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A comprehensive estimate of life cycle greenhouse gas emissions from onshore wind energy in China

Kang Xu [a], Jinfeng Chang [a,*], Wenji Zhou [b], Shuangcheng Li [c], Zhou Shi [a], Hanwen Zhu [a], Yaoyao Chen [a], Kaiwen Guo [a]

[a] College of Environmental and Resource Sciences, Zhejiang University, 310058, Hangzhou, China
[b] Department of Energy Economics, School of Applied Economics, Renmin University of China, 100872, Beijing, China
[c] College of Urban and Environmental Sciences, Peking University, Beijing, 100871, China

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ABSTRACT

Rapid deployment of wind energy plays an important role in China's proposed energy transition to carbon neutrality before 2060. Greenhouse gas (GHG) emissions are, however, unavoidable during the entire life cycle of wind energy from manufacturing to disposal. It is important to estimate these GHG emissions and the emission intensity for programs of energy transition. In this study, simplified LCA models and engineering-based models were developed to provide a comprehensive estimate of the GHG emission intensity from onshore wind energy in China at provincial and national scales. Results showed that in 2019, the GHG emission intensity per unit power generation was 19.88 g CO_2 eq/kWh (provincial intensity ranges from 13.59 to 34.50 g CO_2 eq/kWh). The results indicated that onshore wind energy in China has an emission intensity more than 98% lower than traditional fossil fuels and the mitigation effect can reach 84%–98% compared to the energy mix in 2020. The effects on emission intensity of shifting the turbine mix towards larger sizes, reducing wind curtailment and using advanced designs to improve efficiency were further investigated. Advanced design of turbines can further decrease GHG emission intensity by 21.6%, more than the scenario of reducing curtailment (5.4%), while the emission intensity could be reduced by 2.1% under the scenario of shifting the turbine mix towards larger sizes. The results will aid future energy-mix scenario design and policy formulation.

1. Introduction

In September 2020, China pledged to reach carbon neutrality before 2060 to tackle climate change. To achieve this target, a deep decarbonization of the energy sector, the biggest source of anthropogenic carbon emissions, is necessary (EF China, 2020). Renewable energy plays an essential role in this transition to a low-carbon energy system (Normile, 2020), and, in particular, wind energy is the cornerstone of long-term plans to achieve carbon neutrality, and to mitigate climate change, air pollution and other energy-related environmental impacts (Davidson et al., 2016). Wind energy was the fastest-growing renewable energy source in the past decade in China, with increasing numbers of wind farms with large-scale turbines being built. The total installed wind capacity of China reached 210 GW in 2019, accounting for 34% of the global installed capacity (IRENA, 2020) and more than the sum of the capacities of the next nine biggest capacity countries.

Over the past ten years, the wind energy market of China has been heading towards increasingly large wind turbines for higher energy efficiency and faster returns on investment. The mean capacity of newly-installed wind turbines in China reached 2.18 MW per turbine in 2018, while the proportion of turbines ≥2 MW increased from 9% in 2008 to 96% in 2018 (CWEA, 2019). Larger wind turbines with higher nominal power are generally more economically efficient than smaller ones. Electrical efficiency is expected to reach 96–97% for turbines rated at 2.5–3 MW, but only 60–70% for turbines with 0.5–10 kW (McTavish et al., 2013). Increasing rotor diameters and hub heights also have great potential to increase the efficiency of energy capture and thus annual production (Arias-Rosales and Osorio-Gómez, 2018). Furthermore, wind energy curtailment, has been reduced from 21% in 2016 to 4% in 2019 (Table S1; NEA, 2017; NEA, 2020) through the expansion of electric power transmission networks and the rapid development of pumped hydro storage and electric boilers. The policy on the development of wind energy, set out in the 14th five-year plan of China, claims the target is energy quality improvement while simultaneously considering both

* Corresponding author.
E-mail address: changjf@zju.edu.cn (J. Chang).

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environmental and economic potential (CPC, 2020). Therefore, the development of larger and more efficient wind turbines, as well as the improvement of power grids, is becoming an imperative trend.

Although renewable energy is low-carbon energy, it is not carbon free across its entire life cycle. Considering all the stages from ‘cradle’ to ‘grave’, wind systems unavoidably generate greenhouse gas (GHG) emissions during turbine manufacturing, system installation, material transportation and final disposal. For example, the global median GHG emission intensity (expressed as g CO_2-equivalent per kWh) of wind energy is 19 ± 13 g CO_2 eq/kWh (Schlömer et al., 2014), and is of the same order of magnitude as other renewable energy sources, such as solar power, geothermal and hydropower (usually less than 100 g CO_2 eq/kWh; Sathaye et al., 2011). However, the emission intensity of wind energy is affected by factors such as turbine size (nominal power, rotor diameter and hub height), turbine design, wind capacity and curtailment rate (Lu et al., 2016; Bhandari et al., 2020). To quantify the actual emission reduction and mitigation potential due to wind energy in China, it is essential to understand how GHG emission intensity changes with increasing turbine size, more efficient design and decreasing wind curtailment rate, and to comprehensively assess the regional and national emission intensities of wind energy. Taken together with the emission intensities of other renewable energy sources and fossil fuels, such an assessment will also be useful for strategically optimizing the energy mix during China’s energy transition.

Life cycle assessment (LCA) is a common method for estimating the emission intensity of renewable energy sources. A number of LCA studies have analyzed and estimated GHG emissions of wind energy in China (Table 1) and in other countries (e.g. Alsaleh and Sattler, 2019; Šerešová et al., 2020; Teffera et al., 2021). However, most of these studies focused on specific wind farms or turbines, and thus there are large variations in the results, caused by differences in assumptions regarding turbine size, turbine design and site-specific wind potential. This variation hampers the accurate assessment of GHG emissions at the regional and national levels, and makes comparisons with alternative renewable energy sources difficult. The studies also have technical limitations, such as the misuse of capacity factors and a lack of life cycle

Table 1
Overview of LCA studies of China’s wind energy.

GHG intensity (g CO_2 eq/kWh)	Number of environmental indicators being studied	Nominal power of each turbine (MW per turbine)	Total capacity of the wind farm (MW)	Load factor	Methods*	Citation
6.93	1	1	10	22.83%	PLCA	Zou and Ma (2003)
3.60	1	0.6	2.4	42.60%	PLCA	Lee and Tzeng (2008)
	1	0.66	2.54	30.90%		
	1	1.75	3.5	18.90%		
7.20	1	1.25	30	24.88%	PLCA	Chen et al. (2011)
9.47	1	1	50	29.51%	PLCA	Guo et al. (2012)
28.08	2	2	–	30.82%	PLCA	Gao et al. (2012)
57.38	4	3	–	–	PLCA	Shao et al. (2012)
39.31	2	1.5	49.5	23.63%	PLCA	Wang (2012)
7.20	1	1.5	49.5	25.76%	PLCA	Yang and Chen (2013)
12.89	1	1.5	49.5	22.81%	PLCA	Zhao and Wang (2014)
47.10	5	1.5	198	25.37%	PLCA	Li et al. (2015)
20.70	1	2	–	23.27%	PLCA	Yang et al. (2015)
7.55	1	2	48	25.80%	PLCA	Ji and Chen (2016)
9.50	3	1.5	49.5	–	PLCA	Jia et al. (2016)
13.06	1	2	–	27.77%	PLCA	Wang and Qiu (2017)
8.65	11	–	–	27.00%, 22.5%	PLCA	Xu et al. (2018)
28.56	10	1.5	49.5	23.66%	PLCA	Wang et al. (2019)
51.50	7	1.5	–	–	PLCA	Gao et al. (2019)
86.50	7	0.85	120.7	–		
65.90	7	0.85	22.1	–		
31.36	5	1.5	49.5	23.63%	PLCA	Li et al. (2020a)
2.02	1	0.6	2.4	42.19%	PLCA	Xie et al. (2020)
2.71	1	0.66	2.54	26.74%		
7.80	1	1.75	3.5	22.11%		
4.43	1	1.5	49.5	27.31%	PLCA	Li et al. (2020b)
69.90	2	–	–	–	IO-LCA	Li et al. (2012)
25.89	4	1.25	30	–	IO-LCA	Xue et al. (2015)
5.6	1	–	–	–	IO-LCA	Wang et al. (2016)
	2	–	–	–	IO-LCA	Zhang et al. (2017)
8.42	1	–	–	51.37%	Not specified	Ding et al. (2017)
45.00	7	2	24	24.57%	IO-LCA	Yue et al. (2019)
19.30	19	–	150	26.12%	Not specified	Li et al. (2019)
8.49	3	–	–	–	Not specified	Ding et al. (2019)

*Methods used in the study: PLCA, process-based LCA method; IO-LCA: input-output LCA method; Not specified, the method was not specified in the original study.

inventories (for details, see Section 2). Detailed LCA work is sophisticated, time-consuming and may be impractical in some cases. Therefore, it is both useful and necessary to propose generic LCA models, based on harmonized data from LCA studies (Mendecka and Lombardi, 2019), for estimating GHG emissions from wind energy in China.

This paper aims to: 1) quantify the effects of wind turbine size on GHG emissions; 2) propose a robust and generic methodology to produce simplified LCA models for China based on nominal power; 3) estimate the GHG emissions of China's onshore wind energy at provincial and national scales based on the simplified LCA models; 4) predict GHG mitigation potential under scenarios of business as usual (BAU), reducing wind curtailment and using advanced designs to improve efficiency.

The remaining part of the paper is organized as follows. In Section 2, we review existing LCA studies of China's wind energy and describe the simplified LCA models that could potentially be used for the regional estimation of GHG emissions from wind energy. In Section 3, we describe the methods, database and harmonization procedures used. Section 4 concerns the proposed models and their predictions, while in Section 5, we interpret the model output and discuss the limitations and implications of this work. Finally, we present concluding remarks and recommendations for future studies.

2. Review of LCA studies of China's wind energy and simplified LCA models

2.1. Brief review of LCA studies

LCA is a systematic and comprehensive method for assessing the energy uses, resources and the related environmental impacts of a product or service. There has been extensive research employing LCA to analyze the environmental impacts of China's wind farms, which provides a good overview of the energy consumption and associated environmental pollution of the wind power industry. GHG emission is the most widely covered index in the existing studies, with the GHG emission intensity for China, expressed as 100-year global warming potential, reported to vary from 0.28 to 86.50 g CO_2 eq/kWh with a median value of 12.97 g CO_2 eq/kWh and a mean of 24.28 g CO_2 eq/kWh (Table 1). This mean value is slightly higher than the mean value for European countries (15 g CO_2 eq/kWh; Schlömer et al., 2014). In all the studies, the manufacturing, construction, operation and disposal stages are included within the system boundary. The manufacture of materials usually dominates the GHG emissions in all life cycle stages, and can account for more than 90% of total emission values (Jia et al., 2016). The steel and concrete consumption of turbines and foundations is always the greatest contributor to emissions in the manufacturing stage. When land use change (e.g. deforestation) is considered, construction and installation can supersede manufacturing as the most important part with regard to energy use and emissions (Gao et al., 2019). Emissions associated with transportation are generally found to be negligible and are sometimes integrated into the construction stage (Xie et al., 2020). Some studies consider the recycling of materials and thus obtain negative emissions for the disposal stage (Xu et al., 2018; Yang et al., 2015).

Current knowledge and the methods used in Chinese LCA studies are, however, still limited in the following ways. First, the wind turbine load factors used in these studies are significantly higher than the practical capacity factor values. The practical capacity factor for China is roughly 19.31% (Table S1), whereas the values assumed in the studies vary from 22.11% to 51.37% with a mean of 26.87% (Table 1). Second, emission factors for the same material are not consistent across the different studies. For example, the GHG emission factor for copper used by Li et al. (2015) is 18.38 kg/kg, while that used by Li et al. (2020b) is 0.632 kg/kg. Third, a life cycle inventory is not provided in some studies, meaning that there is a lack of information on the emission contributions of different materials, making re-analysis difficult. Fourth, different system boundaries are used in different studies. These inconsistencies in system boundaries, load factors and the emission factors of materials lead to large discrepancies in the results and contribute to their unreliability. Fifth, few studies focus on regional and national GHG emissions of wind energy. "Top-down" input-output LCA (IO-LCA) at regional and national scales can help to pinpoint crucial areas of consumption and drivers of environmental impacts (Hellweg and Canals, 2014). However, it is problematic to use IO-LCA results based only on data from a limited number of wind farms in China to support wind-development policy-making decisions. Furthermore, these studies do not cover all turbine types, in particular the huge newly-built modern turbines. Taking all these points into account, it is clear that harmonization of the previous LCA results is essential if the LCA models for China are to be developed further.

2.2. Proposed simplified LCA models

Detailed LCA analysis is a sophisticated and rather time-consuming approach which may be impractical in some cases (Mendecka and Lombardi, 2019). Simplified LCA modelling, which usually predicts environmental impacts based on regressions between the impacts and the main affecting parameters, is a fairly effective method for quantifying GHG emissions compared to the comprehensive LCA and can supplement detailed LCA work for policy support (Caduff et al., 2012; Mendecka and Lombardi, 2019). It can provide a synthetic and universal mechanism for predicting total emissions and their variations and the effects of independent parameters. Being an empirical model, the construction of a simplified LCA model depends on the availability of a large quantity of published data from processed-based LCA studies (i.e. LCA studies using the bottom-up method). LCA models are usually set in specific geographical conditions, which require further validation when applied in certain regions. For example, the model of Caduff et al. (2012) was tuned assuming a wind shear exponent of 1/7 and wind velocity of 5 m/s at a height of 10 m.

Several simplified LCA models have been developed based on LCA studies (Table 2). For example, Caduff et al. (2012) developed an empirical scaling model, using data from 12 published studies, to describe the negative relationship between GHG emission and nominal power. Padey et al. (2013) proposed a generic model of GHG emission for wind turbines over 500 kW using a Monte Carlo simulation. Scaling relationships were defined between material consumption and nominal power, and determined emission performance based on load factor. Mendecka and Lombardi (2019) synthesized 143 studies, consisting of 115 onshore and 28 offshore wind farms, and developed simplified LCA models using power functions to predict four factors: GHG emissions, acidification potential, eutrophication potential and cumulative energy demand based on nominal power. The results showed that the size-related effects of offshore wind turbines are much greater than those of onshore turbines, and that wind velocity affects the different impact factors in different ways. However, these LCA models are usually based on LCA studies of wind turbines and farms in Europe, which cannot be directly applied to quantifying the GHG emissions of China's wind energy due to differences in technology and design. To do this, simplified LCA models for China are required.

Table 2
Overview of studies using simplified LCA models.

Nominal power range (kW)	Types of turbine	Number of sources	Region	Study
1–5000	148	73	Europe	Arias-Rosales and Osorio-Gómez (2018)
500–3000	116	2	Europe	Padey et al. (2013)
30–3000	12	8	Europe	Caduff et al. (2012)
600–3000	24	20	China	This study

3. Methods

Harmonization procedure was conducted following LCA steps in accordance with the ISO 14040/44 standard: goal and scope definition, inventory analysis, impact assessment, and interpretation (ISO 2006a; ISO 2006b). The intended aim of the work is to develop an empirical LCA model to estimate emission intensities of wind energy under different scenarios. The data from previous LCA studies was harmonized to create the life cycle inventory and construct simplified LCA models for estimating GHG emissions from wind energy in China. To develop the simplified LCA models used here, the nominal power (kW) of turbines was treated as the size variable and GHG emissions were expressed as 100-year global warming potential (g CO_2 eq). GHG emissions occurring during the life cycle of wind turbines essentially depend on four factors: (i) turbine size, (ii) turbine design, (iii) region-specific wind conditions and (iv) manufacturing process (Bhandari et al., 2020). We constructed engineering-based models to quantify the effects of design efficiency, using a database of installed wind turbines in China (https://www.thewindpower.net). Practical capacity factors (annual electricity production divided by installed capacity) for different regions were used to represent the region-specific wind conditions. The parameters of the simplified LCA models were then validated by the regression results of engineering-based models. Three scenarios were established to quantify the effects on the GHG emission intensities of: i) shifting the turbine mix towards larger sizes; ii) using more-efficient advanced turbine designs; iii) increasing the wind generations through reducing wind curtailment. The detailed process of this work is shown in Fig. 1.

3.1. LCA study search strategy

We conducted a search on the Web of Science using the following strategy: 'life cycle assessment/LCA' and 'China' and 'greenhouse gas/GHG' or 'global warming potential/GWP' or 'carbon footprint' and 'wind energy' or 'wind turbine'. A total of 39 peer-reviewed papers were found, and 28 process-based LCA studies (using the bottom-up method) of onshore wind farms or turbines that contained at least one environmental indicator were selected for further analysis and for constructing the simplified LCA models.

3.2. Harmonization procedure

To ensure that the GHG emissions results were comparable, the life cycle inventories of the selected studies were harmonized with regard to system boundaries, background processes, emission factors, load factors and lifetime. We improved the harmonization procedure used by Mendecka et al. (2019) by integrating more parameters. The harmonized system boundaries consisted of: manufacturing, construction and installation, operation and maintenance, and transportation and disposal. The GHG emission contributions of the missing stages in several studies were identified using the ratio to the manufacturing stage. For example, the emissions from the disposal stage were treated as 10% of those from the manufacturing stage (Xie et al., 2020). The emission factors of materials were unified (Table S2). The selected wind turbines and the harmonized GHG emissions of the different materials in each turbine are provided in Table S3. The electricity production efficiency (annual electricity production/installed capacity) was treated as the capacity factor of China and each province in 2019, rather than using the load factor of a single turbine, which might eliminate the geographical effects of different regions (Table S1). Wind turbine lifetime was harmonized to 20 years. We recalculated the GHG emissions using these harmonized parameters (Table 3).

3.3. Simplified LCA models

After the harmonization described in Section 3.2, the data from the 28 LCA studies were used to construct the simplified LCA models of the

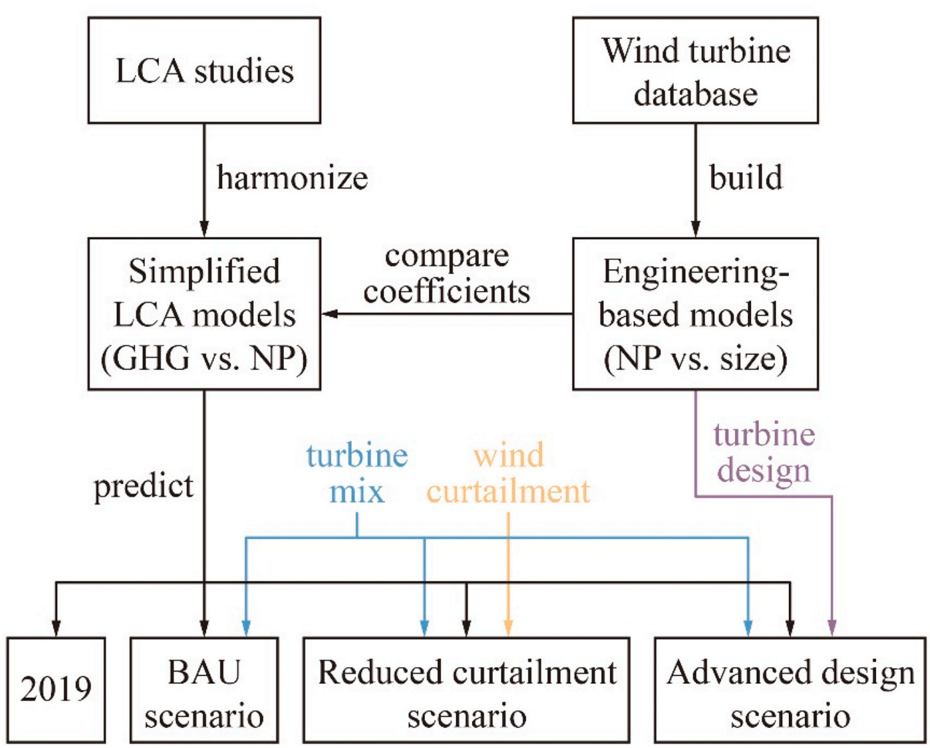

Fig. 1. Illustration of the research process. The detailed LCA data from selected studies was harmonized to construct simplified LCA models (GHG vs. nominal power). The wind turbine database was used to build engineering-based models. Then, the regression coefficients of simplified LCA models and engineering-based models (nominal power vs. engineering-based size) were compared to test their consistency. A series of scenarios were built to quantify the mitigation potential of installation of larger turbines, reduction in wind curtailment, and advancement in turbine design. Finally, the constructed models were used to estimate GHG emission intensities in 2019 and under different scenarios.

Table 3
Methods, parameters, and equations used in the harmonization procedure. The procedure involved harmonization for system boundary, lifetime, emission factors and capacity factor. The harmonized system boundaries of the GHG emissions consist of the following five stages: (1) manufacturing (GHG_{manu}), (2) construction and installation (GHG_{cons}), (3) operation and maintenance (GHG_{oper}), (4) transportation (GHG_{trans}) and (5) disposal (GHG_{disp}). Lifetime of wind turbines in different publications (LT_{pub}) was harmonized to 20 years. The emission factor ($EF_{pub,\ i}$) of each material was unified using values from the IPCC report and previous studies (EF_i, see Table S2). The capacity factor (CF) of wind power for China and for each province was calculated as the ratio of electricity generation to installed capacity in 2019.

Harmonization parameter	Harmonization method	Harmonization formula of GHG emissions
System boundary	Five stages: manufacturing, construction and installation, operation and maintenance, transportation, and disposal	$GHG_{harm} = GHG_{manu} + GHG_{cons} + GHG_{oper} + GHG_{trans} + GHG_{disp}$
Lifetime, LT	20 years	$GHG_{harm} = GHG_{pub}\frac{LT_{pub}}{20}$
Emission factors, EF	According to the IPCC	$GHG_{harm} = GHG_{pub}\sum \frac{EF_{pub,i}m_{pub,i}}{EF_i}$
Capacity factor, CF	Electricity production efficiency	CF = electricity generation/ capacity

relationships between GHG emissions and size parameters (size-based models) or power (GHG-NP models). Given the fact that nominal power is the most accessible data and a critical indicator related to electrical power generation, a GHG-NP model was used in this study to predict GHG emissions. The GHG-NP model was expressed as a power equation (Caduff et al., 2012; Mendecka and Lombardi, 2019; Mendecka et al., 2018):

$$GHG = b\mathrm{NP}^{\alpha} \tag{1}$$

The scaling factor α was defined as the environmental efficiency indicator that represents the effects of size on emission reduction; NP is nominal power; b is the regression coefficient. The size parameters used in the simplified models were total mass (M_{total}), turbine mass ($M_{turbine}$), foundation mass ($M_{foundation}$) and engineering-based size $D^2h^{3/7}$ and D^2. The GHG-NP model, fitted by harmonized GHG emissions and nominal power from the detailed LCA data, was used to estimate GHG emissions at the provincial and national scales.

3.4. Engineering-based models

We introduced engineering-based models for: 1) comparing with simplified LCA models to test their robustness and consistency due to the limited data available from selected studies; 2) providing estimates of the average and potential maximum design efficiency based on the current productivity of the wind power industry. Engineering-based models relate to the relationship between nominal power and engineering-based size factors such as rotor diameter (D), hub height (h), swept area, and turbine mass (M_{total}). The specific rating of wind turbines, defined as nominal power per rotor swept area and expressed in watts per square meter (W m^{-2}), is one of the key metrics of turbine design (Malcolm and Cotrell, 2004). Arias-Rosales and Osorio-Gómez (2018) showed that nominal power is proportional to D^2. Considering the swept area and average wind speed at hub height, Caduff et al. (2012) suggested that nominal power and GHG emission should be proportional to $D^2h^{3/7}$ and turbine mass. Therefore, in this work, the scaling factor of nominal power and engineering-based size (i.e., $D^2h^{3/7}$ and D^2) were defined as the metric of turbine design efficiency. All the theoretical engineering-based scaling laws previously used are listed in Table 4 for comparison with the engineering-based models for China.

Table 4
Theoretical engineering-based scaling factors between variables.

Parameter	proportional to	
Nominal power	$\propto D^2$	Arias-Rosales and Osorio-Gómez (2018)
Nominal power	$\propto D^2h^{3/7}$	Caduff et al. (2012)
GHG emission	$\propto M_{total}$	
GHG emission	$\propto D^2h^{3/7}$	

D: rotor diameter (m); h: hub height (m); M: mass (t).

The engineering-based models for China have been developed to describe the scaling relationships between D, h and nominal power, and represent the current turbine design efficiency implemented in China. A total of 83 types of wind turbine, from 361 wind farms, were used to establish these engineering-based models. The database containing nominal power, rotor diameter, hub height, turbine model and developer was downloaded from the Wind Energy Market Intelligence (https://www.thewindpower.net) on October 30th, 2020. A practical engineering-based model was constructed based on the relationships between nominal power and size parameters, following the predicted power form (Table 4), to identify the actual and potential design efficiency of turbines.

3.5. Scenario design

We assessed the current GHG emission intensity (for the year 2019) and built a series of scenarios to quantify the mitigation potential of installation of new turbines (i.e., shifting the turbine mix towards larger sizes), reduction in wind curtailment, and advancement in turbine design. The current status and the assumptions for the three mitigation scenarios were developed as follows:

- 2019: the situation with the current proportions of installed wind turbines rated at different powers in each province (i.e. at the national scale, 20% of turbines rated at less than 1.5 MW; 45% between 1.5 and 2 MW; 29% between 2 and 2.5 MW; 4% between 2.5 and 3 MW; and 2% rated at 3 MW or more. See Table S4 for the proportions for different provinces). All turbines are assumed to follow the average design efficiency (nominal power per engineering-based size) obtained from the engineering-based model.
- BAU scenario: In this case, economic potential and energy policy determines the installed proportions of wind turbines of different sizes (i.e., the turbine mix). The recent and current trend is towards ever larger wind turbines with higher nominal power (McKenna et al., 2016), and so for this scenario it is assumed that the current turbines are gradually replaced by newly-installed ones with higher nominal power, and that the proportions of different turbines in the new installations follow the national proportions of newly-installed turbines in 2018 (i.e., 4% of turbines in the range 1.5–2 MW; 73% in the range 2–2.5 MW; 10% in the range 2.5–3 MW; and 13% with 3 MW or more; CWEA, 2019). Therefore, the installed turbine proportions eventually reach those of 2018.
- Reduced curtailment scenario: A high wind-energy curtailment rate was once a major factor contributing to low wind-energy generation (Lu et al., 2016). Although wind-energy curtailment has been largely reduced at the national scale (from 21% in 2016 to 4% in 2019; NEA, 2017; NEA, 2020), it is still a serious problem in the three northern regions (Table S1). Therefore, there are significant geographic variations in the further mitigation potential of reducing curtailment. In this scenario, on top of the assumptions of the BAU scenario, it is assumed that the curtailment of wind energy would reduce to 0.5% with no transmission constraints (Jorgenson et al., 2017) due to increasing transmission capacity and the rapid development of pumped hydro storage and electric boilers.
- Advanced design scenario: In this study, it is assumed that the relationships of GHG vs. $D^2h^{3/7}$ and nominal power vs. $D^2h^{3/7}$ follow the scaling power law (Caduff et al., 2012):

$$GHG \propto (D^2h^{3/7})^{\beta} \quad (2)$$

$$NP \propto (D^2h^{3/7})^{\gamma} \quad (3)$$

Theoretically, the scaling exponents β and γ are equal to 1 (Table 3). The scaling factor γ indicates the design efficiency of the turbines while the scaling factor β indicates the marginal efficiency of manufacturing production. From equations (1)–(3), we find that $\alpha = \beta - \gamma$. Without further development of production technique or efficiency, there can be no further change in the scaling factor β. Advanced design to improve efficiency can be defined as a larger nominal power per D^2 or $D^2h^{3/7}$ for a turbine (i.e., a higher γ in equation (3)). Such an increase in design efficiency then leads to a decrease of emission intensity (i.e., a smaller α in the simplified LCA models) defined as total GHG emissions per nominal power (as in equation (1)). Therefore, in the advanced design scenario, in addition to the assumptions in the BAU scenario, it is assumed that all installed turbines are replaced by well-designed ones that reach the potential efficiency (i.e., a high γ) given by the engineering-based models. Here, the potential efficiency was calculated from the higher γ predicted as the 95% quantile regression (QR95) result from the engineering-based models.

3.6. Calculating GHG emissions and emission intensities

The simplified LCA models (i.e., the GHG-NP models) for China's wind energy were used to estimate provincial GHG emissions. The national GHG emissions from wind energy were then calculated as the sum of the emissions from the individual provinces. The GHG emission intensities were calculated by dividing the total GHG emissions (tonne CO_2 eq) by the total power generated (kWh). The numbers of installed wind turbines with different nominal power outputs were derived from the global Wind Energy Market Intelligence database (https://www.thewindpower.net). This database contains details of the number of turbines and the total installed capacity for 48% of the wind farms included.

3.7. Statistical analysis

The variables were log-transformed for the analysis to normalize the distributions and minimize patterns in the residuals (Sibly et al., 2012). Thus, for the analysis, the power functions of the engineering-based models and simplified LCA models were transformed into linear functions. Ordinary least-squares regression was used to develop the models. Quantile regression was used to explore the potential maximum nominal power in response to engineering-based size under the potential design efficiency. The R package *quantreg* (Koenker, 2018) was used to conduct the quantile regression, and the R package *simba* (Nekola and White, 2004) was used to test the similarity of coefficients between engineering-based models and simplified LCA models. All the regressions and ANOVAs were implemented in R version 3.4.2 (R Development Core Team, 2017).

4. Results

4.1. Engineering-based models of China's wind turbines

The results show that the designed nominal power of China's wind turbines was sublinearly scaled with engineering-based size from rotor diameter D and hub height h (i.e., the scaling factor was less than 1). The designed nominal power was allometrically related to $D^2h^{3/7}$ with a scaling factor of 0.67 (Fig. 2a) and scaled against D^2 with a scaling factor of 0.75 (Fig. 2b). Using the most efficient turbines with the highest specific rating (i.e., the QR95), the scaling factor reached 0.82 for the NP-$D^2h^{3/7}$ relationship and 0.91 for the NP-D^2 relationship.

4.2. Simplified LCA models based on reviewed studies

The results of the simplified modelling show that the nominal power scaled against $D^2h^{3/7}$ with a scaling factor of 0.66 and against D^2 with a factor of 0.77 (Fig. 3), values which were consistent with the scaling factors derived from the regression results of engineering-based size models (Fig. 2; $P < 0.05$). The results indicate that the wind turbines used in previous LCA studies could effectively represent the current design efficiency of China's turbines.

Harmonized GHG emissions were scaled against nominal power, $D^2h^{3/7}$, D^2 and M_{total} with scaling factors of 0.94, 0.81, 0.94 and 1.05, respectively (Fig. 4). All the scaling factors, with the exception of GHG-$D^2h^{3/7}$, were not significantly different from 1 ($P_{1.0} \geq 0.05$). The GHG emission contributions of turbines and foundations were significantly different, with the GHG emission observed to be 1.00 when scaled with the foundation mass, $M_{foundation}$, but 0.96 when scaled with the turbine mass, $M_{turbine}$ (including components of tower, nacelle, rotor and hub).

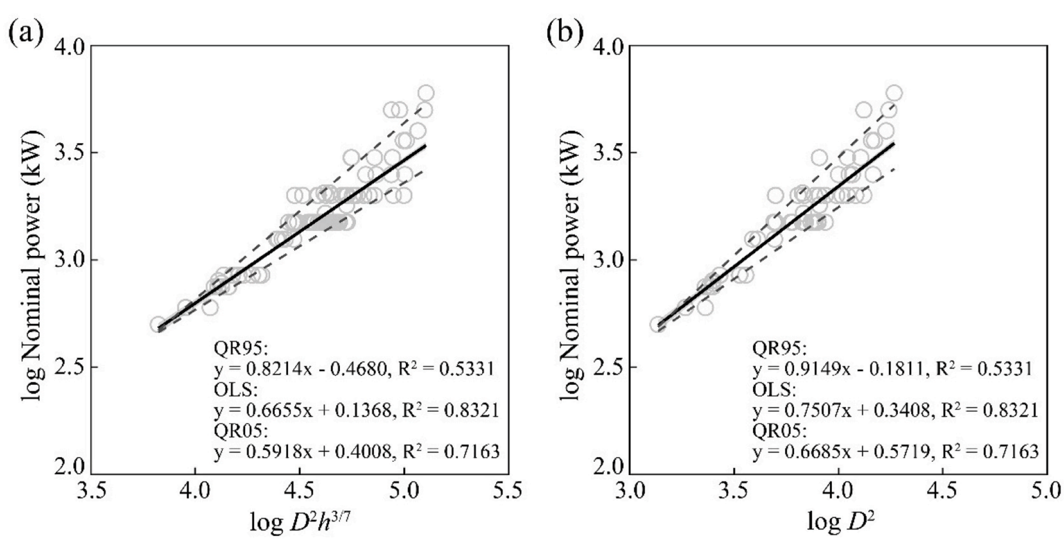

Fig. 2. Engineering-based relationships of nominal power versus engineering-based size using a database of installed wind turbines in China (https://www.thewindpower.net). Solid lines represent the ordinary least-squares regressions (OLS), and dashed lines represent the quantile regressions (QR05 and QR95).

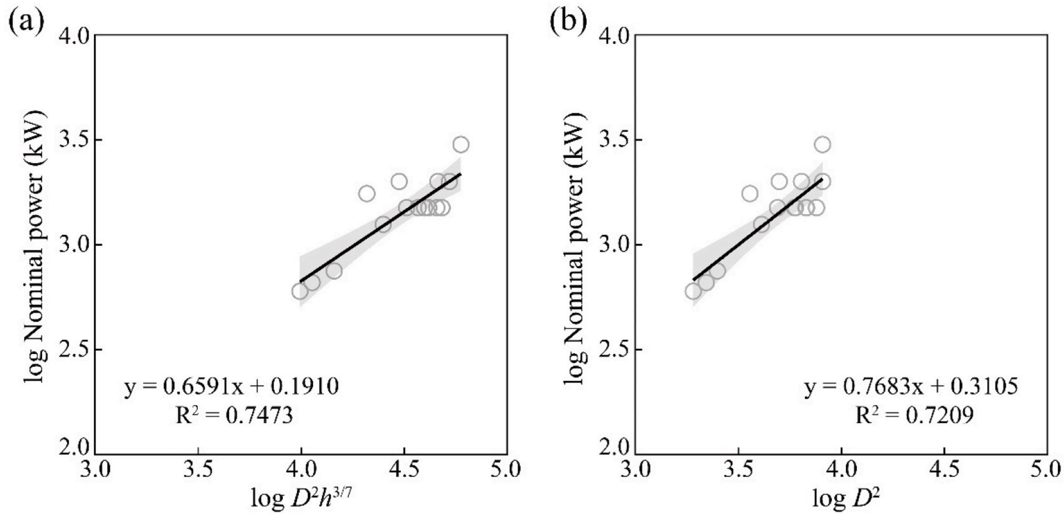

Fig. 3. Empirical relationships of nominal power versus engineering-based size based on the LCA studies reviewed here.

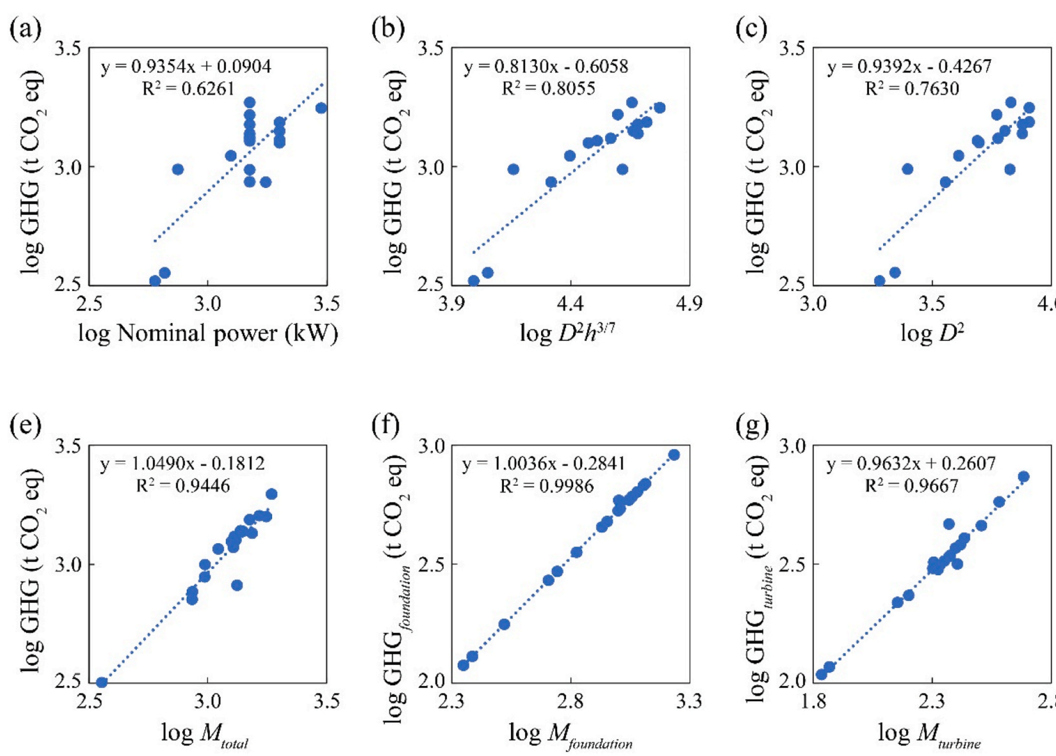

Fig. 4. Empirical relationships of GHG emission versus parameters of engineering-based size: nominal power, engineering-based size $D^2h^{3/7}$ and D^2, total mass (M_{total}), foundation mass ($M_{foundation}$), and turbine mass ($M_{turbine}$).

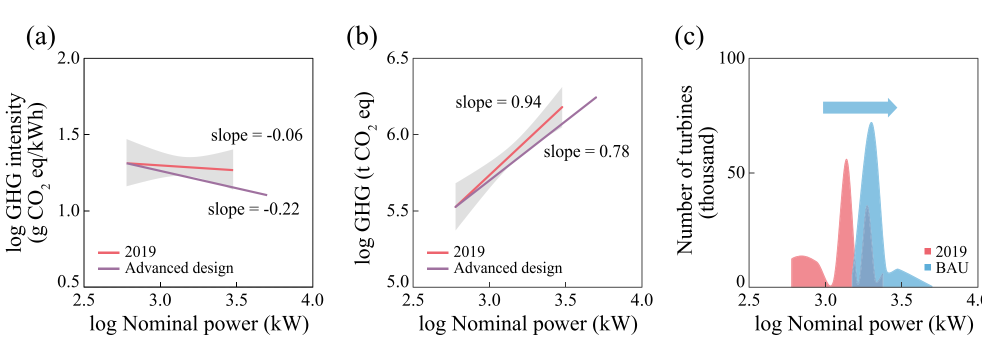

Fig. 5. Models of GHG emission intensity (a) and total GHG emissions (b) versus nominal power, and the shift of turbine mix from the 2019 status towards larger sizes assumed in the BAU scenario (c). Red and purple lines in (a) and (b) represent the simplified LCA models based on reviewed studies for the 2019 status, and under the advanced design scenario, respectively. Red and blue shades in (c) represent the distributions of turbines rated at different nominal power in 2019 and under the BAU scenario.

Fig. 5 shows the regression results for these models at the national scale. Considering the capacity factor of each province (Table S1), simplified models were developed based on nominal power for estimating the GHG emission intensity for each province. In 2019, there is only a marginal decrease in the GHG emission intensity following the increase in nominal power (red line in Fig. 5a), resulting in a total GHG emission increase following nominal power with a scaling factor (α; see equation (1)) close to 1 (red line in Fig. 5b). In Fig. 5c the distribution of turbines rated at different nominal power in 2019 is shown in red, while the turbine mix of the BAU scenario is shown in blue. The models of GHG emission intensity and total GHG emissions versus nominal power for the BAU and "Reduced curtailment" scenarios are the same as those of 2019 (i.e., the red lines in Fig. 5a and b). In the scenario with advanced design to reach high efficiency, the scaling factor of GHG emission intensity versus nominal power dipped from −0.06 to −0.22 and that of total GHG emission vs. nominal power dipped from 0.94 to 0.78.

4.3. National and regional GHG estimates under different scenarios

The results show that the national GHG intensity per unit power generation was 19.88 g CO_2 eq/kWh in 2019 (Fig. 6). For the three scenarios, the BAU scenario, the reduced curtailment scenario, and the advanced design scenario, the national average GHG emission intensities were 19.47 g CO_2 eq/kWh, 18.80 g CO_2 eq/kWh and 15.59 g CO_2 eq/kWh, respectively. The corresponding mitigation potentials for GHG intensity compared to the 2019 value were 2.1%, 5.4% and 21.6%.

The distribution of provincial GHG emission intensity was significantly different from that of the national GHG emissions (Fig. 7a). There were wide variations between different provinces, ranging from 13.59 to 34.50 g CO_2 eq/kWh. 18 of the 31 provinces have a GHG intensity higher than the national average of 19.88 g CO_2 eq/kWh (Fig. 7b). Henan province has the highest GHG emission intensity, while Yunnan province has the lowest.

For most provinces, GHG emission intensity under the BAU scenario was lower than that in 2019 (Fig. 7b). In the reduced curtailment scenario, provinces with a larger installed capacity have higher mitigation potentials. The top 5 provinces for GHG mitigation through reducing wind curtailment account for 43% of the national total generation. In the advanced turbine design scenario, the GHG emission intensity remained higher than the current national average in only two provinces (Henan and Qinghai).

5. Discussion

5.1. Effects of advanced design and turbine size in China

We found that the engineering-based scaling factor of China's wind turbines is lower than the theoretical value of 1 (Fig. 2), indicating that there are great opportunities for the enhancement of wind turbine design efficiency in China. The scaling factors of European turbines are 0.76 for nominal power vs. $D^2h^{3/7}$ (Caduff et al., 2012) and 0.96 for nominal power vs. D^2 (Arias-Rosales and Osorio-Gómez, 2018). Compared to the European turbines, the design efficiency of China's turbines is still low, with scaling factors of 0.67 and 0.75 for nominal power vs. $D^2h^{3/7}$ and vs. D^2, respectively. The values can reach 0.82 and 0.91, respectively, under optimized design efficiency, according to the QR95 regression from the most efficient turbines with the highest specific rating in China (Fig. 2). Our results show that the turbines with high design efficiency (i.e., the QR95 regression) have reached a similar efficiency level to that in Europe. Increases in D and h have a larger potential to increase power generation than improvements to turbine structure and materials, but there has been a divergence between the benefits of larger rotor swept areas and larger hub height (McKenna et al., 2016). When considering the levelized cost of electricity (€/kWh), taller hubs are more efficient than larger swept areas, especially in sites with low wind potential (Rinne et al., 2018). Therefore, the desirability of installing bigger turbines with larger rotors or a taller tower depends on both geographical and economic potential.

According to data from the LCA studies reviewed here, the GHG emission intensity only decreases by 4% when doubling the nominal power of turbines (derived from the slope of the 2019 line in Fig. 5a). But the GHG emission intensity can be decreased by 14% with advanced turbine design with high efficiency, providing an additional emission reduction per kWh of power generated. This value is close to the mitigation potential due to the increased turbine nominal power of European wind energy (Bhandari et al., 2020; Caduff et al., 2012; Mendecka and Lombardi, 2019).

5.2. GHG emissions of wind energy

This study provides a comprehensive estimate of China's GHG emission intensity from wind energy at the provincial and national scales. We obtained a value of emission intensity of 19.88 g CO_2 eq/kWh for all installed onshore turbines by the year 2019. Our intensity estimate is higher than those made in previous studies. Wang et al. (2016) reported an emission intensity of 5.6 g CO_2 eq/kWh based on wind energy production. Using data from 2013 as a baseline, Ding et al. (2017) reported a value of 8.42 g CO_2 eq/kWh with a capacity factor of 51%. If a capacity factor of 19.31%, as used in this study, had been used, the emission intensity value would have been 22.24 g CO_2 eq/kWh, close to our estimate. There are two reasons for the possible estimation bias in previous studies: 1) top-down input-output methods based on life-cycle inventory from different sectors may underestimate the emissions of low quantity materials or life-cycle stages such as transportation (e.g. Wang et al., 2016); 2) studies, such as Li et al. (2018), focusing on the GHG emissions of power generation systems, use emission factors from the IPCC report directly, ignoring geographical and technological variations.

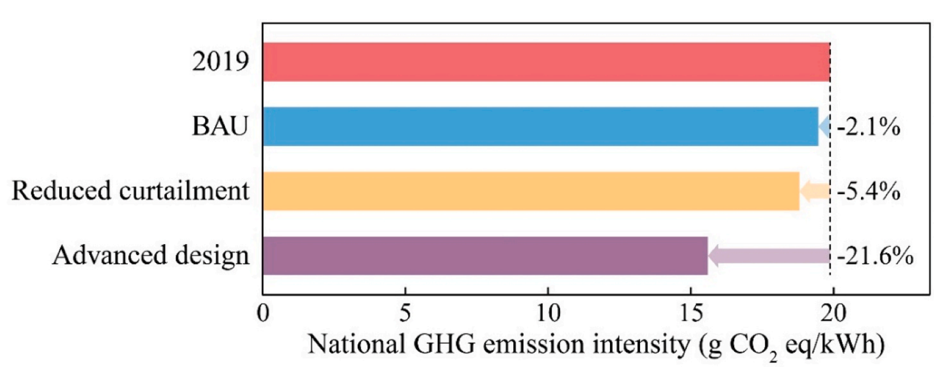

Fig. 6. National GHG emission intensities of wind energy of China in 2019 and under different scenarios. The arrows represent the mitigation potential under different scenarios compared to the 2019 value.

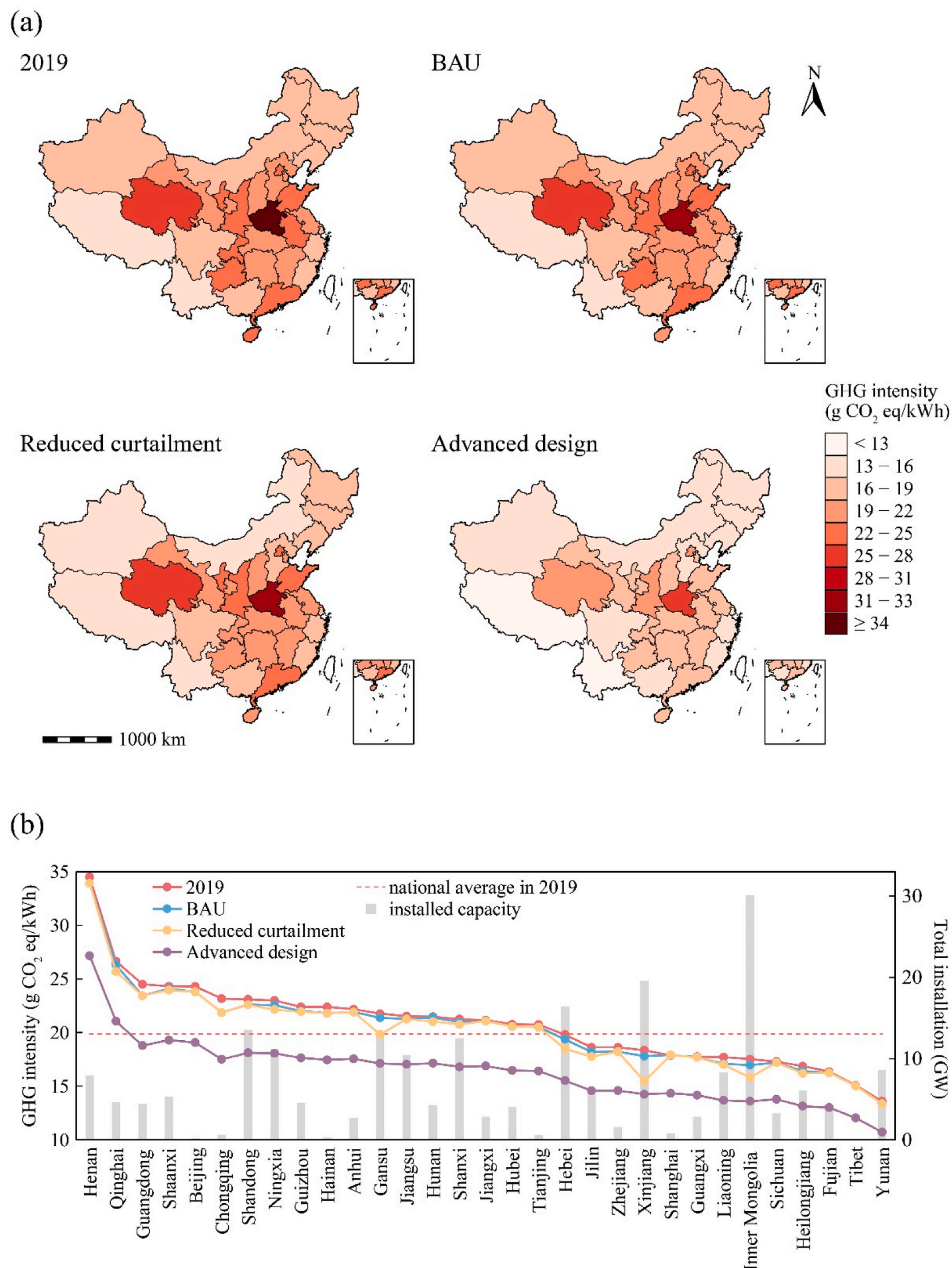

Fig. 7. The GHG emission intensity of wind energy by province. (a) The spatial distribution of GHG emission intensity in 2019 and under different scenarios. (b) National mean GHG emission intensity in 2019 (dashed line) and the intensity for each province in 2019 and under different scenarios (ordered from high to low; solid lines and dots), and installed wind capacity for each province by 2019 (grey bars).

The average GHG emission intensity of onshore wind power in China (19.88 g CO_2 eq/kWh) is close to the global average (19 ± 13 g CO_2 eq/kWh; Schlömer et al., 2014). The value is much lower than those in developing countries, such as Ethiopia (33.6 g CO_2 eq/kWh; Teffera et al., 2021), and is close to, or higher than, those of developed countries, such as the United States (18 g CO_2 eq/kWh, Alsaleh and Sattler, 2019), Czech Republic (19 g CO_2 eq/kWh; Šerešová et al., 2020), Denmark (15 g CO_2 eq/kWh; Besseau et al., 2019) and Australia (12.85 g CO_2 eq/kWh; Wolfram et al., 2016).

Our results show that wind energy in China has an emission intensity more than 98% lower than traditional fossil fuels (1050 g CO_2 eq/kWh in China) (Ding et al., 2016) and the mitigation effect can reach 84%–98% compared to the energy mix in 2020 (with emission intensity ranges from 117 to 771 g CO_2 eq/kWh in China; Li et al., 2018). The intensity is also lower than that of hydropower (24 g CO_2 eq/kWh; Xia and Zhong, 2020), solar power (44 g CO_2 eq/kWh; Ludin et al., 2018), and geothermal power (72 g CO_2 eq/kWh; Zhao et al., 2019) in China and lower than the global intensities for fossil fuels (>500 g CO_2 eq/kWh), solar power (85 g CO_2 eq/kWh), biomass (45 g CO_2 eq/kWh), geothermal (27 g CO_2 eq/kWh) and hydropower (26 g CO_2 eq/kWh)

(Amponsah et al., 2014; WNA, 2011). Wind energy has great economic potential with a lower levelized cost of electricity compared with other renewables (LAZARD, 2020) and, if allowed by geographical conditions, it has been shown to be one of the most suitable energy sources for GHG emission mitigation.

The results revealed large differences in GHG emission intensities between different provinces in China. Henan had the highest provincial emission intensity (34.50 g CO_2 eq/kWh), nearly three times than that in Yunnan (13.59 g CO_2 eq/kWh). Geographical position is one of the dominant factors affecting the environmental performance (as with GHG emission intensity) of all renewable sources. For example, geothermal energy is only available in specific locations, while the LCA emissions of solar power also depend on the duration and strength of sunlight (Ludin et al., 2018). In most areas hydro plants have emissions comparable with other types of renewables (3–70 g CO_2 eq/kWh), but the GHG emissions of those located in tropical regions can reach 8–6647 g CO_2 eq/kWh, a value which is even higher than fossil fuel emissions (Song et al., 2018).

Within China, Inner Mongolia has the largest provincial wind power industry, with high power generation efficiency and good control of unit emissions (Fig. 7b). As the province with the fastest growth of power generation systems in China, the energy transition of Inner Mongolia, from coal power to high-efficiency wind power, has made a great contribution to the emission reduction of the energy sector, decreasing from the highest level in China in 2013 to the national average in 2019 (Ding et al., 2017; Li et al., 2018).

5.3. Emission reduction strategy of China's wind energy

The development direction of wind power in China will shift from quantity assurance specified in the 13th five-year plan to quality improvement in the 14th five-year plan (CPC, 2020). Our research shows that the shift towards larger wind turbines (the BAU scenario) as well as reduced curtailment and advanced design to improve efficiency can all lead to further emission mitigation of wind energy (Fig. 6). Compared to further reducing wind curtailment, advanced design was shown to be more efficient in mitigating GHG emissions. The results show that advanced design would reduce GHG emission intensity by 21.6% from 19.88 to 15.59 CO_2 eq/kWh. The value of 15.59 CO_2 eq/kWh is in line with the global 2 °C target for the 2050 CO_2 intensity of electricity production without negative emissions from carbon capture and sequestration (CCS) (Bruckner et al., 2014). Selection of turbines requiring fewer manufacturing materials and with higher nominal power increases environmental performance and decreases the energy input. No size effects on emission of increasing foundation inputs (Fig. 4e and f) indicated that the structure and materials of foundations need to be further optimized and upgraded. In 2012, a high curtailment rate and poor turbine quality contributed to the low efficiency of China's wind industry (Lu et al., 2016). We have shown that, currently, turbine quality may be the sole factor for improving wind-energy efficiency. In the future, a substitution of large and high-efficiency turbines for dismantled power systems should be an effective strategy for emission mitigation in the case of unchanged production techniques. However, considering the increasing cost of energy inputs (Ederer, 2014) and environmental impacts such as the collision risk posed to birds (Tabassum et al., 2014), it is unreasonable to construct turbines with nominal power greater than 10 MW.

The curtailment of wind electricity was once a primary factor in the low efficiency of wind farms in China, especially in northern regions of the country (Lu et al., 2016). In these regions, coal-fired combined-heat-and-power plants account for most of the electricity generation to meet the demand for heating systems in winter when wind conditions are most favorable but often wasted. The curtailment level for most regions in the United States dropped to 1%–4% in the mid-2010s (Bird et al., 2014), while that of China was at a massive 21% in 2016 (NEA, 2017). The curtailment level dropped to 4% in 2019 (NEA, 2020) due to the expansion of transmission networks and the rapid development of pumped hydro storage and electric boilers. Further mitigation potential under the reduced curtailment scenario is effective in northern regions, including Xinjiang, Inner Mongolia and Gansu which account for a third of the national total installation, while limited in other regions (Fig. 7b).

In addition to turbine size, design efficiency and wind-energy curtailment, lifetime and manufacturing production are also contributors to the reduction of emission intensity (Padey et al., 2013). Installed sites with a large wind resource potential have been preferentially selected for deployment in China, especially in the northern and northeastern regions, which ensures that the theoretical capacity factor is approached (Davidson et al., 2016). Further improvement of lifetime and manufacturing production will be reached mainly through the use of new materials and more efficient mechanical design and structures. Development of technology, such as drive machinery with superconducting generators, blades possessing automatic adaptivity and intelligent power networks, could reduce the loss from energy capture and power generation, increase annual operating hours and improve the reliability of wind systems (McKenna et al., 2016). Furthermore, the use of natural, rather than man-made, fibers and biological materials such as wood, bamboo, flax and straw, along with the application of novel paints containing nano-composites, can all reduce emissions during manufacturing, reduce the replacement frequency of components during operation and make components fully-recyclable (Zangenberg and Brøndsted, 2015). The development of new materials could result in the decrease of GHG emissions per engineering-based size (i.e., decrease the scaling factor β in equation (2)) which is assumed to be constant in this study. Such techniques suggest that the GHG emissions of wind energy could be decreased further by future technology developments.

5.4. Uncertainty

We specifically accounted for provincial differences in capacity factor as well as in the height of turbines, which directly relate wind geopotential to annual energy production (Sedaghat et al., 2017), and thus play important roles in the GHG estimates for the electricity produced (Mendecka and Lombardi, 2019). However, there are still geographical differences within each province, especially for some areas with large differences in elevation or surface roughness. These differences will lead to variations in wind speed conditions at different installation sites and changes in the practical load factor. Power performance in centralized wind farms can also be influenced by wind wake, which is determined by the layout of turbine arrays (Dupont et al., 2018).

Material manufacturing is the main source of GHG emissions in LCA studies. Despite the harmonization of the main materials, there may be differences and omissions in the materials lists of the selected studies. For example, rare materials such as NdFeB are not considered in some cases, which will impact on our emission estimates. In addition, the remaining stages are usually considered as a percentage of the manufacturing stage because replacement parts during operation and final disposal are expected to be proportional to the input materials. However, determining whether or not the size of turbines affects the proportion allocated to different stages requires further study. Furthermore, if the GHG emissions caused by different land use changes are considered in the construction and installation stage, the emission value of this stage will be significantly increased, possibly even exceeding the material manufacturing stage (Gao et al., 2019). Therefore, the uncertainty of the system boundary and the proportions allocated to different stages need further exploration.

6. Conclusion

We reviewed LCA studies of wind energy systems in China, and developed a simplified LCA model based on the reviewed studies to estimate the GHG emission intensities of China's wind power at provincial and national scales. The emission intensity of China's wind energy is 19.88 g CO_2 eq/kWh (ranging from 13.59 to 34.50 g CO_2 eq/kWh for different provinces), close to the global average intensity. Based on the results of three scenarios, we found that the shift towards larger wind turbines and reduced curtailment can lead to further emission mitigation of wind energy at the national level by 2.1% and 5.4%, respectively. Furthermore, developing turbines with more advanced design and higher efficiency can effectively reduce GHG emission intensity by 21.6%. Our study provides a comprehensive estimate of GHG emissions of China's wind power system, and the results can be used in designing scenarios and formulating policy regarding the future energy mix. Simplified LCA models rely strongly on the detailed LCA works for different turbines. More detailed LCA works of turbines made in China and for various newly-designed turbines could further increase the accuracy of the emission predictions. In addition, future works to estimate mitigation contribution of wind energy under different climate policy scenarios could help formulate climate and energy policy.

CRediT authorship contribution statement

Kang Xu: Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing – original draft. **Jinfeng Chang:** Conceptualization, Writing – review & editing, Visualization, Supervision, Project administration. **Wenji Zhou:** Conceptualization, Writing – review & editing. **Shuangcheng Li:** Conceptualization, Writing – review & editing. **Zhou Shi:** Conceptualization, Writing – review & editing. **Hanwen Zhu:** Investigation, Data curation, Writing – review & editing. **Yaoyao Chen:** Investigation, Data curation. **Kaiwen Guo:** Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.130683.

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