used in prospect theory. The product of probability and deviation (after normalization) yields the indicator \( I_i \) in Fig. 1 (note that Fig. 1 is only for illustration; the details of this process are not shown). Next, we will use the results to construct individual utility function.

2.3.2. Individual Utility Function (IUF). From an individual’s survey results, we first calculate the weight to each of the 5 indicators:

\[
W_i = \frac{S_i}{\sum_{i=1}^{5} S_i}
\]

The first three sustainability indicators derived from LCA are shown in Eqs (1)-(3). For the remaining two social indicators based on community survey, we have:

\[
I_i = N(P_i (\Pi_i) \cdot \Delta_i(V_i)) \quad (i = 4,5)
\]

where \( N(x) \) is a normalization function that maps the maximum value of \( x \) to 1 and the minimum value of \( x \) to 0. By doing this, all 5 indicators are in the range \([0, 1]\).

The IUF is defined as follows:

\[
IUF = 0.2 \sum_{i=1}^{5} W_i \cdot I_i
\]
It is obvious that IUF has a value between 0 and 1. The higher the value is, the more benefit the corresponding individual experiences from the WES.

2.3.3. Social welfare function (SWF). After obtaining IUF for each individual surveyed, we then calculate the cluster averages (CAs):

$$CA_s = \frac{1}{n_s} \sum_{k=1}^{n_s} IUF_{s,k}$$  \hspace{1cm} (7)

where $s = 1, 2, 3$ is the cluster index, $n_s$ is the sample size of cluster $s$, and $IUF_{s,k}$ is the IUF value of the $k$th person in cluster $s$. Now assuming that the weight associated with cluster $s$ is specified as $\Omega_s$, two simplest forms of SWF can be defined by [26]:

$$SWF = \sum_{s=1}^{3} \Omega_s \cdot CA_s$$  \hspace{1cm} (8)

$$SWF = \min_s(CA_s)$$  \hspace{1cm} (9)

The SWF in Eq. (8) taking weighted average of individual utilities is called utilitarian or Benthamite form. The SWF in Eq. (9) on the basis of the welfare of the least well-off group is called Max-Min or Rawlsian form. They not only reflect different philosophical views of the social welfare status, but also imply different practical approaches to improving the social welfare.

3. Examples and discussions

3.1. Effect of cluster weight $\Omega_s$

Although the procedure outlined above is easy to follow, it is somehow strange to find that previous SR works did not provide complete dataset for an individual case. For now we can generate some random number for most of the parameters and variables needed to evaluate SWF. Then varying some parameters while keeping others the same, we can explore the effects of these parameters.

The first example is the cluster weights in Eqs. (8) or (9). We fix $\Omega_3 = 0.2$ (the people just living nearby but without direct interaction with WES), and choose three $(\Omega_1, \Omega_2)$ combinations with $\Omega_1 + \Omega_2 = 0.8$. The results are presented in Table 3, from which it can be see that the SWF defined by Eq. (8) decreases with $\Omega_1$, indicating that in this case the people whose properties overlap with the WES have less positive opinions than people who have direct economic ties with WES.

| SWF Eq. (8) | $\Omega_1 = 0.2$ | $\Omega_1 = 0.4$ | $\Omega_1 = 0.6$ |
|-------------|-----------------|-----------------|-----------------|
| SWF Eq. (9) | 0.83            | 0.80            | 0.78            |

3.2. Effect of SWF definition

From Table 3, one can also see the difference between the two definitions of SWF. The SWF defined by Eq. (9) represents the minimum cluster-averaged IUF, which does not depend on the cluster weights. It can also be inferred that 0.75 in this case is $CA_3$. If using Eq. (9), the implication is that the cluster 3 should be the focus of work to improve SWF.

3.3. Discussions

Due to page limits, this work does not provide details of the above calculations or more case studies. Here we only make some general discussions. Since the key innovation of this work is the inclusion of prospect theory concepts in the development of IUF, it is needed to understand the nature and
consequences of the conversion from decision weight and value to outcome probability and deviation. When individuals give answers to survey, their choice can be viewed as decision under uncertainty. Because of behavioural biases, the answers may deviate from the actual or objective conditions. As a result, this will tend to depreciate the negative perceived value which was exaggerated due to loss aversion and adjust the outcome probability to make low/high probabilities lower/higher. It will be the subject of further work to determine the parameters for these two functions.

4. Conclusion
In this work, we propose a framework of social welfare assessment of a wind energy system combining life cycle assessment and community stakeholder survey. The proposed framework is an extension to LCA which focus on the environmental impacts of WES. It is implemented after several years operation of WES and aims to learn what actually influence all aspects of people’s wellbeing. This could eventually lead to policies setting standards for WES planning and operation.

5. References
[1] AWEA, “U.S. wind industry third quarter 2018 market report,” [online], available: https://www.awea.org/Awea/media/Resources/Publications%20and%20Reports/Market%20Reports/3Q-2018-AWEA-Market-Report-Public-Version.pdf
[2] European Wind Energy Association, “Wind energy - The facts,” [online], available: https://www.wind-energy-the-facts.org/home--about-the-project.html
[3] BusinessDictionary.com, “Social welfare,” [online], available: http://www.businessdictionary.com/definition/social-welfare.html
[4] ISO, “ISO 14040:2006,” [online], available: http://www.iso.org/cms/render/live/en/sites/isoorg/contents/data/standard/03/74/37456.html
[5] ISO, “ISO 14044:2006,” [online], available: http://www.iso.org/cms/render/live/en/sites/isoorg/contents/data/standard/03/84/38498.html
[6] L. Schleisner, Renew Energy, 20, no. 3, 279–288 (2000)
[7] Vestas Wind Systems A/S, “LCA of electricity produced from onshore sited wind power plants based on Vestas V82-1.65 MW turbines (Date: 2006-12-29),” [online], available: https://www.vestas.com/~media/vestas/about/sustainability/pdfs/lca%20v82165%20mw%20onshore2007.pdf
[8] R. H. Crawford, Renew Sust Energ Rev, 13, no. 9, 2653–2660 (2009)
[9] K. B. Oebels and S. Pacca, Renew Energy, 53, 60–70 (2013)
[10] S. H. Al-Behadili and W. B. El-Osta, Renew Energy, 83, 1227–1233 (2015)
[11] J. Yang, Y. Chang, L. Zhang, Y. Hao, Q. Yan, and C. Wang, J Clean Prod, 180, 316–324, (2018)
[12] S. Wang, S. Wang, and J. Liu, J Clean Prod, 210, 804–810 (2019)
[13] A. Zamagni, Int J Life Cycle Assess, 17, no. 4, 373–376 (2012)
[14] N. C. Onat, M. Kucukvar, A. Halog, and S. Cloutier, Sustainability, 9, no. 5, 706 (2017)
[15] D. Bell, T. Gray, and C. Haggett, Env Polit, 14, no. 4, 460–477 (2005)
[16] C. R. Warren, C. Lumsden, S. O’Dowd, and R. V. Birnie, J Environ Manage, 48, no. 6, 853–875 (2005)
[17] R. Wüstenhagen, M. Wolsink, and M. J. Bürer, Energy Policy, 35, 2683–2691 (2007)
[18] M. Wolsink, Renew Sust Energ Rev, 11, 1188–1207 (2007)
[19] P. L. Spath, M. K. Mann, and D. R. Kerr, United States: N. p., Web. doi:10.2172/12100 (1999)
[20] C. Wang and D. Mu, J Ind Eng and Manage, 10, no. 1, 311–335, (2014)
[21] R. Kannan, K. C. Leong, R. Osman, H. K. Ho, and C. P. Tso, Energy Convers Manag, 46, no. 13–14, 2145–2157 (2005)
[22] K. Phumpradab, S. H. Gheewala, and M. Sagisaka, Int J Life Cycle Assess, 14, no. 4, 354–363, (2009)

[23] National Energy Technology Laboratory, “Natural gas combined cycle (NGCC) power plant,” [online], available: https://www.netl.doe.gov/node/7518

[24] K. P. Bhandari, J. M. Collier, R. J. Ellingson, and D. S. Apul, Renew Sust Energ Rev, 47, 133–141, (2015)

[25] D. Kahneman and A. Tversky, Econometrica, 47, no. 2, 263–292 (1979)

[26] Wikipedia.org, “Social welfare function,” [online], available: https://en.wikipedia.org/wiki/Social_welfare_function.