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Impact of wind energy deployment on job creation in the wind power industry

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Abstract

Europe needs to increase wind energy capacity to reach 440 GW installed capacity by 2030. Wind energy deployment has multiple impacts, of which some negative impacts have resulted in opposition to its implementation. However, the job creation is a positive impact, and could contribute to increasing social acceptance. Assessing the job creation impact from wind energy deployment thoroughly, requires an accurate and consistent quantification method. As this is missing in the current literature, this research provides such a method and a model. The main research question is: How does job creation of wind energy deployment in the wind power industry differ per location within Europe by 2030?

This research applies multiple methodological approaches to define a job quantification method. We performed a systematic quantitative literature review, from which job creation quantities for different job creation stages (development, construction, manufacturing, operation and maintenance and decommissioning) were retrieved. Additionally, semi-structured interviews have been conducted to enhance the collected data. An employment factor approach has been used to quantify job creation in job-years/MW installed capacity (job-years/MW_i). A multivariate regression analysis has been performed on the collected data, creating model input. We validated the model using the data retrieved from the interviews. Also, a sensitivity analysis has been performed on multiple parameters.

Results show that the number of wind turbines per park does not influence the employment factor. Higher turbine capacities results in higher employment factors for operation and maintenance. Over the entire lifetime, onshore job creation is 15.26 job-years/MW_i lower than offshore job creation. Overall, Europe and North America show lower employment factors than other locations for similar wind parks. Within Europe, the only difference in job creation is related to the manufacturing stage. Manufacturing jobs are created internationally, or nationally if a manufacturing organization is present. Germany, Spain and Denmark might benefit most from wind energy deployment, as these countries have a manufacturing organization. From 2023 to 2030, a total of 15.7 million job-years could be created if Europe reaches 440 GW installed capacity. This corresponds to 724 thousand direct jobs in 2030, of which only a small share will be created locally. Its potential for increasing local acceptance of wind energy deployment therefore seems limited. Still, this research increased insight into the variables influencing job creation, and provides a consistent job quantification model. Additional data points, especially for decommissioning, could increase model accuracy and enable using smaller locational scales.

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Abbreviations

AF	Africa
AS	Asia
CAPEX	Capital expenditure
CO_2	Carbon dioxide
EF	Employment factor
EU	Europe
GHGs	Greenhouse gases
GDP	Gross domestic product
IO	Input-output
NA	North America
NIMBY	Not in my backyard
Nr.T	Number of turbines
OPEX	Operating expenses
O&M	Operation and maintenance
OS	Onshore/offshore dummy
RY	Reference year
SA	South America
TC	Turbine capacity
WIMBY	Wind in my backyard

1. Introduction

1.1 Societal background

Human overexploitation of fossil fuels for the production of energy has resulted in increased atmospheric concentrations of greenhouse gases (GHGs), consequently leading to global warming (Al-Ghussain, 2019). From the start of industrial revolution until 2020, atmospheric carbon dioxide (CO_2) concentrations have increased from 285 to 415 ppm, resulting in an average global temperature increase of around 1.2 degrees Celsius (Chen, 2021). Rising sea levels and melting glaciers are examples of currently noticeable effects of global warming (Kumar et al., 2012). Future effects of global warming could result in species extinction and more extreme weather conditions, with long periods of drought and more frequent storms (Kumar et al., 2012). Recognizing the threats of global warming, 196 parties adopted the Paris Agreement in 2015 (UNFCCC, 2023). The main objective of the Paris Agreement is limiting global warming to 2.0 degrees Celsius and pursuing to stay below 1.5 degrees Celsius compared to pre-industrial levels (Ourbak & Magnan, 2018). In persuasion of limiting global warming to 1.5 degrees Celsius, 124 countries pledged reducing GHGs drastically and becoming carbon neutral by the year 2050 or 2060 (Chen, 2021).

The energy sector has the highest contribution to annual CO_2 emissions, and was responsible for 38.8% of global CO_2 emissions in 2019 (Yoro & Daramola, 2020). Reaching carbon neutrality requires significant CO_2 emission reductions. This can be achieved by reducing fossil fuel energy production and increasing renewable energy production (Halkos & Gkampoura, 2020). Reduction of fossil fuel energy production has proven difficult, as last decades global energy production from coal, natural gas and oil has significantly increased (Ritchie et al., 2022). At the same time, renewable energy production has increased. However, as global wind and solar energy production only equaled 4% of total energy production in 2020, its share remains relatively small (Ritchie et al., 2022). A significant increase in global renewable energy production is required to reduce fossil fuel dependency and to comply with the Paris Agreement (Pablo-Romero et al., 2022).

Wind energy is a renewable energy source that contributes to the decarbonization of the energy sector (Saidur et al., 2011). The technology is not entirely GHG emission free due to emissions released during construction, operation and maintenance (O&M) and decommissioning (Kumar et al., 2016). However, the lifecycle carbon intensity of wind energy equals 5 grams of CO_2 per KWh (Li et al., 2020), whereas for a coal fired power plant this equals around 900 grams of CO_2 per KWh (IEA, 2022). Despite this significant contribution of wind energy to reduce CO_2 emissions, wind energy has received opposition to its implementation. Wind energy is often linked to the 'not in my backyard' (NIMBY) effect, which refers to situations where individuals' positive attitude towards wind energy changes once the turbines are placed close to their homes (Wolsink, 2012). Locally, individuals feel they only get the burden and not the benefits of wind energy, resulting in opposition (Jørgensen et al., 2020). This local burden is caused by negative impacts created by wind energy deployment (Enevoldsen & Sovacool, 2016).

1.2 Impacts of wind turbines

Potential negative environmental, visual and socioeconomic impacts are attributed to wind energy (Enevoldsen & Sovacool, 2016). Environmental impacts refer to the reduction of flora, fauna and wildlife. Wind turbines could form a threat to wildlife due to the rotations of wind turbine blades, potentially killing birds and bats (Saidur et al., 2011). However, as shown by Erickson et al. (2005), bird mortality caused by wind turbines only accounts for a fraction of total bird mortality from anthropogenic causes. Visual impacts of wind turbines include the visual pollution of the landscape and the flicker effect created by the shadow of the turbine blades. Another impact of wind energy is the noise resulting from the rotating blades. There are however technologies available to mitigate this impact (Deshmukh et al., 2019). Socioeconomic impacts of wind turbines consider the reduced attractiveness of the area, in some cases resulting in reduced land and property values (Enevoldsen & Sovacool, 2016). Besides, wind turbines could interfere with radio and TV signals leading to signal losses (Angulo et al., 2014; Mohtasham, 2015). These negative impacts mainly arise locally whereas most positive impacts arise nationally (Brown, 2011).

Nationally, wind energy creates multiple positive impacts on the environment (Jaber, 2014). During operation wind energy does not emit CO_2 emissions, release hazardous waste and does not require natural resources (e.g. oil, gas, biomass or coal) for energy production (Jaber, 2014). Besides national positive impacts, wind energy also creates local positive impacts. An example is the potential to increase local tourism with tours at the wind park (Jaber, 2014). Another important positive impact of wind energy, that could be both locally and nationally, is job creation. Job creation should be stimulated as it reduces unemployment and could increase gross domestic product (GDP) (Bulavskaya & Reynès, 2018). Due to the increased installed wind energy capacity, the global amount of jobs created by wind energy deployment has almost doubled from 2010 to 2020 (Haidi & Cheddadi, 2022).

1.3 Knowledge gap

Local resistance to wind energy should be reduced in order to enable wind energy to contribute to the decarbonization of the energy sector. In an effort to reduce resistance and increase social acceptance of wind energy, the EU funded the Wind in My Backyard (WIMBY) project (European Commission, 2023). The aim of the WIMBY project is to model social impacts of wind energy, in order to increase social acceptance of wind energy. Reducing local opposition to wind energy deployment could be achieved by finding locations where negative impacts are the least and positive impacts are the most. Determining these locations requires accurate quantification methods for the different impacts. Regarding job creation, quantifying jobs created by wind energy deployment is difficult due to multiple reasons. Firstly, no specific job quantification method is available and secondly there is inconsistency and non-transparency in the current literature.

Instead of providing precise wind energy job quantification methods for wind energy job creation, current literature mainly focuses on general job creation values. Rutovitz et al. (2015) provide a method to quantify energy jobs based on a general job creation value, which should be adapted based on a country's GDP. Esteban et al. (2011) also use a general job creation value, and include a technological decline factor to project a future job creation value. Both methods project wind energy job creation by using a general job creation value and only adapting it with one variable. More specific job quantification models are required to provide a detailed job creation value for different wind parks at different locations.

Inconsistency in current literature occurs both in the different job types and sectors included in quantification, and in the unit in which job creation is measured. Considering job types, Fragkos & Paroussos, (2018) include direct, indirect and induced jobs in quantifying job creation, whereas Hondo & Moriizumi (2017) only consider direct and indirect jobs. Some other papers only include direct jobs or do not specify what job types are included. Regarding different job sectors included in job quantification, current literature is not consistent. As shown in the article of Simas & Pacca (2014) previous studies included different job sectors in quantifying job creation. Often Manufacturing, construction and O&M jobs are included in quantifying job creation. However, only limited studies include project development in job creation. Regarding the entire lifecycle of wind turbines, decommissioning should also be considered in quantifying total job creation (Trypolska et al., 2022). A third inconsistency in literature is the unit in which job creation is expressed. Job creation is expressed in jobs or job-years per MW installed capacity (MW_i) or GWh, in money invested or value generated. Also, most articles do not distinguish between onshore and offshore job creation, whereas Simas & Pacca (2014) suggest offshore wind creates slightly more jobs per MW_i.

As there is a lot of inconsistency and no specific modelling method, it is difficult to determine the impact of wind energy deployment on job creation. Especially when aiming to identify locations with a high positive impact on job creation, more available data is required. Most studies quantify (a part of) job creation without mentioning a specific location. The article of Fragkos & Paroussos (2018) identifies job creation in Europe. Whereas the article of Trypolska et al. (2022) quantifies job creation in Ukraine, however this only focuses on job creation for decommissioning. As a result, the current literature lacks a consistent and comparable wind energy job quantification method for different wind parks at different locations.

1.4 Research aim and questions

The aim of this research is to create insight into the impact of wind energy deployment on job creation within European countries. First of all, this research has developed a consistent and transparent method to quantify job creation of wind energy deployment at different locations and for different wind parks. Job creation has been quantified as precisely as possible. It therefore includes all job types and sectors related to the different lifecycle stages of a wind turbine. To ensure consistency and transparency, all lifecycle stages, related jobs and job types are explored. The purpose of a transparent and consistent method of quantifying job creation is to enable comparison between job creations for different wind power projects (onshore or offshore and scale) at different locations. By accurately quantifying the wind energy job creation potential, this research contributes to the WIMBY project to increase social acceptance of wind energy. This research answers the following research question:

How does job creation of wind energy deployment in the wind power industry differ per location within Europe by 2030?

Answering this research question requires answers to five related sub questions. These sub questions are provided below:

1) How does the wind turbine capacity and the number of wind turbines per wind park influence job creation of wind energy deployment?
2) How does onshore wind deployment job creation differ from offshore wind deployment job creation?
3) What is the geographical context in which wind energy jobs are created?
4) How does job creation from wind energy deployment differ per location?
5) How many wind energy jobs will be created in Europe if Europe reaches its 2030 renewable wind energy target?

The first sub question is required to determine any scale effects of wind turbines on job creation. It identifies the relationship between different wind turbine capacities and the number of wind turbines on job creation. Sub question two determines the relationship between onshore and offshore wind parks on job creation. The third sub question elaborates on the likeliness of local, national or international job creation. Sub question four quantifies job creation of different wind power projects for different locations. Answering the fourth sub question required national data regarding job creation of wind energy deployment in combination with the relationships found under sub questions one, two and three. The last sub question quantifies future total job creation in Europe in 2030. The combination of all sub questions provides the answer to the main research question.

1.5 Scientific relevance

This research collects all available wind energy job creation data in existing literature and converts it to the same units to enable comparison. It therefore contributes to increasing transparency and consistency in the quantification of wind energy jobs. Based on this data a model has been developed, which enables quantification of the impact of wind energy development on job creation. This model could be used to identify locations where the deployment of new wind energy parks create the highest positive impact on job creation. Deploying wind turbines at high positive job creation impact locations, potentially leads to increased social acceptance of wind energy deployment. This research therefore contributes to enabling strategic placement of wind turbines, which might reduce local resistance. Besides, it creates insight into the number of new wind energy jobs that will be created for a certain wind energy park at a certain location. Additionally expected future wind energy jobs in Europe have been quantified. The elaboration on locally versus internationally generated jobs offers valuable information on which locations will benefit most from new wind energy deployment.

2. Theoretical background

This section provides a definition of the wind power industry jobs, and of the approach used to quantify job creation. It discusses the different lifecycle stages of wind parks and their related jobs, which will be referred to as job sectors. Secondly it provides different job types used in current literature for job quantification.

2.1 Wind power industry jobs (job sectors)

According to Llera et al. (2013) renewable energy technologies generally have a lifecycle consisting of five different stages. The first stage includes the research, project design and development. The second stage is manufacturing of the renewable energy technology (wind turbines in this case). The third stage includes the transport, installation and commissioning of the wind farm. Operation and maintenance is the fourth stage of wind parks. The last stage relates to renovation or decommissioning of the wind turbines. IRENA (2011) mentions: processing of raw materials, manufacturing, project design and management, installation and or construction, operation and maintenance, and eventually decommissioning as different jobs related to wind energy. The different jobs mentioned by IRENA (2011) correlate with the five different lifecycle stages mentioned by Llera et al. (2013). This research will therefore consider the same five lifecycle stages and refer to these as job sectors. The job sectors are: development, manufacturing, construction, O&M and decommissioning.

The duration of each job sector is of importance for quantifying job creation. Construction and decommissioning are often seen as temporary jobs, whereas planning, manufacturing and O&M are regarded as permanent jobs (Llera et al., 2013). This is largely supported by Hanna et al. (2022), who also consider O&M as a permanents job. Manufacturing of a single turbine could be seen as temporary, however, regarding the expected increase in wind turbines, it could also be seen as a permanent job (Hanna et al., 2022). Permanent jobs are often expressed in number of jobs, whereas temporary jobs are expressed in job-years. One job-year refers to work for the duration of one year for one employee. Another aspect of jobs creation is whether the job is created locally, nationally or internationally. According to Hanna et al. (2022) manufacturing jobs can be created both locally, nationally and internationally, the other jobs are likely created locally or nationally. Local, national or international job creation of manufacturing jobs depends on the presence of wind turbine manufacturing organizations.

2.2 Job types

Generally, there are three different job types in the wind power industry: direct, indirect and induced jobs (IRENA, 2011). According to IRENA (2011) direct jobs refer to jobs related to the core activities of a sector, indirect jobs refer to jobs supplying the renewable power (wind power) industry, and induced jobs refer to jobs created due to additional expenditure resulting from increased wealth. Direct jobs for the wind energy sector are jobs directly related to any of the previously mentioned job sectors. Indirect wind energy jobs could be jobs required for the production of steel for wind turbines. Current literature mainly focusses on direct job creation, and lesser attention is given to indirect and induced jobs (Bowen, 2016). Only considering direct job creation will give a lower job creation value than what the job creation value will be in reality (Ram et al., 2022). To give the most accurate value of jobs created by wind energy, all job types are included in this research. Values for indirect and induced jobs can be estimated based on a local job multiplier. Local job multiplier accounts for additional jobs created due to new job creation (Bartik & Sotherland, 2019). According to Bartik & Sotherland (2019) additional jobs can be created by supplier linkages or worker demand. Supplier linkages account for additional jobs created at the supplier side due to the increase in employees in the industry. This can therefore be seen as indirect jobs. Worker demand refers to the additional expenditure of the new employees, resulting in additional job creation. This can therefore be seen as induced jobs.

2.3 Employment factor approach

There are two main approaches for the quantification of job creation of renewable energy, which are the input-output model (IO) and employment factor approach (EF) (Breitschopf et al., 2013). The IO approach quantifies job creation based on the output and employment of a sector. It therefore includes both direct and indirect job creation (Fragkos & Paroussos, 2018). However, it does not clearly determine the share of direct and indirect jobs on total job creation (direct, indirect and induced). The EF approach quantifies job creation based on number of jobs related to installed capacity (Fragkos & Paroussos, 2018). It projects the number of employees required per job sector, for a wind park with a specific capacity. This approach typically includes direct job creation. Since this research aims to include all job categories, the IO approach seems the better option. However, in literature it is found that the EF approach is used, and indirect and induced jobs are also included. As is the case in the article of Simas & Pacca (2014), where direct, indirect and induced jobs are included while using the EF approach. Besides, local job multipliers enable estimating indirect and induced jobs. Another difference between the EF and IO model approach is that the EF approach is generally more straightforward and transparent (Fragkos & Paroussos, 2018). For these reasons this research applies the EF approach for quantifying job creation.

Typically, the EF approach quantifies job creation in jobs/MW_i (jobs per MW installed capacity) or job-years/MW_i (job years per MW installed capacity). The calculation for the employment factor is shown in Equation (1).

$$employment\ factor = \sum \frac{employment\ per\ job\ sector\ (jobs)}{installed\ capacity\ (MWi)} \tag{1}$$

However, in literature sometimes values are provided per Gigawatt hour (GWh). Job creation is then quantified in jobs/GWh or job-years/GWh, where GWh refers to produced energy.

3. Methodology

This quantitative research required a total of three different steps to provide an answer to the research questions. The first research step consists of data collection, for which scientific and grey literature and semi-structured interviews will be used. The second step involves data analysis, after which the first three research questions have been answered. During the final step a model has been developed to project job creation values, and to allow the fourth and fifth research questions to be answered. **Error! Reference source not found.** is a visual representation of the different research steps and shows what research questions have been answered during which research step.

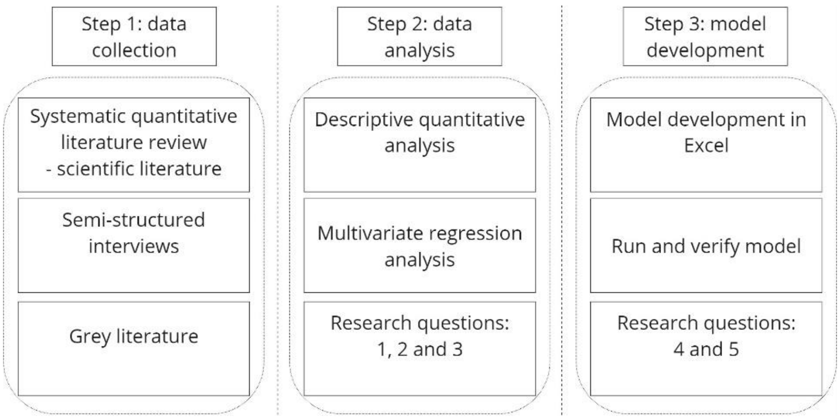

Figure 1: Methodological framework.

3.1 Step one: data collection

3.1.1 Scientific literature review

A systematic quantitative literature review has been performed as defined by (Pickering & Byrne, 2014). This method is used to systematically select scientific literature and collect quantitative data. The selection of literature involved two different phases. The first phase provided a list of primary, secondary and tertiary key words used to retrieve literature. As the objective of the research is to quantify job creation, primary key words used were: jobs, job creation, employment, employment creation and employment factor. As job creation has been quantified for wind energy deployment, the secondary key words used were: wind energy, wind power and wind turbines. As the focus of this research is on job creation of wind energy in Europe, the tertiary key words used were: Europe and EU. For the collection of scientific literature there has been made use of a script in the Python programming language. This script searches in the scientific literature database of Scopus using the Scopus API. The script uses the different (primary, secondary and tertiary) key words to search for literature. To increase the amount of literature, the script has also been run only on the primary and secondary key words. This enabled retrieving wind energy job creation literature from outside Europe. The Python script provided the bibliography and abstract of the references.

Phase two involved the inclusion or exclusion of references from the literature review. Firstly, all abstracts have been read and assessed on relevance to the research questions. References were considered relevant to the research questions if they included information or data directly related to job creation in the wind power industry. Based on the abstract, references have been included or excluded from the remainder of the literature review. Secondly, articles that were eighter not accessible to the author, or that were written in another language than English or Dutch (these are the languages spoken by the author) have been excluded from the literature review. All included references have been read in full, and relevant quantitative data concerning job creation has been documented and organized in numerical tables.

Additionally to scientific literature, grey literature has been used to retrieve supplementary data. A lack of available scientific data resulted in data gaps. Grey literature helped reduce data gaps and provided additional indications for an EF.

3.1.2 Semi-structured interviews

Next to scientific literature, interviews have been conducted to collect additional data and increase overall understanding of wind energy job creation. The main aim of the interviews was to retrieve specific quantitative data on job creation, and to determine factors that may influence job creation. As it is difficult to provide exact EF values, the interviews were of a semi-structured nature. Semi-structured interviews allowed for additional questions to be asked that might give indications for an EF, or other data from which an EF could be derived. The semi-structured interviews have been conducted with organizations associated with the Horizon Europe project WIMBY. These organizations are active within the wind power industry, and therefore could provide valuable practical data and information. Due to confidentiality of the type of information provided during the interviews, the interviewees and the organizations have been made anonymous. A total of four interviews have been conducted during this research, from which the transcripts can be found in appendix C. Interviewee A is self-employed and works as a consultant on small to large scale wind energy parks. He/she is involved in a wind energy project mainly during the construction stage. Interviewee B is a sustainable energy manager for a large energy provider. He/she is involved during the development stage of wind projects. Interviewee C and D both work for the same large energy provider. Interviewee C works as a renewable global project portfolio manager and interviewee D is a wind park decommissioning expert.

3.2 Step two: data analysis

During step two the collected data has been analyzed. First all, collected data has been converted into the same unit. As most EFs in the literature were provided in job-years/MW_i, this unit has been used to quantify job creation. This reduced conversion time from one unit to the other unit. Conversion from jobs/GWh to jobs/MW_i is based on the capacity factor and lifetime of the wind park. Values provided in jobs/MW_i have been converted to job-years/MW_i. Values in jobs/MW_i can be normalized to job-years/MW_i by multiplying by the lifetime of the technology or job duration (Dufo-López et al., 2016). If no job duration was provided for the job sector, a typical duration value was applied. This typical duration value has been determined based on most frequently used job durations found in literature.

The collected data has been analyzed using a descriptive analysis approach. This type of analysis generally analyzes data based on statistical techniques, such as mean, median, mode, standard deviation, frequency distribution and correlation (Siedlecki, 2020). Mean, median and mode values have been determined and used if multiple data points were collected for the same wind park. More interesting however, is the correlation or relationship among different variables influencing the EFs found in literature. These relationships have been determined using a multiple linear regression analysis. This analysis accounts for the variation of multiple independent variables on the dependent variable. The general equation for this multivariate regression analysis is provided in equation 2, as adopted from Uyanık & Güler (2013).

$$\gamma = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \qquad (2)$$

Where: $\gamma = dependent\ variable, \beta_i = parameter, x_i = independent\ variable, \varepsilon = error.$

In this case, the dependent variable is the EF of the different job sectors. The independent variables are the variables that influence the EF. The respective values of the parameters corresponding to the independent variables have been derived using ANOVA statistics. A significance level of 5% has been applied to the regressions, to determine if the independent variables likely determine the dependent variable. If the regression significance is above 5%, the regression has been considered as not significant. A regression significance of 5% or lower, suggests that the independent variables likely determine the dependent variable. Therefore, regressions with a regression significance of 5% or lower, are considered as significant. A significance level of 5% has been applied, as this is the most commonly applied value, and results in only a small chance that a significant regression does actually not determine the dependent variable (Fang & Yang, 2019). The significant regressions provided the answer to research questions one, two and three. Research questions one and two could directly be answered from the derived relationships.

3.3 Step three: model development

Step three involved the creation of a model to quantify job creation for different wind parks (number of turbines, turbines capacity, onshore or offshore) at different locations. The model is based on the significant regressions for the different job sectors found during step two. The total function to quantify job creation includes all regressions of the EFs for the different job sectors. As all EFs of all job sectors are converted to the same unit, one total job creation EF is provided. This job creation EF (in job-years/MW_i) is therefore the sum of all EFs of the job sectors. Quantifying total job creation for a specific wind park requires the total EF to be multiplied by the amount of MW that will be installed. The equation is shown in equation 3.

$$job\ creation = (EF_{dv} + EF_m + EF_c + EF_{o\&m} + EF_{dc}) \times MW_i \tag{3}$$

Where: *EF is the employment factor (job-years/MW_i) and the subscripts dv, m, c, o&m and dc represent the development, manufacturing, construction, operation and maintenance and decommissioning job sectors respectively.*

Based on this job creation function a model has been developed in Excel. This model is created based on all available data collected during step one. Preferably the model had been created based on 80% of the retrieved data, to allow for model validation based on the other 20%. Due to limited retrieved data however, all retrieved data was required to serve as model input. Therefore, model validation is based on a comparison of model results with other methods and trends or relationships provided during the interviews. Model results allow research questions four and five to be answered.

3.4 Uncertainties

During the study, two factors made the creation of a robust model difficult. First of all, the lack of data made it difficult to perform a regression analysis. As a result, not all EFs have been determined from the regressions. If a regression analysis was not possible, due to too little data, the EF has been determined from average, minimum and maximum values. Also, due to a lack of data, all data was required as input data. Therefore, the accuracy of the model cannot be checked using other available data points. Model validation is therefore done by examining similar trends retrieved from the interviews and from other job creation methods. Secondly, only 4 interviews were conducted in this research. Preferably more interviews were conducted to increase total data points. Besides, more interviews would make model validation more robust. As a result, it is possible that the model provides job creation values that are too high or too low. This problem has been minimized by creating a range for the EFs and the total EF in the model. The model provides the projected job creation EF, as well as this value plus and minus one standard deviation. This increases the chance that actual job creation falls within the range projected by the model.

4. Results

4.1 Results literature review

Running the Python script, retrieved a total of 526 unique references. Of these references, 162 were found to be relevant for the literature review based on their abstract and title. All 162 articles have been thoroughly reviewed, and job creation data has been documented. However, not all references have been used to collect data. First of all, 8 articles were in a different language and were therefore not reviewed. Secondly, two articles were not accessible, and 85 articles did not contain job creation data. As a result, a total of 67 references have been used to retrieve data. An overview of the 162 references, and their reason for exclusion, can be found in the appendix (Appendix A).

It was noted during the literature review that multiple articles provided the same job creation quantities. This is explained by the fact that these articles often used the same job creation quantities as provided by another article. The article of Simas & Pacca (2014) is included in the literature review, and their employment factor has also been used in the articles of Vasconcellos & Caiado Couto (2021), that is also included in the review. Another article that multiple articles referred to was the article of Rutovitz et al. (2015). This paper was not retrieved from the literature search in Scopus, and was therefore not included in the literature review. However, as multiple articles referred to this article, it has been added manually. Two other articles have also been added manually to the literature review, as these were suggested by organizations when asked for an interview and relevant data about job creation of wind energy. Therefore, the total literature review included 165 references, of which 70 provided useful data (Appendix A). The data from the articles using the employment factors from Simas & Pacca (2014) or Rutovitz et al. (2015) have been documented, but have not been used in the regression analysis as this would lead to double counting. Data from the articles of Okkonen & Lehtonen (2016), Greene & Geisken (2013) and Ejdemo & Söderholm (2015) have also been documented, but have not been used in the regression analysis. These articles only quantified created jobs in a smaller town or region. These values do not represent all the created jobs but only a certain share (for a specific town). As this is not further specified, values cannot be compared with total job creation quantities.

Appendix B provides an overview of all data points that have been collected from the literature. There are many variations in the data that has been collected from the literature. This is caused by different included job sectors, job types, and the unit in which jobs have been quantified. All data has been collected and grouped per job sector. However, some articles did not specifically provide job creation values per job sector separately, but provided one total value. Some other articles only mentioned job quantities referring to a construction phase. The construction phase includes the job sectors of development, construction and manufacturing.

Regarding the different job types, only limited articles provided job creation values for all three job types (direct, indirect and induced). Some mentioned a total value without specifying what job types were included in the total job quantity. Other articles quantified job creation for direct plus indirect jobs combined.

Also, articles quantified job creation in different units. The two most common job creation units used were jobs/MW_i or job-years/MW_i. All data found in the literature has been converted to job-years, if necessary. If jobs were quantified in jobs/MW_i and no duration was determined, a typical duration for the job sector was used. However, in the current literature different durations are used. For instance, a 20-year O&M duration is used by Slattery et al. (2011), and a 40-year O&M duration is used by Jacobson et al. (2014). Corresponding direct job-years/MW_i values are 0.9 and 6.2 respectively. However, if a 25-year job duration had been used, it would have resulted in 1.1 and 3.9 job-years/MW_i respectively. The job duration can therefore have a great impact on the job creation quantity. Ranges for job duration per sector found in the literature were: a few years to 5 years for development, half a year to 2.5 years for construction and manufacturing, 20 to 40 years for O&M, and 1 to 3 years for decommissioning. If job quantities were provided in jobs/MW_i, a job duration of 1 year has been used for construction, manufacturing and decommissioning, 3 years for development, and 25 years for

O&M, as these were the most commonly used durations. Figure 2 shows the different job sectors and their duration ranges found in the literature.

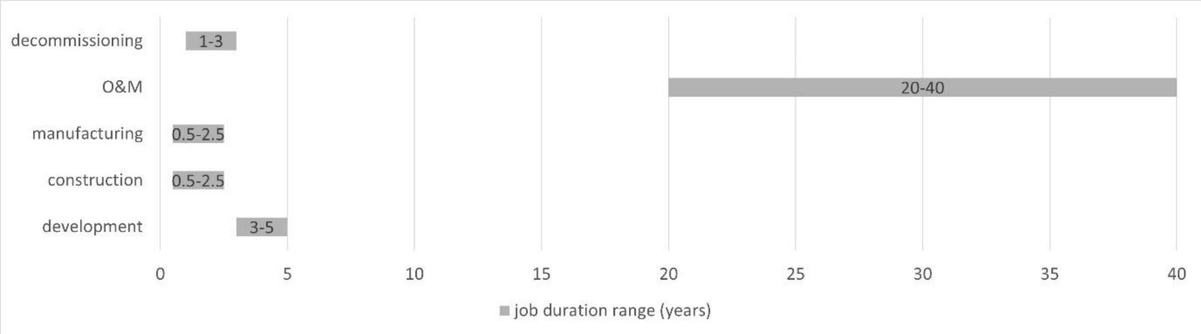

Figure 2: Job sectors and their duration (range) in years.

Apart from using different job sectors, job types and units, only limited articles described the wind park. Some articles provided different employment factors for onshore and offshore wind, while others only provided an EF for wind in general. Besides, not all articles described the wind farm in terms of the number of turbines, turbine capacity or total capacity. The same is true for the reference year on which the EF is based. If no clear reference year was provided, the publishing year has been used as a reference year.

Next to job creation quantities, data has been retrieved regarding the local nature of job creation. This data showed the share of jobs created locally and internationally, and can also be found in Appendix B. Also, 2 articles discussed the educational level of jobs required in the wind power industry. Swift et al. (2019) found that the worker profile in the wind power industry was 79.9% vocational training and 27.1% university degree. According to Pegels & Lütkenhorst (2014), manufacturing, construction and operation and maintenance jobs require 14%, 6% and 17% university degree workers, respectively.

4.2 results regression analysis

This section provides the results of the different regression analysis per job sector. The independent variables included in the regression analysis were: Onshore/offshore dummy (OS), locations in Europe (EU), North America (NA), South America (SA), Asia (AS) and Africa (AF), turbine capacity (TC), number of turbines (Nr.T), and reference year (RY).

4.2.1 development

A total of five different data points have been retrieved from the literature for the development stage of wind energy. As a result, performing a regression analysis is only based on limited data points. On all possible combinations, a regression analysis has been performed. Of all regression runs, none were significant and could be used to project job creation for the development stage. Therefore, the minimum, maximum, average, median and standard deviation are the only values that can be used to quantify job creation. All these values for direct, indirect, induced and total jobs are presented in table 1. The induced and total jobs are only based on two different values resulting in similar average and median values.

Table 1: Direct, indirect, induced & total EFs for the development stage. Values provided in job-years/MW_i.

Development	Direct jobs	Indirect jobs	Induced jobs	Total jobs
Min	0.21	0.26	0.48	1.34
Max	1.41	1.09	0.70	2.37
Average	0.69	0.59	0.59	1.86
Median	0.58	0.41	0.59	1.58

St.dev	0.52	0.44	0.16	0.73

4.2.2 construction

All significant regressions found for direct, indirect and induced jobs during the construction are shown in table 2. For direct jobs, a total of three different significant regressions have been determined. Direct jobs run one and run two are both based on the same independent variables. These independent variables were the locations in EU and NA and at onshore or offshore. The difference between run one and run two is the observation count. Run one included two outlier values, which have been removed in run two. As a result, the regression analysis result changed slightly. First of all, the intercept and independent variable coefficients changed. Secondly, the regression significance, R^2, and standard deviation changed. The R^2 value increased, meaning that the found regression better fits the model data than in run one. Therefore, direct jobs run two is more suitable for the model than run one. Direct jobs run three was significant for the number of turbines, turbine capacity, reference year and the location EU and was based on 18 observations. However, for this run only two data points were actually in the EU. Removing these data points or running the regression without checking for the location EU, the regression was no longer significant. Besides, following direct jobs run 3, a wind turbine with a capacity of more than 2.4 MW could result in a negative EF, depending on the location. This makes direct jobs run three unsuitable for job creation projection. The EF for direct construction jobs is therefore based on the direct jobs run 2.

Indirect run one and run two and induced run one and run two, all show significant regressions with high R^2 values. As can be seen, for both indirect and induced runs, run one and run two have exactly the same independent variables coefficients and P-values, but for different independent variables. This is caused by the fact that all onshore wind data points are also outside the EU, and all offshore data points are within the EU. Both independent variables are dummy variables. Although the independent variables are different, for the regression they are the same and show identical results. Running the regression analysis, including both onshore/offshore and EU in combination with turbine capacity, resulted in a non-significant regression. Following indirect jobs run one, the indirect EF for an onshore wind turbine is negative (no matter the turbine capacity). Following indirect jobs run two, the indirect EF for a wind turbine outside Europe is negative (no matter the turbine capacity). According to induced jobs run 2, a 5 MW onshore wind turbine in the EU creates 6.65 job-years/MW_i. This seems a plausible EF value. However, the same wind turbine creates -2.47 job-years/MW_i following induced job run 1, which is unrealistic. A 5 MW offshore wind turbine outside the EU creates -2.47 job-years/MW_i or 6.65 job-years/MW_i according to induced jobs run 2 and run 1, respectively. All four significant regressions suggest unrealistic EFs for realistic wind turbine situations. Therefore, job creation of indirect and induced jobs in this research is based on their minimum, maximum and average values as shown in table 3.

Table 2: Significant EF regressions for the construction stage.

Dependent variable	Obs.	Int. coef	Int. P-value	Independent variable(s) coef	Independent variable(s) P-value	Regres. sig F	R^2	St.dev
Direct jobs run 1	48	11.281	8E-10	OS) -5.477 EU) -4.454 NA) -4.295	OS) 2E-06 EU) 0.0028 NA) 0.0006	9E-07	0.502	2.561
Direct jobs run 2	46	9.457	3E-11	OS) -3.653 EU) -4.072 NA) -4.372	OS) 2E-05 EU) 0.0002 NA) 3E-06	2E-07	0.551	1.801

Direct jobs run 3	18	13.560	0.0005	Nr.T) 0.000353 TC) -1.803 OS) -9.402 EU) 7.159	Nr.T) 0.0041 TC) 0.0070 OS) 0.0010 EU) 0.0176	9.6E-05	0.819	1.772
Indirect jobs run 1	8	20.769	0.00059	TC) -2.136 OS) -15.463	TC) 0.0247 OS) 0.0064	0.0106	0.838	1.681
Indirect jobs run 2	8	5.306	0.01275	TC) -2.136 EU) 15.463	TC) 0.0247 EU) 0.0064	0.0106	0.838	1.681
Induced jobs run 1	7	11.787	0.00508	TC) -1.026 OS) -9.125	TC) 0.0309 OS) 0.0046	0.0044	0.933	0.777
Induced jobs run 2	7	2.662	0.01768	TC) -1.026 EU) 9.125	TC) 0.0309 EU) 0.0046	0.0044	0.933	0.777

Table 3: Indirect, induced and total EFs for the construction stage. Values provided in job-years/MW_i.

Construction	Indirect jobs	Induced jobs	Total jobs
Min	0.08	0.15	0.48
Max	11.10	14.40	44.30
Average	3.08	4.16	9.11
Median	2.11	1.50	3.32
St.dev	2.70	4.98	13.55

4.2.3 manufacturing

A total of three regressions retrieved significant values for direct jobs in the manufacturing sector, and are presented in table 4. One regression was significant for direct and indirect jobs together. Direct run 1 only included one independent variable, which is the onshore/offshore dummy variable. Its EF is 13.37 job-years/MW_i for offshore wind and 3.87 job-years/MW_i for onshore wind. Direct run two is based on three independent variables: turbine capacity, EU and reference year. Although the regression is significant, the intercept values raise some questions. Both intercept values are high negative values. As a result, an 8 MW wind turbine outside the EU in 2020 creates an EF of -4.16 job-years/MW_i following run 2, and an 8 MW wind turbine onshore in 2020 results in an EF of -7.02 job-years/MW_i according to run 3. Besides, both regressions are only based on 6 observations. Of these 6 observations, two data points included a 0.06 or 0.08 MW wind turbine from the reference year 1985. These turbine capacities are very low and not representative for current and future wind turbines. Removal of the two data points resulted in non-significant values. As a result, the found regressions runs two and run three are not usable to project job creation.

The direct and indirect jobs combined regression was significant for the reference year and the location AS. Also, this regression shows a high negative intercept value and a high coefficient value for the reference year. This suggest that the reference year has a high influence of the EF. As a result, a wind park in Asia in 2050 creates 11.55 job-years/MW_i, whereas the same park in Asia in 2025 creates -25 job-years/MW_i. The found regression is therefore unsuitable for projecting job creation. This leaves only direct jobs run one to project direct job creation. Indirect and induced jobs are based on their minimum, maximum and average values as shown in table 5.

Table 4: Significant EF regressions for the manufacturing stage.

Dependent variable	Obs.	Int. coef	Int. P-value	Independent variable(s) coef	Independent variable(s) P-value	Regres. sig F	R^2	St.dev
Direct jobs run 1	24	13.366	9.8E-16	OS) -9.496	OS) 1E-05	1E-05	0.595	3.964
Direct jobs run 2	6	-826.4	0.00463	TC) -1.814 EU) 7.292 RY) 0.414	TC) 0.0066 EU) 0.0057 RY) 0.0046	0.0119	0.992	0.336
Direct jobs run 3	6	-282.5	0.0146	TC) -1.916 OS) -10.152 RY) 0.149	TC) 0.0078 OS) 0.0068 RY) 0.0134	0.0144	0.990	0.370
Direct + indirect jobs	10	-2926	0.0132	RY) 1.456 AS) -47.689	RY) 0.0129 AS) 0.0202	0.0355	0.615	8.377

Table 5: Indirect, induced & total EFs for the manufacturing stage. Values provided in job-years/MW_i.

Manufacturing	Indirect jobs	Induced jobs	Total jobs
Min	2.26	3.20	1.25
Max	16.90	4.10	39.40
Average	5.68	3.65	14.77
Median	3.89	3.65	10.99
St.dev	4.55	0.64	13.09

4.2.4 operation and maintenance

Running all possible regressions for operation and maintenance resulted in a total of five significant regressions. Firstly, two regressions on direct jobs were found to be significant, which are direct job run one and run two in table 6. Both regressions were run on the independent variables of turbine capacity, EU, NA and AS. The values for EU, NA and AS were significant in both runs. However, the turbine capacity variable is in both cases slightly above the significant value of 0.05. Direct jobs run 1 contains one outlier value, where the difference between the projected EF and the actual data point is 19 job-years/MW_i. This could be caused by the job duration of 40 years for this specific data point. If a job duration of 25 years had been used the difference would have been reduced to 11 job-years/MW_i. Direct jobs run 2 is based on a 25-years job duration for this data point. Differences between direct jobs run one and run two is the higher R^2 and a lower standard deviation for run 2. This suggests that run 2 better fits the data points. Only the P-value for turbine capacity slightly increased to a just not significant value, considering an alpha value of 0.05. However, as it is close to this value and it is the best fit from all regressions, run two is used in the model.

Only one significant regression was found for indirect jobs. This run was significant for turbine capacity. The turbine capacity variable has a value of 1.71, which suggests that larger capacity wind turbines result in a higher EF. This run is based on 10 observations with a relatively high R^2 value. However, as the intercept P-value is not significant the regression has not been used in the model.

Two significant regressions were found for induced jobs. Induced run 1 is based on 11 observations and is significant for turbine capacity. Again, the intercept P-value is not significant, and the regression is therefore not used in the model. Induced jobs run 2 is based on 15 observations, but has a much lower R^2 value. Overall regression significance F shows a significant value. The intercept coefficient is

-3554 and the reference year coefficient has a value of 1.77. According to this run, the EF for all wind parks commissioned before 2007 are negative. This seems highly unlikely, and therefore induced jobs run 2 has not been used in the model.

Table 6: Significant EF regression for the O&M stage.

Dependent variable	Obs.	Int. coef	Int. P-value	Independent variable(s) coef	Independent variable(s) P-value	Regres. sig F	R^2	St.dev
Direct jobs run 1	25	18.835	0.0013	TC) 1.5598 EU) -19.05 NA) -19.34 AS) -19.29	TC) 0.0507 EU) 0.0128 NA) 0.0016 AS) 0.0073	0.0121	0.4588	5.0183
Direct jobs run 2	25	19.382	8E-06	TC) 0.91638 EU) -15.74 NA) -18.83 AS) -17.59	TC) 0.0722 EU) 0.0022 NA) 2.2E-05 AS) 0.0004	0.0002	0.6531	3.2291
Indirect jobs	10	-0.950	0.5526	TC) 1.7145	TC) 0.0031	0.0031	0.6855	2.7272
Induced jobs run 1	11	-1.544	0.2881	TC) 1.9645	TC) 0.00062	0.00062	0.7452	2.6659
Induced jobs run 2	15	-3554	0.0297	RY) 1.7703	RY) 0.0293	0.0293	0.3157	15.733

For direct, indirect and induced jobs a regression has been found. However, all regressions show slightly insignificant values. Therefore, also the min, max and average values are shown in table 7. The direct jobs regressions include a just not significant value for turbine capacity, whereas both indirect and induced regressions include insignificant intercept values. The indirect and induced regressions have both been run on turbine capacity. As turbine capacities included ranges from 0.9 to 8 MW, the regression cannot provide a significant intercept value. Potentially the found regression could be used but only for wind turbines with a higher capacity than 0.9 MW. However, the indirect and induced jobs in the model are based on the minimum, maximum and average values.

Table 7: Direct, indirect, induced and total EFs for the O&M stage. Values provided in job-years/MW_i.

O&M	Direct jobs	Indirect jobs	Induced jobs	Total jobs
Min	0.90	0.20	1.00	2.63
Max	52.50	63.50	71.50	46.30
Average	7.87	9.36	12.53	15.56
Median	5.00	5.00	4.94	9.81
St.dev	7.87	13.07	18.72	14.61

4.2.5 decommissioning

A total of six data points were available for the regression analysis on decommissioning. A lack of data only allowed for regressions on direct jobs with the independent variables of reference year, location, onshore/offshore dummy and total wind park capacity. All possible combinations have been used in the regression analysis. Results show that the analysis was significant for directs jobs for onshore or offshore wind parks. This suggests that direct decommissioning jobs can be determined based on whether it is an onshore or offshore park. The regression coefficients and P-values are shown in table 8. Even though the regression is only based on six observations, the result is still significant, and shows a high R^2 value (0.988). The reason for the high R^2 value and the low standard deviation results from data points with only marginal different values. This could be caused by the fact that four out of six observations based their employment factors on Rutovitz et al. (2015). The values were only slightly adapted to the specific regions or years, and are therefore close to each other.

Table 8: Significant EF regression for the decommissioning stage.

Dependent variable	Obs.	Int. coef	Int. P-value	Independent variable(s) coef	Independent variable(s) P-value	Regres. sig F	R^2	St.dev
Direct jobs	6	2.8225	8.1E-06	OS) -2.111	OS) 5.8E-05	5.8E-05	0.988	0.136

Regarding indirect jobs, only 2 data points were available. For induced and total jobs, only 1 data point was available. This made performing a regression analysis impossible. Indirect jobs are therefore based on the average value, whereas induced and total jobs are only based on one value. Minimum, maximum and average values for indirect, induced and total jobs can be found in table 9.

Table 9: Indirect, induced & total EFs for the decommissioning stage. Values provided in job-years/MW_i.

Decommissioning	Indirect jobs	Induced jobs	Total jobs
Min	0.615	1.005	4.275
Max	1.186	1.005	4.275
Average	0.901	1.005	4.275
Median	0.901	1.005	4.275
St.dev	0.404	-	-

4.2.6 construction phase

Some references provided job creation quantities for the construction phase, roughly referring to the job sectors: development, construction and manufacturing. Some mentioned including all before operation, whereas others referred to construction and manufacturing. It was therefore not always clear if the development stage was also included. Besides, combining three different job sectors into one, makes the model less detailed. As a result, the found significant regressions have not been used in the model. The significant regressions are however used to compare with the regression and model results from the development, construction and manufacturing stages combined. In total two different significant regressions have been found based on only 7 observations. These regressions can be found in table 10. Both regressions include the independent onshore/offshore dummy variable. However, direct jobs run 1 also included the location variables EU and NA. Direct jobs run 1 includes more independent variables, and shows a higher R^2 value and lower standard deviation. Therefore, direct jobs run 1 has been used to compare with the development, construction and manufacturing job sector values and regressions.

Table 10: Significant EF regressions for the construction phase.

Dependent variable	Obs.	Int. coef	Int. P-value	Independent variable(s) coef	Independent variable(s) P-value	Regres. sig F	R^2	St.dev
Direct jobs run 1	7	18.100	0.0004	OS) -8.31 EU) -4.075 NA) -7.55	OS) 0.0054 EU) 0.0205 NA) 0.0071	0.0045	0.9809	0.9914

Direct jobs run 2	7	18.100	0.002	OS) -10.927	OS) 0.026	0.0258	0.6627	3.2274

The minimum, maximum and average values for all different job types are shown in table 11 and have been used to check for similar values when adding up development, construction and manufacturing jobs.

Table 11: Direct, indirect, induced & total EFs construction phase. Values provided in job-years/MW$_i$.

Construction phase	Direct jobs	Indirect jobs	Induced jobs	Total jobs
Min	2.24	2.79	2.80	16.92
Max	18.10	25.70	12.27	52.00
Average	8.35	12.53	7.22	31.89
Median	8.60	9.63	6.90	29.80
St.dev	4.22	9.38	4.03	12.67

4.2.7 local and international share of job creation

Based on the data retrieved from the literature, it has been determined where the jobs are created. For the development and decommissioning stages, jobs could be created locally and nationally (Schallenberg-Rodriguez & Inchausti-Sintes, 2021). Construction and O&M jobs are also found to be created locally or nationally. Vasconcellos & Caiado Couto (2021), found a 90% local job share for construction and O&M jobs with a total national share of 95%. In the article of Slattery et al. (2011) a 100% local share of direct O&M jobs is provided. Therefore, construction and O&M jobs are expected to be created locally or nationally. Manufacturing jobs can be created both nationally and internationally. Charles Rajesh Kumar et al. (2019) found a 40% share of manufacturing jobs in India. This is based on the share of nationally produced wind turbines of the total amount of installed wind turbines. Whether manufacturing jobs are created nationally or internationally, depends on the presence of a large manufacturing organization.

In 2017, a total of 5 European wind turbine manufacturers (Vestas, SGRE, Enercon, Nordex and Senvion) were present in the global top 10 wind turbine manufacturers market (Lacal-Ar, 2018). In 2019, only three European wind turbine manufacturers (Vestas, SGRE and Nordex) were still present in this top 10 (Gönül et al., 2021). Enercon lost world market share and Senvion filed for bankruptcy. Vestas, SGRE and Nordex are European manufacturers located in Denmark, Spain and Germany respectively, Enercon is also located in Germany. As a result, manufacturing jobs in any of these countries are regarded as nationally created jobs. If a wind park is commissioned in another European country than the previously mentioned countries, the manufacturing jobs are regarded as internationally created jobs. Potentially, part of the internationally created manufacturing jobs are created in Germany, Denmark or Spain. The location where jobs per job sector are assumed to be created is shown in table 12.

Table 12: Location of the job creation per job sector.

Job sectors	Locational nature
Development	Local/national
Construction	Local/national
Manufacturing	National/international
Operation and maintenance	Local/national

Decommissioning	Local/national

4.3 Job quantification model

4.3.1 Model input

The significant and useful regressions retrieved from the regression analysis have been used to create the job quantification model. If no (significant) regression was found, the average value retrieved in literature was used. To create a job creation range, the value of the average plus or minus one standard deviation is provided in the model. The average values and the range are provided in table 13. If the average minus one standard deviation gives a value below the lowest value retrieved from the data, this minimum value is used instead. All used regressions in the model are shown in equations 4 till equation 7.

$$EFcon, dir = 9.46 - (3.65 \times OS) - (4.01 \times EU) - (4.37 \times NA) \quad \text{(eq. 4)}$$

$$EFmanu, dir = 13.37 - (9.50 \times OS) \quad \text{(eq. 5)}$$

$$EFo\&m, dir = 19.38 + (0.92 \times TS) - (15.74 \times EU) - (18.83 \times NA) - (17.59 \times AS) \quad \text{(eq. 6)}$$

$$EFdecom, dir = 2.82 - (2.11 \times OS) \quad \text{(eq. 7)}$$

Where TC is the turbine capacity in MW, and OS, EU, NA, and AS are dummy variables having a value of 1 or 0. As a result, job creation is projected based on its location, whether it is onshore or offshore and on the turbine capacity.

Table 13: EF model input (range) values (job-years/MW_i).

	-1 St.dev	Average	+1 St.dev
Development			
Direct	0.21	0.69	1.21
Indirect	0.26	0.59	1.03
Induced	0.48	0.59	0.70
Construction			
Indirect	0.38	3.08	5.78
Induced	0.15	4.16	9.14
Manufacturing			
Indirect	2.26	5.68	10.23
Induced	3.20	3.65	4.10
O&M			
Indirect	0.20	9.36	22.43
Induced	1.00	12.53	31.25
Decommissioning			
Indirect	0.62	0.90	1.19
Induced	1.01	1.01	1.01

4.3.2 Model results

The model retrieves the EF for different wind parks. For comparison, results are presented for 5 MW wind turbines, as 5 MW is within the range of current onshore and offshore wind turbines (Enevoldsen & Xydis, 2019). The different EFs, for all job types and sectors for a 5 MW offshore wind turbine in the EU, are shown in figure 3. Keeping wind turbine capacity at 5 MW, but for different locations, onshore and offshore, results in slightly different EFs for the job types and job sectors. However, the development sector EFs and all indirect and induced EFs for the other job sectors, remain the same.

Only the direct EFs, for the construction, manufacturing, O&M and decommissioning sectors, change. Differences in these direct EFs, for the job sectors of a 5 MW wind turbine for different locations, are shown in figure 4. The total EFs (range), for the 5 MW wind turbines at different locations, are presented in table 14.

Comparing a 5 MW onshore wind turbine in the EU with a 5 MW offshore wind turbine in the EU, a total difference of 15 job-years/MW_i can be observed (Table 14). This difference is mainly created by many more manufacturing job-years/MW_i for offshore wind turbines than for onshore wind turbines (Figure 4). Also, direct construction and decommissioning EFs for offshore are more than a threefold of direct onshore EFs. Although, in absolute terms this difference is smaller than the difference in manufacturing EFs. Comparing 5 MW onshore wind turbines in the EU with similar turbines in North America, shows only a relatively small difference. The total EF in North America is 3.4 job-years/MW_i less than in the EU. Most values between the EU and North America remain the same, except for the direct construction and O&M EFs. The construction sector shows a relatively small difference, whereas in North America, the wind turbine creates 3 job-years/MW_i less for the O&M sector. Larger differences are found when comparing 5 MW onshore wind turbines in the EU or North America to similar wind turbines in other locations. For both Asia, Africa and South America, the direct construction EFs are roughly 3.5 times higher compared to the EU or North America. The O&M EF is slightly higher in Asia than in North America, but lower than in the EU. However, the direct O&M EFs in Africa and South America are much higher than for other regions. This higher EF value could have multiple causes. Conflicts between the local community and the wind park operator, required additional security jobs for a wind park in Northern Kenya (Schilling et al., 2018). Also, new roads needed to be built before construction could start at this wind park. Besides, people from the local community were used for digging holes and mixing cement for wind turbine foundations. Potentially, the efficiency (in terms of job duration and number of employees required) of the local community is lower than the efficiency of a construction organization, resulting in a higher EF.

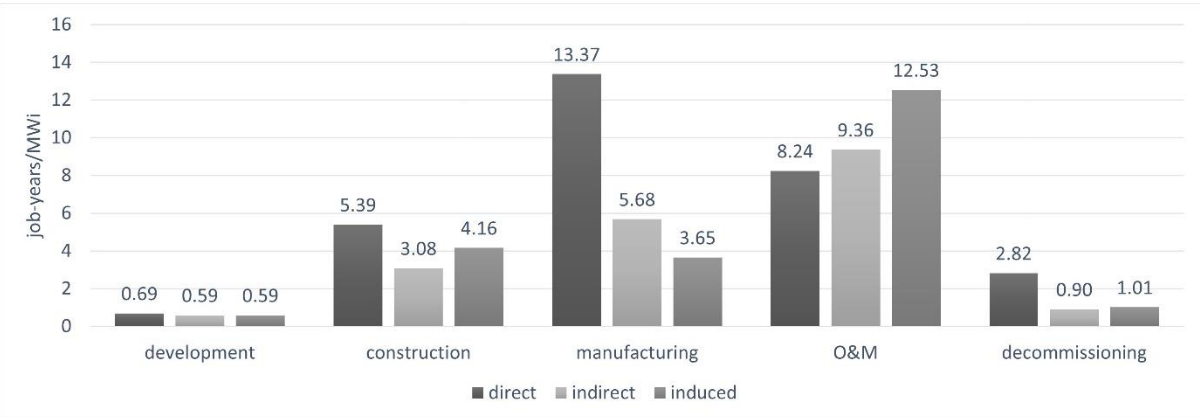

Figure 3: Direct, indirect and induced EFs (job-years/MW_i) for a 5 MW offshore wind turbine in the EU.

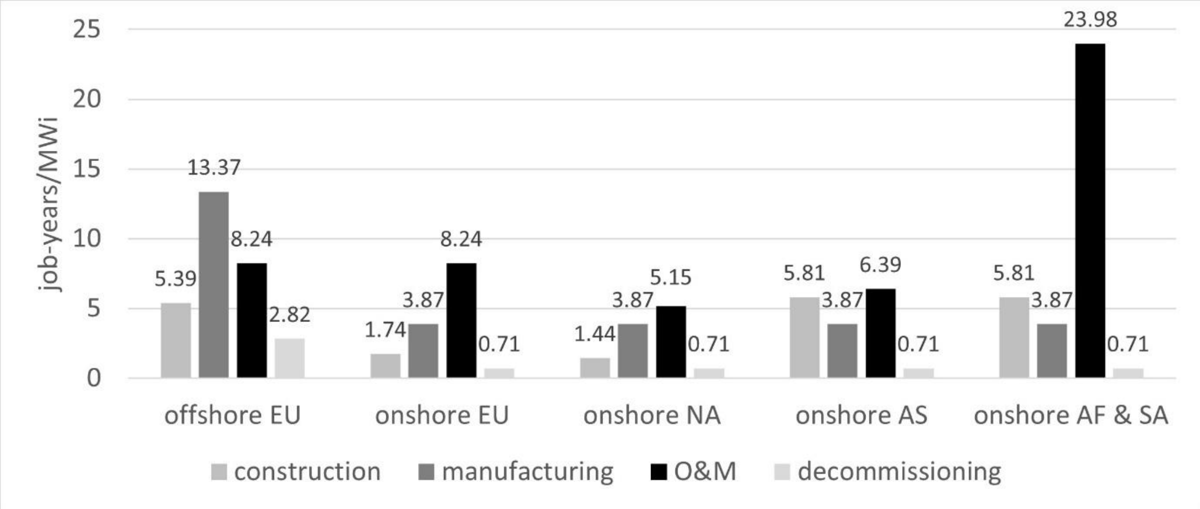

Figure 4: Direct EFs for a 5 MW wind turbine at different locations.

Table 14: Total EFs range (job-years/MW$_i$) for a 5 MW wind turbine at different locations.

	Offshore EU	Onshore EU	Onshore NA	Onshore AS	Onshore AF
Total – st.dev	30.46	16.25	13.16	18.17	35.76
Total	72.06	56.80	53.41	59.02	76.61
Total + st.dev	127.02	111.76	108.37	113.98	131.57

Differences in direct EFs between the different locations, have resulted in different job sector shares to the total EF. The different job sector shares for the different locations are shown in figure 5. The high O&M EF for Africa and South America, results in a relatively high O&M job sector share (60%). The absolute difference in EFs for the other job sectors is smaller. This is also visible in the different job sector shares.

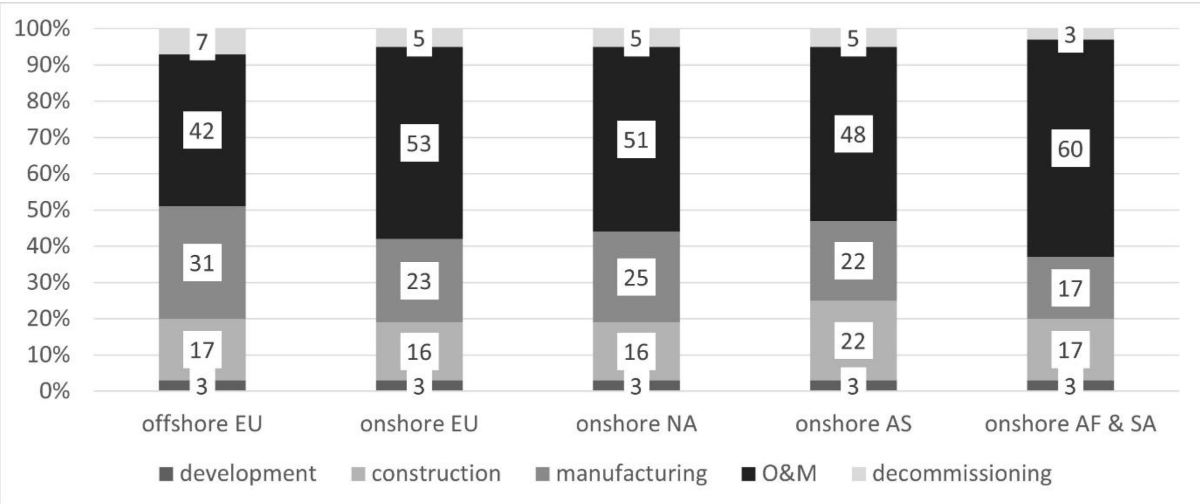

Figure 5: Total job sector shares for a 5 MW wind turbine at different locations.

In the past, wind turbine capacities were much smaller. In 1998, onshore capacities started at 1 MW and offshore capacities at 1.5 MW (Enevoldsen & Xydis, 2019). Future wind turbine capacities are expected to increase up to 8 MW for onshore and 10 to 15 MW for offshore (Nejad et al., 2022). Therefore, differences in job creation shares for 2 MW, 8 MW and 12 MW wind turbines in the EU are presented in figures 6 (onshore) and 7 (offshore). Generally, it can be observed that onshore wind, regardless of the turbines capacity, has a higher O&M share of total jobs than offshore wind. Offshore wind, on the other hand, has a higher manufacturing share of total jobs than onshore wind. Furthermore, it can be observed that larger turbines (both onshore and offshore) have a higher O&M job share from total jobs. This is caused by the fact that in the model only O&M jobs depend on turbine capacity. This results in more job-years/MW_i for larger wind turbines in the O&M stage.

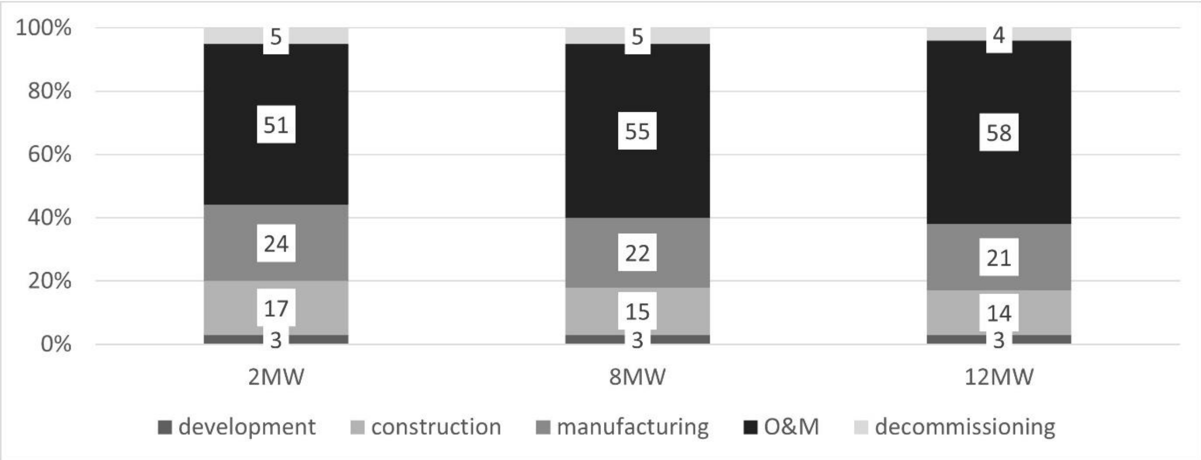

Figure 6: Total job sector shares for 2, 8 & 12 MW onshore wind turbines in the EU.

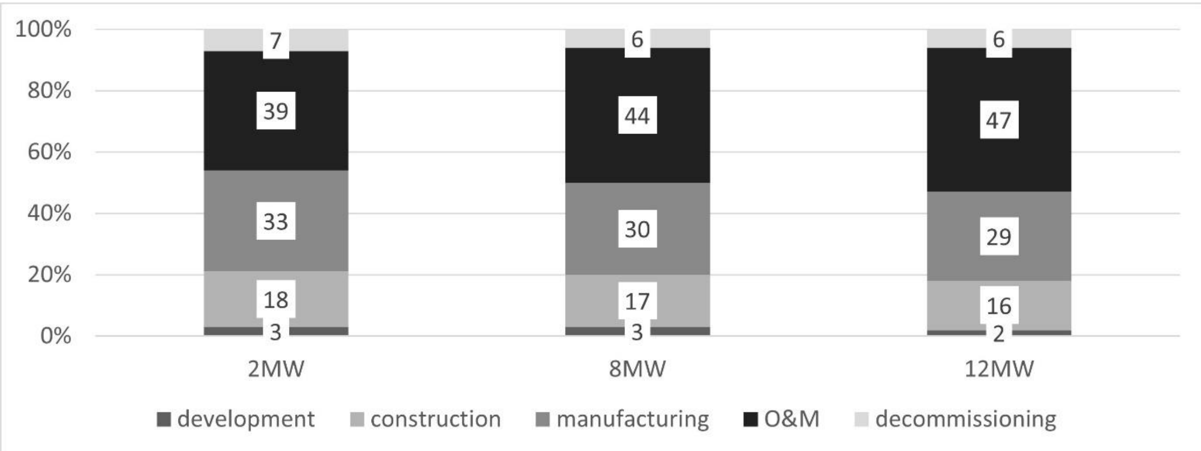

Figure 7: Total job sector shares for 2, 8 & 12 MW offshore wind turbines in the EU.

4.3.3 Model validation & comparison

Model validation based on interviews:

Job duration values retrieved from the different interviews were; 1 to 2 years for the construction and manufacturing stage, 5 to 7 years for the development stage, 20 years for the O&M stage with a life extension of a couple of years. These values are in line with the values used in the model if jobs were provided in jobs instead of job-years. No value was retrieved during the interviews for the decommissioning stage.

The assumptions in the model regarding the local nature of jobs are also confirmed by the interviews. Interviewee A mentioned that manufacturing jobs are likely created internationally, as the Netherlands for instance, does not have a large wind turbine manufacturer. This statement was also assumed in the job creation model. Besides, the regression also found no significant values for the independent location variables. This means that no matter the location of the wind turbines, job creation per MW_i remains the same. This could be explained by the international nature of manufacturing jobs, as most wind turbines are manufactured by the same manufacturers.

Other jobs are likely created nationally according to interviewee A, B and C, but not locally. Most construction organizations are large international organizations with national divisions. As a result, the jobs are mostly created nationally and some even internationally. Interviewee A also mentions that 1/3 of all construction jobs are flex jobs. Most of these flex jobs are lower skilled work and are typically performed by employees from low income countries. Therefore a part of the construction jobs could also be created internationally. Another reason for low local job creation, provided by interviewee A and C, is the requirement for highly skilled people. Both state that finding highly skilled people locally is difficult. O&M jobs also require highly skilled people according to interviewee A and C. Therefore local job creation is low and most jobs are created nationally. According to interviewee C, the EU and North America have a lot of highly skilled employees, but elsewhere there is more manual and less efficient work, making it require more people. This is in line with the regression used in the model. For the construction stage, 4 job-years/MW_i need to be subtracted from the total EF if the wind park is located in the EU, or in North America. All other regions create 4 more job-years per MW_i compared to the EU and North America.

However, secondary jobs (induced jobs) have a higher chance to be created locally according to interviewee C. The construction employees need a restaurant, a place to sleep, rent a car etc. These jobs could be created locally. Interviewee B states that development jobs are typically created locally. Developers typically work with many local stakeholders. It is therefore preferred for developers to have a local developing team to ensure knowing all the different stakeholders, according to interviewee B.

From the interviews it was concluded that no direct scaling effects can be determined during the construction stage. A larger wind park will result in some efficiency increase leading to less employees per turbine or per MW_i. However, interviewee A and C both mentioned that larger wind parks have a larger budget available. This budget will therefore be spent on more employees (and more expensive employees) to create more quality and performance. This will therefore reduce the efficiency effect. Interviewee C also mentioned that locational complexity largely influences job duration and creation. A more complex location may require additional work to make it accessible. For the development stage, only a limited scaling effect is expected according to interviewee B. Whether 100 or 15 MW needs to be developed, all the permits and procedures remain the same. A larger difference is expected between onshore and offshore for the development stage. It is stated that offshore wind is more complex and therefore a larger development team will be required, according to interviewee B. The same is true for O&M. During the construction stage also more employees are required for offshore wind, although it will be only a bit more according to interviewee C. Offshore also requires even more highly skilled employees mentions interviewee C. This is also reflected in the model, where offshore requires 3.7 more job-years/MW_i than onshore wind.

Regarding the decommissioning sector, the model is only based on average values due to a lack of data. This could be caused by the fact that the decommissioning sector of wind turbines is not a mature sector according to interviewee C. Interviewee D also mentioned that there is no clear view or strategy on how to recycle wind turbines in the future. It is expected therefore that the decommissioning and recycling sector of wind turbines will change and become more organized, due to higher future volumes. As a result, the job creation potential of decommissioning jobs could change in the future.

Comparison construction phase with construction, manufacturing and development:

The construction phase roughly consists of the development, construction and manufacturing stages. The sum of these three stages and the construction phase model output are represented in figure 8. The development, construction and manufacturing stage EFs are dependent on the locations EU and North America and for onshore and offshore. This is the same for the construction phase regression. The influence of these locations and onshore or offshore have similar values in both regressions. As a result, both the sum of development, construction and manufacturing and the construction phase show similar trends, with relatively small differences in values. Figure 8a and figure 8b, shows the difference for onshore and offshore. It can be observed that both show higher values for offshore than for onshore. Comparing onshore wind turbines in the EU with onshore wind turbines in North America (Fig. 8b and Fig. 8c) again shows similar trends. However, the difference in the direct EF projections for the construction phase regression is much smaller than for the sum of the development, construction and manufacturing stage in North America. This is caused by different independent variable coefficients between the construction phase run and the other runs. For the construction phase regression, the independent variable coefficient for North America is minus 7.55 job-years/MW_i whereas it is only minus 4.37 job-years/MW_i in the construction stage. The dependent variable coefficients for the EU are minus 4.08 job-years/MW_i and minus 4.07 job-years/MW_i for the construction phase and construction stage respectively. Therefore, the difference in the projected EF is smaller for the EU projections. Regarding other locations than the EU or North America, values provided by the construction phase regression are close to the sum of the development, construction and manufacturing stages (Fig. 8d). The values are however higher than the values for the EU and North America. Overall, EF projections for the construction phase regression and the sum of the development, construction and manufacturing regressions show similar trends and provide relatively similar values. Besides, in both cases the EF is only dependent on onshore or offshore and the locations EU and North America.

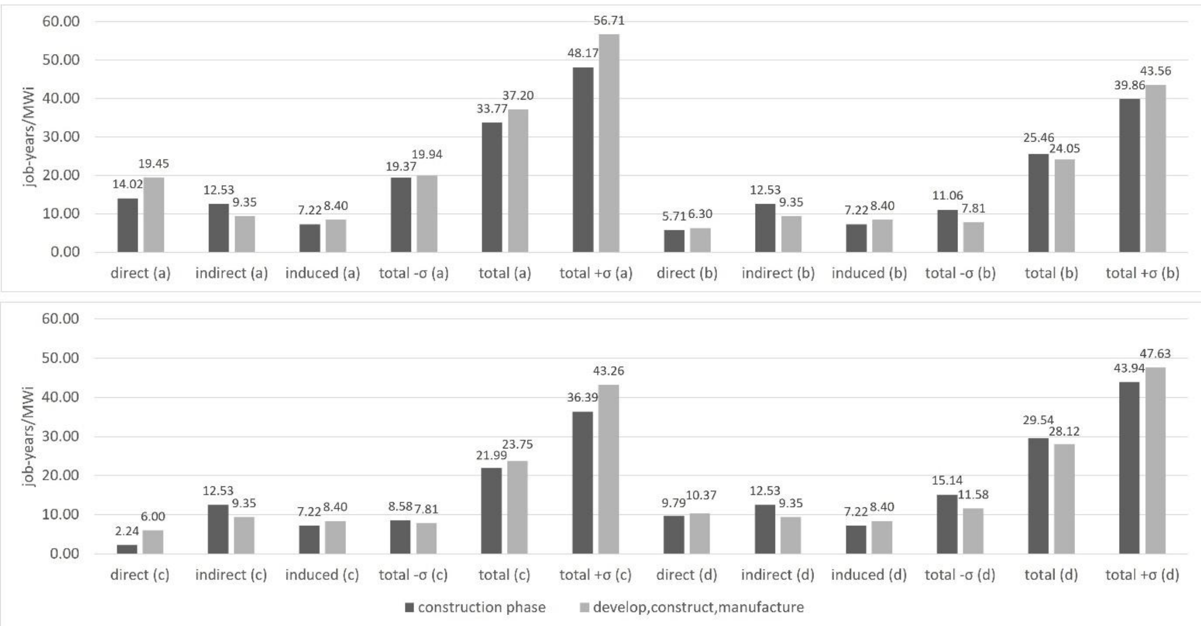

Figure 8: EFs (job-years/MW_i) for the construction phase and for the development, construction and manufacturing stages combined, for a 5 MW wind turbine in: a) offshore in EU, b) onshore in EU, c) onshore in NA, d) onshore in AS, AF or SA.

Comparison model with other methods:

Rutovitz et al. (2015) provide a method to determine an EF. This EF is a value for OECD countries and has a reference year of 2015. From this value other EFs in different years and countries can be derived. To do so, Rutovitz et al. (2015) make use of regional job multipliers and a technological decline factor.

The regional job multiplier is based on the GDP per capita of the country compared to OECD countries. Rutovitz et al. (2015) provide regional job multipliers for different regions in the years 2015, 2020 and 2030. On average these regional job multiplier values are; 5.2 for Africa, 2.1 for China, 4.9 for Eastern Europe/ Eurasia, 5.5 for India, 3.2 for Latin America, 1.3 for the Middle East, and 2.2 for Non-OECD Asia (Rutovitz et al., 2015). These differences between the regions are also represented in the model created during this study. However, the method provided by Rutovitz et al. (2015), distinguishes between different locations than the model created during this study. As Europe and North America are both part of the OECD countries, their EFs should be lower than non-OECD countries, where job multipliers should be applied. This effect is also visible in the modeling results of the model created in this study. For the construction stage EF and for locations in the EU or North America, respectively, a value of 4.01 job-years/MW_i or 4.37 job-years/MW_i should be subtracted from the intercept value. This suggests that OECD countries create around 4 job-years/MW_i less than other regions. During the O&M stage, similar results are found. However, also for locations in Asia, a similar to OECD countries value, should be subtracted. This could be caused by the fact that part of the countries in Asia also belong to the OECD countries, resulting in similar values. The regional job multiplier effects are therefore also represented in the model created during this study. However, the regional job multiplier for Africa should be 5.2 according to Rutovitz et al. (2015). Results of the model created during this study, show higher values for Africa, but not with a factor of 5.2. This is likely caused by the fact that the model created during this study, due to limited data points, uses average values for some direct jobs, and for all indirect and induced jobs. This potentially results in a lower overall differences between the regions.

The technological decline factor should result in lower EFs over the years. Esteban et al. (2011) also use a decline rate in the EF for offshore wind due to technological learning. For the period of 2010 till 2020, an annual decline factor of 3.90% is used and an annual decline factor of 1.50% is used for the years 2020 till 2030. Ram et al. (2020) based the annual decline factors on capital expenditure (CAPEX) or operating expenses (OPEX) values. This shows that multiple other methods include a decline factor over time, to determine current and future EFs of wind energy deployment. In the model created during this study however, no similar trends have been observed. This could be caused by a lack of data points, making the regressions not significant for reference year.

Overall model results and trends are in line with the interviews and the EF method using regional job multipliers. Also model results for the sum of development, construction and manufacturing and the construction phase show similar trends and values. Only a technological decline factor, resulting in a lower EF over time, is not represented in the model results.

4.4 European wind jobs quantification

Modern average wind turbine capacities for onshore wind turbines is 4.1 MW, and 8.0 MW for offshore wind turbines (WindEurope, 2023). The employment factor for onshore wind turbines of 4.1 MW equals 14.42 job-years/MW_i and 55.97 job-years/$MW_{i,}$ for direct and total jobs respectively. The employment factor, as derived from our model, for offshore wind turbines of 8.0 MW equals 33.27 job-years/MW_i and 74.82 job-years/$MW_{i,}$ for direct and total jobs respectively. The shares of the different job sectors contribution to the total job creation value, for the 4.1 MW onshore and 8.0 MW offshore wind turbines, are shown in figure 9.

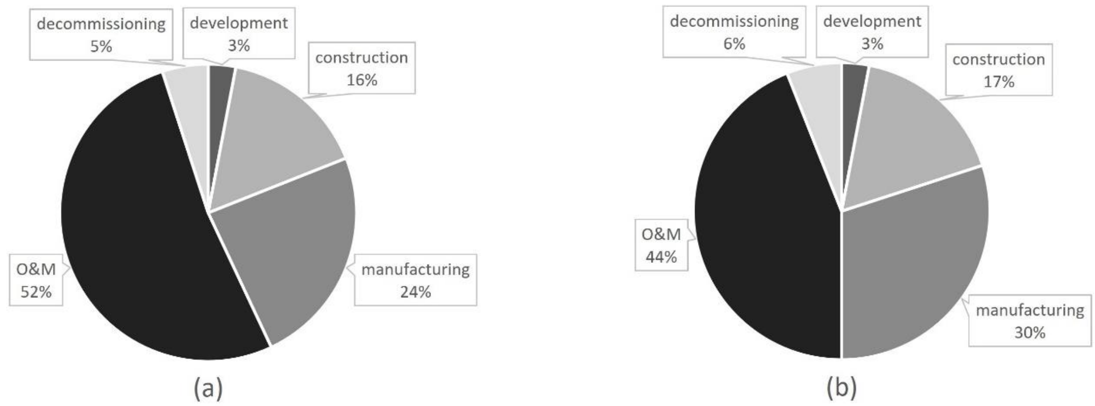

Figure 9: Total job sector shares for: a) 4.1 MW onshore wind turbine in the EU, b) 8.0 MW offshore wind turbine in the EU.

Based on these EFs and the annually expected installed wind capacity in Europe till 2027 (retrieved from (WindEurope, 2023)), the total job creation in Europe has been determined. The results are shown in figure 28. Summing up values from all countries results in a total of 7.9 million total job-years in 5-year time (2023 till 2027). For direct job-years this adds up to 2.5 million, roughly averaging 0.5 million job-years created per year.

Table 15: Direct and total job creation from wind energy deployment in Europe from 2023 till 2027. Values provided in 1000 job-years.

Country	Total combined	Direct combined	Country	Total combined	Direct combined
Slovakia	1	0	**Romania**	94	24
Luxembourg	3	1	**Austria**	112	29
Norway	4	2	**Greece**	114	29
Albania	7	2	**Belgium**	165	56
Montenegro	9	2	**Ireland**	189	57
Switzerland	11	3	**Italy**	261	78
Czechia	17	4	**Finland**	268	69
North Macedonia	21	5	**Poland**	274	99
Ukraine	25	6	**Denmark**	295	110
Bosnia-Herzegovina	26	7	**Sweden**	363	93
Estonia	42	11	**Netherlands**	406	165
Latvia	45	12	**Turkey**	456	118
Portugal	55	14	**France**	690	228
Croatia	59	15	**Spain**	695	181
Lithuania	82	21	**UK**	1358	528
Serbia	86	22	**Germany**	1655	516

The job sectors of development, construction, O&M and decommissioning could all be created locally or nationally. The exact shares of the local and national jobs vary per wind park and are difficult to estimate. Besides, as all locally created jobs are also nationally created jobs, only a distiction has been made between national and international jobs. Table 16 represents the national and international quantities of job-years created by wind energy deployment from 2023 till 2027. A total of 1.4 million total job-years are created internationally. Potentially, a part of these international jobs can be created in Germany, Spain or Denmark.

Table 16: Job creation Europe (2023-2027). Values provided in 1000 job-years.

Country	National	International	Country	National	International
Austria	85	27	**Poland**	199	75
Belgium	121	44	**Portugal**	42	13
Croatia	45	14	**Romania**	71	23
Czechia	13	4	**Slovakia**	0	0
Denmark	295	0	**Spain**	695	0
Estonia	32	10	**Sweden**	276	87
Finland	203	64	**Albania**	5	2
France	508	182	**Bosnia-Herzegovina**	20	6
Germany	1655	0	**Montenegro**	7	2
Greece	86	27	**North Macedonia**	16	5
Ireland	141	48	**Norway**	3	1
Italy	195	66	**Serbia**	66	21
Latvia	34	11	**Switzerland**	9	3
Lithuania	63	20	**Turkey**	347	109
Luxembourg	2	1	**UK**	975	383
Netherlands	290	117	**Ukraine**	19	6

Considering the European 2030 energy target for wind energy (440 GW installed capacity), annually around 31 GW of wind energy should be installed (WindEurope, 2023). WindEurope (2023) provides a scenario to achieve the European 2030 wind energy target. Following this scenario, from 2023 till 2030, a total of 15.7 million total job-years would be created. The annual number of job-years created are represented in table 17. This value is based on 4.1 MW onshore wind turbines and 8.0 MW offshore wind turbines. If onshore wind turbines of 5 MW and offshore wind turbines of 10 MW are used instead, total job creation from 2023 till 2030 would create 16.0 million job-years. The difference is only 0.3 million job-years over 7 years in Europe. It should be noted that the created job-years are created over the entire lifetime of the wind park. In 2025 therefore, due to newly installed wind turbines in 2025, a total of 1.3 million job-years are created over the entire lifetime of the wind park. Decommissioning jobs will only be created at the end of the lifetime of the wind park. However, Europe currently has 255 GW of wind capacity installed (225 GW onshore and 30 GW offshore) (WindEurope, 2023). This installed capacity still creates O&M jobs, and in the future will create decommissioning jobs. According to WindEurope (2023), Europe will have more than 78 GW of installed capacity wind parks older than 20 years in 2030. Part of these wind parks will be decommissioned.

Table 17: Job creation Europe 2030 target. Values provided in 1000 job-years.

Year	2023	2024	2025	2026	2027	2028	2029	2030
onshore job-years	823	795	879	963	1136	1248	1338	1410
offshore job-years	135	284	426	733	1055	1309	1504	1676

total job-years	957	1079	1305	1696	2191	2557	2842	3086

WindEurope (2017) estimated a total of 716 thousand (direct) jobs in 2030 for the wind energy sector in Europe, based on an installed capacity of 397 GW. The current target is 440 GW installed capacity, which is slightly higher. Considering the 440 GW installed capacity target, job creation in 2030 has been determined using the model data. In 2030, 1676 thousand total offshore job-years and 1410 thousand total onshore job-years will be created based on the 2030 target. This corresponds to 745 thousand direct offshore job-years and 363 thousand direct onshore job-years. Construction and manufacturing jobs are expected to be created in the same year and have a total job duration of 1 year. Therefore, based on the direct jobs share of construction and manufacturing the amount of workers in 2030 has been determined. In 2030, a total of 163 thousand direct construction jobs and 396 thousand direct manufacturing jobs are required. Development jobs typically take 3 years, so in 2030 a total of 11 thousand direct development jobs are required. Regarding O&M jobs, a total of 440 GW of installed wind capacity requires O&M in 2030. This requires a total of 147 thousand direct O&M jobs. Installed wind capacity in 2030 creates a total of 85 thousand direct decommissioning jobs. However, these jobs will only be created in 2055. Therefore, direct decommissioning jobs in 2030 depend on the decommissioned capacity in 2030. In 2005 Europe installed an additional 6 GW of wind power (GWEC, 2006), which will be at the end of its lifetime in 2030. Based on 6 GW of wind power decommissioning, a total of 7 thousand direct jobs will be created in 2030. Including all direct jobs, wind power will create 724 thousand jobs in the year 2030. This value is only slightly higher than the 716 thousand jobs estimation by WindEurope (2017). The results are presented in table 19.

Table 18: Direct job creation (in 1000 jobs) in 2030 within Europe.

	Onshore direct job sector share%	Offshore direct job sector share%	Onshore jobs 2030 in 1000 jobs	Offshore jobs 2030 in 1000 jobs	Total jobs 2030 in 1000 jobs
Development	5	2	6	5	11
Construction	12	16	44	119	163
Manufacturing	27	40	98	298	396
O&M	51	33	98	49	147
Decommissioning	5	9	3	4	7
Total	100	100	249	475	724

4.5 uncertainty analysis

There are a multiple uncertainties within the future job creation potential of wind energy deployment. Firstly, it is difficult to determine what wind turbine capacities will be used for future wind parks. For job quantification therefore an average current installed capacity value has been used. However, per wind park this will differ and potentially lead to a slightly different outcome. As also mentioned by interviewee C, there is a difference between commercially available wind turbines and what they say they are capable of manufacturing. Determining exactly what turbine capacities will be placed in a few years' time is therefore uncertain. However, wind turbine capacities are expected to increase in the next years (WindEurope, 2023). The effect of an increased turbine capacity has already been reflected upon and the difference was limited. A 12 MW onshore wind turbine in Europe is expected to create 63 total job-years/MW_i of which 22 are direct. Compared to the 4.1 MW turbine this is an increase in total jobs of 13%. A 15 MW offshore wind turbine in Europe is expected to create 81 job-years/MW_i

of which 40 are direct. This is an increase of 9% compared to an 8 MW turbine. However, considering jobs per turbine, a 12 MW onshore turbine creates 231% more job-years per turbine than a 4.1 MW onshore turbine, and a 15 MW offshore wind turbine creates 104% more job-years per turbine than an 8 MW offshore turbine.

Next to turbine capacity, the decommissioning job quantification is uncertain. The model is based on only limited data points. Besides, the wind turbine decommissioning sector is not a mature industry yet. As mentioned during the interviews, the future end-of-life treatment for wind turbines is unknow. The fact that in the future more and more wind turbines will be decommissioned, will result in a more mature decommissioning sector. Typically, a more mature industry results in more efficient work. However, future wind turbines ready for decommissioning, will be larger than current wind turbines ready for decommissioning. This could influence future EFs for the decommissioning stage. The effect of a doubling of the decommissioning EF on the total EF is relatively small. For an 8.0 MW offshore wind turbine in Europe, a doubling of the decommissioning EF results in an increase on the total EF of only 6.3%. For a 4.1 MW onshore wind turbine in Europe the effect is even smaller, with only a 4.7% increase on the total EF. Another uncertainty that has a bigger impact on the total EF is the job duration of the O&M sector. Current wind parks have a typical lifetime of around 25 years. However, Lacal-Arántegui et al. (2019) mention, wind turbine decommissioning, refurbishment (or partial repowering), repowering, life extension and run to fail as options for wind turbines approaching the end of their lifetime. Repowering of wind turbines, involves the replacement of old wind turbines by new wind turbines at the same location (Lacal-Arántegui et al., 2019). This could be regarded as a new wind turbine or wind park, and does therefore not extend the current wind turbine lifetime. However, life extension and run to fail, would increase the wind turbine lifetime. An additional lifetime of 5 or 10 years, results in a total EF increase for a 4.1 MW onshore wind turbine in Europe of 10.5% or 20.9% respectively. For an 8.0 MW offshore wind turbine, this increase would be 8.8% or 17.6% respectively.

5. discussion

This research has provided more in-depth insights into the dynamics of wind energy deployment on job creation potential. The created model allows for location and wind park specific job quantification, including direct, indirect and induced jobs. This enables finding the locations where the job creation of wind energy deployment is high, which could be used to increase social acceptance of wind energy deployment.

From the regression analysis it can be observed that the EF can be projected based on multiple independent variables. The independent variables influencing the EF are the locations Europe, North America and Asia, the turbine capacity and also whether the wind park is onshore or offshore. This suggests that the number of wind turbines does not influence the EF. However, in absolute terms, 2 wind turbines create twice as many jobs as one wind turbine. The turbine capacity on the other hand, does influence the EF. A higher turbine capacity results in a higher EF for direct O&M jobs. The independent variable coefficient for turbine capacity is 0.92. This indicates an increase of 0.92 additional job-years/$MW_{i,}$ if turbine capacity increases by 1 MW. Higher turbine capacities therefore result in higher EFs. Onshore and offshore wind turbines also differ from each other regarding the EF. Direct jobs for the construction, manufacturing and decommissioning sector are all dependent on whether the turbines are onshore or offshore. Overall, the difference in EF for onshore and offshore wind turbines is 15.26 less direct job-years/MW_i for onshore wind turbines. For indirect and induced jobs no difference was found between onshore and offshore wind turbines. Regarding the locational nature of wind energy deployment jobs, it is observed that most jobs are created on a national level. Construction, O&M and decommissioning jobs are likely created on a national level, whereas development jobs have a higher chance to be created locally. Manufacturing jobs can be created both nationally and internationally. This depends on the presence of a national wind turbine manufacturer. Within Europe, only for Denmark, Germany and Spain the manufacturing jobs are created nationally. All other countries create manufacturing jobs on an international level. This results in different national job creation potential for European countries. For countries outside Europe, national or international manufacturing job creation, also depends on the national presence of a manufacturing organization. The last influence on the EF for wind energy deployment is the location of the wind park. Differences are observed between Europe, North America, Asia and the rest of the world. The direct construction EF is 4 job-years/MW_i lower for Europe and North America compared to other locations. The direct O&M EF is 15.7, 18.8 and 17.6 job-years/MW_i lower for Europe, North America and Asia respectively, compared to other locations. Overall, North America has the lowest EF, followed by Europe, then Asia, and then other locations. Looking at the expected wind energy job creation in Europe from newly installed capacity till 2027, it can be observed that Germany will create most jobs. Germany, the United Kingdom, Spain, France, Turkey, the Netherlands, Sweden and Denmark will create the most wind energy jobs in Europe till 2027, ranked from highest to lowest. Germany, Spain and Denmark potentially benefit most from additional wind energy deployment. Part of the (international) manufacturing jobs created by European wind energy deployment, could be created in Germany, Spain or Denmark.

The found relationship between the turbine capacity and an increased EF can be explained by the fact that turbines with a higher capacity are larger. larger turbines could require more jobs per MW_i than smaller turbines. Interviewee A mentioned that overall, offshore wind is more complex, and therefore likely requires more jobs compared to onshore wind. This could explain the difference between onshore and offshore wind creation. The relationship between the different locations and the EF could be explained by GDP per capita. Rutovitz et al. (2015) used the GDP per capita to determine the EF for a certain location. This is in line with the differences between the locations retrieved from the model created during this study.

Most jobs are created on a national or international level. The highest chance for local job creation is in the development sector. However, job creation in the development sector is roughly 3% of total job creation, for both, onshore and offshore wind parks. Besides, these jobs typically have a duration of 3 years. This implies that only limited and for a temporary period of time, jobs will be created locally. This could make it difficult to use job creation potential for increasing local support for wind energy. Although, indirect and induced jobs could also be created locally. Quantification of these amounts is however difficult, and these jobs are likely only temporary. Secondly, offshore wind has a higher EF than onshore wind. Regarding the European energy target, around 25% of expected newly installed capacity is offshore and 75% onshore. From a job creation perspective, it would be better to install more offshore wind than onshore wind. Also, from a national job creation perspective, offshore wind creates more national job-years/MW_i than onshore wind.

The results of the research must be placed in the context of some model and research limitations. First of all, jobs are quantified based on an employment factor in job-years/MW_i. It, therefore, quantifies additional job creation for newly commissioned or future wind parks in job-years. This quantification method does not directly provide a value for the total number of employees at any moment in time. It rather quantifies the total job-years the park will create over its entire lifetime. For instance, decommissioning jobs will only be created at the end of the lifetime. Secondly, regarding this decommissioning sector. Only limited wind parks have been decommissioned currently, and many more will be decommissioned in the future. As a result, the EF for decommissioning might increase or decrease significantly. Overall, this impact will be small, as this sector only accounts for a few percent of total jobs. This small share, of the decommissioning sector on total jobs, is also reflected in the number of articles providing job creation data for this job sector. This is the same for the development sector. For both job sectors only limited data points have been retrieved from the literature, resulting in a lack of data. Overall, a lack of data is one of the main limitations of this research. More data points could have made it possible to perform more regressions on more independent variables. Too little data points, for many combinations of independent variables, made it impossible to perform a regression analysis. Thirdly, only the five main job sectors have been included in the model. Actual job creation might therefore be slightly higher. Kalinina et al. (2020) for instance, also included transportation. However, the share of the transportation jobs was only 1% of the total jobs created in their research. Another limitation is data uncertainty. To reduce this uncertainty, a job creation range is provided, and an uncertainty analysis has been performed. However, if data was provided in jobs/MW_i it has been converted to job-years/MW_i based on predefined job durations for the different job sectors. This assumes that job duration has one value and is the same for all locations. It could however be that job duration is slightly different for different locations. Also, the model only provides different job creation values for five different locations. Preferably, the model provides differences between smaller locations than the locations used in the model. Due data limitations this was not possible.

Interesting future research directions are therefore, more regional or locational specific characteristics, influencing job creation of wind energy deployment. Interviewee C also mentioned that the landscape complexity could influence job creation. Complex landscapes might require removal of ice and stones or flattening of the area, before construction can start. Future research could increase insight into the influence of these landscape characteristics on job creation. Besides more available data points would enable performing more, and a more detailed regression analysis. Additionally, more data points could validate, and build upon, the created model in this research. This could potentially lead to additions of more independent variables, to project future job creation more precisely. Therefore, additional research is required to generate data points for multiple wind parks, including the amount of created direct, indirect and induced jobs, as well as the wind park and locational characteristics. Besides, this study's model does not include a decline factor over time, as the regression analysis, including the reference year, was not significant. However, as the technology matures over time, a reduction in the EF could be possible. Potentially, a lack of data resulted in a not significant regression. Future research should determine if a decline factor over time should be applied to any or to all of the job sectors.

6. conclusion

Job creation potential of new wind energy deployment can be projected based on a few independent variables. These variables are the location, onshore or offshore and the turbine capacity. Higher turbine capacities result in a higher EF. Also, offshore wind creates significantly more job-years/MW_i than onshore wind. Different locations also result in different EFs. Overall, Europe and North America have the lowest EFs. Differences in total job quantities between countries depend on the amount of newly installed capacity and the type of wind park. The type of wind park determines the EF, which should be multiplied by the total amount of MW installed to project the job creation. The share of jobs created nationally is equal to the sum of the shares of the job sectors: development, construction, O&M and decommissioning. Only manufacturing jobs are created internationally, except for wind parks in Germany, Denmark or Spain. These countries have large wind turbine manufacturing organizations, which manufacture wind turbines internationally. Germany, Denmark and Spain would therefore be the European countries that could benefit most from new wind energy deployment. Additionally to their national job creation from their own new installed capacity, manufacturing jobs are created due to newly installed capacity in other European (or outside Europe) countries. Overall European job creation is expected to increase in the future. From 2023 till 2027, a total of 7.9 million job-years is expected to be created due to newly installed wind capacity in Europe. From 2023 till 2030 a total of 15.7 million job-years could be created in Europe, with a total of 724 thousand direct wind energy jobs in 2030. Most of the jobs are created on a national scale, and only limited on a local scale. Locally only development jobs are created for a temporary period, resulting in a relatively low positive local job creation impact. As a result, using local job creation to increase local acceptance of wind energy deployment seems difficult. The national positive impact of wind energy deployment is much higher. High capacity and offshore wind turbines have the highest positive job creation impact. This wind park could therefore contribute most to increasing social acceptance of wind energy deployment.

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Appendices

Appendix A: literature review papers

source	Included/excludes	Number
(Ortega-Izquierdo & Río, 2020)	Included	1
(Brunner & Schwegman, 2022)	Excluded, no job creation data	2
(Duarte et al., 2022)	Included	3
(Sharma et al., 2022)	Included	4
(Tănasie et al., 2022)	Excluded, no job creation data	5
(Janikowska & Jebreel, 2022)	Included	6
(Sohrab et al., 2019)	Included	7
(Gönül et al., 2021)	Included	8
(Wabukala et al., 2021)	Excluded, no job creation data	9
(Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	Included	10
(Y. Chen & Li, 2021)	Included	11
(Shoeib et al., 2021)	Excluded, no job creation data	12
(Estévez et al., 2021)	Excluded, no job creation data	13
(Costa & Veiga, 2021)	Excluded, no job creation data	14
(Connolly, 2020)	Excluded, no job creation data	15
(Gonçalves et al., 2020)	Excluded, no job creation data	16
(Dorrell & Lee, 2020)	Excluded, no job creation data	17
(Vicuña & Pérez, 2020)	Excluded, different language	18
(Kalinina et al., 2020)	Included	19
(de Oliveira Noronha et al., 2019)	Excluded, no job creation data	20
(Charles Rajesh Kumar et al., 2019)	Included	21
(Ciupăgeanu et al., 2019)	Excluded, no job creation data	22
(Du & Takeuchi, 2019)	Excluded, no job creation data	23
(Lacal-Arántegui, 2019)	Excluded, no job creation data	24
(Gebauer & Binz, 2018)	Excluded, no job creation data	25
(Swift et al., 2019)	Included	26
(Martínez Mendoza et al., 2019)	Excluded, different language	27
(Schilling et al., 2018)	Included	28
(Kahouli & Martin, 2018)	Included	29
(Jaraitė et al., 2017)	Excluded, no job creation data	30
(Varela-Vázquez & Sánchez-Carreira, 2017)	Included	31
(Ortega et al., 2015)	Included	32
(Akuru & Kamper, 2015)	Excluded, no job creation data	33
(Varela-Vázquez & Sánchez-Carreira, 2015)	Excluded, no job creation data	34
(Heinbach et al., 2014)	Excluded, no job creation data	35
(Pegels & Lütkenhorst, 2014)	Included	36
(Varela Vázquez & Sánchez Carreira, 2014)	Excluded, different language	37
(Corsatea, 2014)	Included	38
(Simas & Pacca, 2014)	Included	39
(Aretz et al., 2013)	Excluded, different language	40

(Collins et al., 2012)	Included	41
(Langbroek & Vaclav, 2012)	Excluded, no job creation data	42
(Ulrich et al., 2012)	Excluded, no job creation data	43
(Dalton & Lewis, 2011)	Excluded, no job creation data	44
(Bilgili et al., 2011)	Excluded, no job creation data	45
(Mostafaeipour, 2010)	Excluded, no job creation data	46
(Blanco & Rodrigues, 2009)	Excluded, no job creation data	47
(Williams et al., 2008)	Included	48
(Varela-Vázquez et al., 2019)	Excluded, no job creation data	49
(Cibinskiene et al., 2021)	Excluded, no job creation data	50
(Tingley, 2021)	Excluded, no job creation data	51
(Vieira et al., 2019)	Included	52
(Barthelmie, 1998)	Excluded, no job creation data	53
(Hassan et al., 2022)	Excluded, no job creation data	54
(Hansen et al., 2021)	Excluded, no job creation data	55
(Zhou et al., 2020)	Included	56
(Fragkos & Paroussos, 2018)	Included	57
(Zerrahn, 2017)	Excluded, no job creation data	58
(Khan et al., 2017)	Excluded, no job creation data	59
(Matatiele & Gulumian, 2016)	Excluded, no job creation data	60
(Coon et al., 2015)	Included	61
(Hill, 2014)	Excluded, no job creation data	62
(Brown et al., 2012)	Included	63
(Morgan et al., 2012)	Excluded, no job creation data	64
(Bolinger & Wiser, 2012)	Excluded, no job creation data	65
(Greenwald & Gray, 2012)	Excluded, no job creation data	66
(Schubel, 2010)	Excluded, no job creation data	67
(Grover, 2002)	Included	68
(Twidell, 1986)	Included	69
(Renner et al., 2008)	Excluded, no job creation data	70
(Warren & Birnie, 2009)	Excluded, no job creation data	71
(Koasidis et al., 2022)	Included	72
(Trypolska et al., 2022)	Included	73
(Satir et al., 2018)	Excluded, no job creation data	74
(Buchmayr et al., 2022)	Included	75
(Ruiz Romero et al., 2012)	Excluded, no job creation data	76
(EL Kinani et al., 2023)	Included	77
(Kursun, 2023)	Excluded, no job creation data	78
(Osorio-Aravena et al., 2022)	Included	79
(R. Li et al., 2022)	Excluded, no job creation data	80
(Garsous & Worack, 2022)	Included	81
(Ma et al., 2022)	Excluded, no job creation data	82
(Zhou et al., 2022)	Excluded, no job creation data	83
(Attaullah et al., 2022)	Excluded, no job creation data	84
(Ullah et al., 2021)	Excluded, no job creation data	85
(Suman, 2021)	Excluded, no job creation data	86
(Vasconcellos & Caiado Couto, 2021)	Included	87
(Oyewo et al., 2021)	Excluded, no job creation data	88
(Zwarteveen et al., 2021)	Excluded, no job creation data	89
(Heras & Martín, 2020)	Included	90

(Faturay et al., 2020)	Excluded, no job creation data	91
(van der Waal, 2020)	Excluded, no job creation data	92
(Ram et al., 2020)	Included	93
(Kandrot et al., 2020)	Included	94
(Aldieri et al., 2020)	Included	95
(Rahmanifard & Plaksina, 2019)	Excluded, no job creation data	96
(Lee & Chang, 2018)	Included	97
(De Fátima Barbosa Góes et al., 2018)	Excluded, different language	98
(Nakano et al., 2018)	Excluded, no job creation data	99
(Mu et al., 2018)	Included	100
(Jacobson et al., 2017)	Included	101
(Waewsak et al., 2017)	Excluded, no job creation data	102
(Child et al., 2017)	Included	103
(Sun et al., 2016)	Excluded, no job creation data	104
(Hayashi et al., 2016)	Excluded, no job creation data	105
(Behrens et al., 2016)	Included	106
(Loomis et al., 2016)	Included	107
(Bates & Firestone, 2015)	Excluded, no job creation data	108
(Ek & Matti, 2014)	Excluded, no job creation data	109
(Hoagland et al., 2015)	Excluded, no job creation data	110
(Jacobson et al., 2015)	Excluded, no job creation data	111
(Şengül et al., 2015)	Included	112
(Hosking et al., 2015)	Excluded, no job creation data	113
(Hartley et al., 2015)	Included	114
(Walwyn & Brent, 2015)	Excluded, no job creation data	115
(Jacobson et al., 2014)	Included	116
(Kosenius & Ollikainen, 2013)	Excluded, no job creation data	117
(Landry et al., 2013)	Included	118
(Katinas et al., 2013)	Excluded, no job creation data	119
(Van der Zwaan et al., 2013)	Included	120
(Moldvay et al., 2013)	Included	121
(Jacobson et al., 2013)	Included	122
(Simas & Pacca, 2013a)	Excluded, different language	123
(Simas & Pacca, 2013b)	Included	124
(Greene & Geisken, 2013)	Included	125
(Morris et al., 2012)	Excluded, no access	126
(Brown, 2011)	Included	127
(Slattery et al., 2011)	Included	128
(Borgford-Parnell, 2011)	Excluded, no job creation data	129
(Esteban et al., 2011)	Included	130
(Cai et al., 2011)	Excluded, no job creation data	131
(Rodgers, 2011)	Excluded, no access	132
(Munday et al., 2011)	Excluded, no job creation data	133
(Renewable Energy Magazine, 2010)	Excluded, no job creation data	134
(Starling, 2010)	Excluded, no job creation data	135
(webzell, 2010)	Excluded, no job creation data	136
(Peltier, 2009)	Excluded, no job creation data	137
(Energy Institute, 2023)	Excluded, no job creation data	138
(Larry Leistritz & Coon, 2009)	Included	139
(Michael, 2001)	Excluded, no job creation data	140

(Rose et al., 2022)	Included	141
(Haidi & Cheddadi, 2022)	Excluded, no job creation data	142
(Nagle et al., 2022)	Excluded, no job creation data	143
(Stebbings et al., 2020)	Excluded, no job creation data	144
(Grechukhina et al., 2016)	Excluded, different language	145
(Dedrick et al., 2014)	Included	146
(Matsumoto & Matsumura, 2022)	Excluded, no job creation data	147
(Shoeib et al., 2022)	Included	148
(Mayfield & Jenkins, 2021)	Excluded, no job creation data	149
(Kim & Kim, 2021)	Included	150
(Oh et al., 2020)	Excluded, no job creation data	151
(Mauritzen, 2020)	Excluded, no job creation data	152
(Kabayo et al., 2019)	Included	153
(Keček et al., 2019)	Included	154
(Mikuli et al., 2018)	Included	155
(Silva et al., 2016)	Excluded, no job creation data	156
(Okkonen & Lehtonen, 2016)	Included	157
(Ejdemo & Söderholm, 2015)	Included	158
(Regueiro Ferreira & Sánchez Sellero, 2014)	Excluded, different language	159
(Fischer et al., 2008)	Excluded, no job creation data	160
(Bergmann et al., 2006)	Excluded, no job creation data	161
(Roy et al., 2022)	Included	162
(Deloitte, 2021)	Included, added manually	163
(Hanna et al., 2022)	Included, added manually	164
(Rutovitz et al., 2015)	Included, added manually	165

Appendix B: collected data

B1: development data

	JOBS (JOB-YEARS/MW_l)					SCALE			ONSHORE / OFFSHORE	LOCATION	REFERENCE YEAR
SOURCE	Direct	Indirect	Direct + indirect	Induced	Total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	1.41	0.26	1.67	0.7	2.37	40	5	200	Offshore	Gran Canaria	2021
(Kalinina et al., 2020)	0.69	1.09	1.78					798.8	Onshore	Ukraine	2019
(Kahouli & Martin, 2018)	0.46	0.41	0.87	0.48	1.34	62	8	496	Offshore	France	2020
Varela-Vázquez & Sánchez-Carreira, 2017)			3			99	5	495	Offshore	Spain	2030
(Dedrick et al., 2014)	0.21					50	2	100	Onshore	US	2014
(Okkonen & Lehtonen, 2016)			0.6	0.15	0.75	31	0.9	27.6	Onshore	Northern Scotland	2009 **

** = only regional impact/job creation/part of job creation, * = values based on Rutovitz et al (2015).

B2: construction data

	JOBS (JOB-YEARS/MW_l)					SCALE			ONSHORE/ OFFSHORE	LOCATION	REF. YEAR
Source	Direct	Indirect	Direct + indirect	induced	total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
(Ortega-Izquierdo & Río, 2020)	2.217	1.667	3.884						onshore	EU-28	2016
(Ortega-Izquierdo & Río, 2020)	3.128	2.346	5.474						offshore	EU-28	2016
(Sharma et al., 2022)	1.83							65000	onshore	US	2019
(Janikowska & Jebreel, 2022)			11.4						onshore	Poland	2022
(Sohrab et al., 2019)	1.97	4.93	6.9						onshore	Iran	2050
Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	15	11.1	26.1	7.1	44.3	40	5	200	offshore floating	Gran Canaria	2021
(Kalinina et al., 2020)	3.057	4.861	7.918					798.8	onshore	Ukraine	2019
(Kahouli & Martin, 2018)	3.04	2.67	5.71	3.13	8.84	62	8	496	offshore	France	2020

Varela-Vázquez & Sánchez-Carreira, 2017)			1.5			99	5	495	offshore floating	Spain	2030
Ortega et al., 2015)	2.5	1.88	4.38						onshore	Global	2012
Ortega et al., 2015)	4.28	3.28	7.56						offshore	Global	2012
Simas & Pacca, 2014)	6.75	0.84	7.59						onshore	Brazil	2017
(Williams et al., 2008)	1.71							10.5	onshore	US, northern Arizona	2008
(Williams et al., 2008)	1.67							60	onshore	US, northern Arizona	2008
(Williams et al., 2008)	1.67							180	onshore	US, northern Arizona	2008
Vieira et al., 2019)	4.3	3.2	7.5		7.5				offshore	Portugal	2030
Fragkos & Paroussos, 2018)	3.2								onshore	EU-28	2015 *
(Coon et al., 2015)	1.28							147	onshore	US, Oklahoma	2012
(Brown et al., 2012)	1.35								onshore	US	2008
(Grover, 2002)	0.244	0.077	0.321	0.154	0.475	260	1.5	390	onshore	US, Washington	2002
Twidell, 1986)	4								onshore	Denmark	1985
Koasidis et al., 2022)	2.894								onshore	EU	2025
Koasidis et al., 2022)	6.575								offshore	EU	2025
(Buchmayr et al., 2022)	2.48						3		onshore	Belgium	2022
(Buchmayr et al., 2022)	6.09						5		offshore	Belgium	2022
Osorio-Aravena et al., 2022)	3.2					303	2	606	onshore	Spain	2022 *
(Ram et al., 2020)	3.2								onshore	global	2015 *
(Ram et al., 2020)	8								offshore	global	2015 *
Aldieri et al., 2020)	13								nc	Spain	2010
Aldieri et al., 2020)	2.1	6.13	8.23						nc	Japan	2017
Aldieri et al., 2020)	1.48	0.95	2.43					3500	offshore	France	2040

Aldieri et al., 2020)	6	8	14						nc	USA, Montana	2014
(Jacobson et al., 2017)			7.06	9.1					onshore	US	2012
(Jacobson et al., 2017)			9.3	14.4					offshore	US	2012
(Loomis et al., 2016)	0.72	3.49	4.21	1.5	9.2	2223	1.5	3335	onshore	US, Illinois	2012
Hartley et al., 2015)	0.67							100	onshore	US, Texas	2011
(Jacobson et al., 2014)	4.05					24720	5	123600	onshore	US, California	2014
(Jacobson et al., 2014)	7.3					7800	5	39000	offshore	US, California	2014
Landry et al., 2013)	0.81	0.92	1.73	0.52	3.17	33	3	100	onshore	Canada	2013
Landry et al., 2013)	0.99					44	2.3	101.2	onshore	Canada, ON	2013
Landry et al., 2013)	0.91					73	1.5	109.5	onshore	Canada, Qc	2013
Landry et al., 2013)	0.73					32	3	96	onshore	Canada, NB	2013
Landry et al., 2013)	0.81							100	onshore	Canada, NB	2013
Landry et al., 2013)	1.49					126	1.5	189	onshore	Canada, ON	2013
Landry et al., 2013)	0.61					73	1.5	109.5	onshore	Canada, Qc	2013
Landry et al., 2013)	0.42					10	3	30	onshore	Canada, PEI	2013
Landry et al., 2013)	0.67					67	1.5	100.5	onshore	Canada, Qc	2013
Van der Zwaan et al., 2013	1.5	1.125	2.625		2.62 5				onshore	Middle East	2050
Jacobson et al., 2013)	3.05								onshore	New York	2030
Jacobson et al., 2013)	5.04								offshore	New York	2030
Simas & Pacca, 2013b)	7.605								onshore	Brazil	2016
(Brown, 2011)	10.3							520	onshore	Brazil, Ceara	2007
(Slattery et al., 2011)	0.37	1.55	1.92	0.66	2.58	421	1.75	735.5	onshore	US, texas	2011
(Slattery et al., 2011)	0.62	1.86	2.48	0.85	3.32	407	1.63	662.5	onshore	US, texas	2011
(Larry Leistritz & Coon, 2009)	0.85	0.7	1.55			106	1.5	159	onshore	Great plains	2009
(Rose et al., 2022)	14.6							10000	offshore	US, california	2040
(Dedrick et al., 2014)	0.99					50	2	100	onshore	US	2014
(Shoeib et al., 2022)	1.31							100	onshore	US	2015
Kabayo et al., 2019)	3.2					2599	2	5046	onshore	Portugal	2015 *
(Okkonen & Lehtonen, 2016)			1.34	0.33	1.67	31	0.9	27.6	onshore	Northern Scotland	2009 **

Ejdemo & Söderholm, 2015)	0.852	0.19	1.042		1.042			4000	onshore	Northern Sweden	2019 **
(Hanna et al., 2022)	4.2								onshore	global	2022
(Hanna et al., 2022)	7.2								offshore	global	2022
(Rutovitz et al., 2015)	3.2								onshore	global	2015
(Rutovitz et al., 2015)	8								offshore	global	2015
(Rutovitz et al., 2015)	6.7								onshore	Latin America	2015
(Rutovitz et al., 2015)	8.9								offshore	North America	2015
(Rutovitz et al., 2015)	7.1								offshore	EU	2015

** = only regional impact/job creation/part of job creation, * = values based on Rutovitz et al (2015).

B3: manufacturing data

	JOBS (JOB-YEARS/MW_l)					**SCALE**			**ONSHORE/ OFFSHORE**	**LOCATION**	**REF. YEAR**
Source	Direct	Indirect	Direct + indirect	induced	total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
(Ortega-Izquierdo & Río, 2020)	5.466	3.889	9.355						onshore	EU-28	2016
(Ortega-Izquierdo & Río, 2020)	9.216	6.912	16.128						offshore	EU-28	2016
(Sharma et al., 2022)					1.25			65000	onshore	US	2019
Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	9.05	3.835	12.885	4.1	16.985	40	5	200	offshore floating	Gran Canaria	2021
(Kalinina et al., 2020)	1.68	2.67	4.35					798.8	onshore	Ukraine	2019
(Kahouli & Martin, 2018)	3.11	2.72	5.83	3.2	9.02	62	8	496	offshore	France, Brittany	2020
Varela-Vázquez & Sánchez-Carreira, 2017)			33			99	5	495	offshore floating	Spain	2030
Ortega et al., 2015)	7.5	5	12.5						onshore	global	2012
Ortega et al., 2015)	29.61	20.7	50.31						offshore	global	2012
Simas & Pacca, 2014)	3.4	2.26	5.66						onshore	Brazil	2017
Vieira et al., 2019)	22.5	16.9	39.4		39.4				offshore	Portugal	2030

Fragkos & Paroussos, 2018)	4.7								onshore	EU-28	2015 *
Twidell, 1986)	2.92					1500	0.08	120	onshore	Denmark	1985
Twidell, 1986)	3.07					700	0.0605	42.35	onshore	Denmark	1985
Koasidis et al., 2022)	4.25								onshore	EU	2025
Koasidis et al., 2022)	12.821								offshore	EU	2025
(Ram et al., 2020)	4.7								onshore	global	2015 *
(Ram et al., 2020)	15.6								offshore	global	2015 *
Hartley et al., 2015)	3.13							100	onshore	global	2011
Van der Zwaan et al., 2013	6.6	4.95	11.55		11.55				onshore	Middle east	2050
(Moldvay et al., 2013)	0.625								onshore	South Africa	2013
Simas & Pacca, 2013b)	3.51								onshore	Brazil	2016
(Larry Leistritz & Coon, 2009)	3.4	7.02	10.42		10.42	106	1.5	159	onshore	Great plains	2009
(Dedrick et al., 2014)	3.91					50	2	100	onshore	US	2014
Kabayo et al., 2019)	4.7					2599	2	5046	onshore	Portugal	2015 *
(Okkonen & Lehtonen, 2016)			0.12	0.04	0.16	31	0.9	27.6	onshore	Northern Scotland	2009 **
Ejdemo & Söderholm, 2015)					1.442			4000	onshore	Northern Sweden	2019 **
(Hanna et al., 2022)	8								onshore	global	2022
(Hanna et al., 2022)	16.8								offshore	global	2022
(Rutovitz et al., 2015)	4.7								onshore	global	2015
(Rutovitz et al., 2015)	15.6								offshore	global	2015
(Rutovitz et al., 2015)	3.4								onshore	Latin America	2015
(Rutovitz et al., 2015)	20.5								offshore	North America	2015
(Rutovitz et al., 2015)	10.7								offshore	EU	2015

** = only regional impact/job creation/part of job creation, * = values based on Rutovitz et al (2015).

B4: operation and maintenance data

	JOBS (JOB-YEARS/MW$_I$)					SCALE			ONSHORE/ OFFSHORE	LOCATION	REF. YEAR
SOURCE	Direct	Indirect	Direct + indirect	Induced	Total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
(Ortega-Izquierdo & Río, 2020)	8.868	6.651	15.519						onshore	EU-28	2016
(Ortega-Izquierdo & Río, 2020)	4.895	3.671	8.566						offshore	EU-28	2016
(Sohrab et al., 2019)	7.857	19.643	27.5					50	onshore	Iran	2050
Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	14.125	2.375	16.5	6.375	22.9	40	5	200	offshore floating	Gran Canaria	2021
(Kalinina et al., 2020)	5.915	9.405	15.32						onshore	Ukraine	2019
(Schilling et al., 2018)	20.161					365	0.85	310	onshore	Northern Kenya	2018
(Kahouli & Martin, 2018)	8.065	14.8395	22.9	18.105	41.0	62	8	496	offshore	France, Brittany	2020
Varela-Vázquez & Sánchez-Carreira, 2017)	5.25					99	5	495	offshore floating	Spain	2030
Ortega et al., 2015)	10	7.5	17.5						onshore	Global	2012
Ortega et al., 2015)	22.5	17	39.5						offshore	Global	2012
(Corsatea, 2014)	10								onshore	EU	2010
Simas & Pacca, 2014)	14.75								onshore	Brazil	2014
(Collins et al., 2012)	3.81					164	2	328	onshore	US, Appalachia	2010
(Williams et al., 2008)	11.9							10.5	onshore	Northern Arizona, US	2008
(Williams et al., 2008)	12.5							60	onshore	Northern Arizona, US	2008

(Williams et al., 2008)	12.5							180	onshore	Northern Arizona, US	2008
(Vieira et al., 2019)	18	13.6	31.6		31.6				offshore	Portugal	2030
(Fragkos & Paroussos, 2018)	7.5								onshore	EU	2015 *
(Fragkos & Paroussos, 2018)	6								onshore	EU	2011
(Fragkos & Paroussos, 2018)	1.25								onshore	EU	2017
(Fragkos & Paroussos, 2018)	2								onshore	EU	2008
(Fragkos & Paroussos, 2018)	7.5								onshore	EU	2015
(Coon et al., 2015)	2.21							147	onshore	Oklahoma	2012
(Brown et al., 2012)	8.75								onshore	US	2008
(Grover, 2002)	1.41	0.199	1.609	1.81	3.419	260	1.5	390	onshore	US, Washington	2002
(Twidell, 1986)	25								onshore	Denmark	1985
(Koasidis et al., 2022)	6.95								onshore	EU	2025
(Koasidis et al., 2022)	4.575								offshore	EU	2025
(Buchmayr et al., 2022)	4.6475								onshore	Belgium	2022
(Buchmayr et al., 2022)	3.04								offshore	Belgium	2022
(Osorio-Aravena et al., 2022)	7.5					303	2	606	onshore	Spain	2022 *
(Vasconcellos & Caiado Couto, 2021)	12.937	14.765	27.702	18.598	46.3				onshore	Brazil	2023
(Vasconcellos & Caiado Couto, 2021)	14.75								onshore	Brazil	2014 *
(Vasconcellos & Caiado Couto, 2021)	52.5	63.5	116	71.5					onshore	Italy	2023
(Ram et al., 2020)	7.5								onshore	Global	2015 *

(Ram et al., 2020)	5								offshore	Global	2015 *
(Aldieri et al., 2020)	5								nc	Spain	2010
(Aldieri et al., 2020)	9.375								nc	Greece	2020
(Aldieri et al., 2020)	6.75								nc	Italy	2014
(Aldieri et al., 2020)	4.38	3.94	8.32						nc	Japan	2017
(Aldieri et al., 2020)	2.857	3.643	6.5						offshore	France	2040
(Aldieri et al., 2020)	7.5							63.1	nc	Germany	2023
(Aldieri et al., 2020)	2.5								nc	Canada	2020
(Aldieri et al., 2020)	5								nc	Middle east	2050
(Aldieri et al., 2020)	10	7.5	17.5						nc	US, Montana	2014
(Jacobson et al., 2017)			11.1	14.319					onshore	US	2012
(Jacobson et al., 2017)			18.9	25.515					offshore	US	2012
(Child et al., 2017)	5							70	onshore	Aland island	2030
(Child et al., 2017)	5							100	offshore	Aland island	2030
(Loomis et al., 2016)	1.582	2.279	3.861	2.256	6.117	2223	1.5	3335	onshore	US, Illinois	2012
(Hartley et al., 2015)	23.75							100	onshore	US, Texas	2011
(Jacobson et al., 2014)	6.18					24720	5	123600	onshore	US, California	2014
(Jacobson et al., 2014)	26.36					7800	5	39000	offshore	US, California	2014
(Landry et al., 2013)	2.25	1	3.25	1	4.25	33	3	100	onshore	Canada	2013
(Landry et al., 2013)	1.5					44	2.3	101.2	nc	Canada, ON	2013
(Landry et al., 2013)	2.25					73	1.5	109.5	nc	Canada, Qc	2013
(Landry et al., 2013)	1.75					32	3	96	nc	Canada, NB	2013
(Landry et al., 2013)	3					33	3	99	nc	Canada, NB	2013
(Landry et al., 2013)	2.25							100	nc	Canada, NB	2013
(Landry et al., 2013)	2.25					126	1.5	189	nc	Canada, ON	2013

(Landry et al., 2013)	2.25					73	1.5	109.5	nc	Canada, Qc	2013
(Landry et al., 2013)	2.5					10	3	30	nc	Canada, PEI	2013
(Landry et al., 2013)	2.5					67	1.5	100.5	nc	Canada, Qc	2013
(Van der Zwaan et al., 2013)	1.5	1.125	2.625		2.625				nc	Middle East	2050
(Jacobson et al., 2013)	2.82					4020	5	20100	onshore	New York	2030
(Jacobson et al., 2013)	2.81					12700	5	63500	offshore	New York	2030
(Simas & Pacca, 2013b)	11.7								nc	Brazil	2016
(Greene & Geisken, 2013)	2.585034014	8.299319728	10.88435374	9.25170068	20.13605442	98	1.5	147	onshore	Weatherford, Texas, US	2013 **
(Brown, 2011)	12							520	onshore	Brazil, Ceara	2007
(Slattery et al., 2011)	0.897	2.203	3.100	1.768	4.867	421	1.747	735.5	onshore	Texas, US	2011
(Slattery et al., 2011)	0.906	2.234	3.140	1.992	5.132	407	1.628	662.5	onshore	Texas, US	2011
(Esteban et al., 2011)	12								offshore	Britain	2009
(Larry Leistritz & Coon, 2009)	1.572	3.302	4.874	4.874	9.748	106	1.5	159	onshore	Great plains	2009
(Rose et al., 2022)	10.625							10000	offshore	California	2040
(Dedrick et al., 2014)	2.4					50	2	100	onshore	US	2014
(Shoeib et al., 2022)	14.44							100	onshore	US	2015
(Kim & Kim, 2021)	5	5	10	0	10	5	2	10	onshore	Korea	2015
(Kim & Kim, 2021)	5	10	15	5	20	24	5	120	offshore	Korea	2015
(Kabayo et al., 2019)	7.5					2599	2	5046	onshore	Portugal	2015 *
(Okkonen & Lehtonen, 2016)			7.61	2.26	9.87	31	0.9	27.6	onshore	Northern Scotland	2009
(Ejdemo & Söderholm, 2015)	0.3125	0.125	0.4375		0.4375			4000	onshore	Northern Sweden	2019 **
(Hanna et al., 2022)	7.5								onshore	global	2022
(Hanna et al., 2022)	12.5								offshore	global	2022
(Rutovitz et al., 2015)	7.5								onshore	global	2015
(Rutovitz et al., 2015)	5								offshore	global	2015

(Rutovitz et al., 2015)	15								onshore	Latin America	2015
(Rutovitz et al., 2015)	2.25								offshore	North America	2015
(Rutovitz et al., 2015)	5								offshore	EU	2015
(Sharma et al., 2022)	1.97								onshore	US	2019
(Janikowska & Jebreel, 2022)			11.4						onshore	Poland	2022

** = only regional impact/job creation/part of job creation, * = values based on Rutovitz et al (2015).

B5: decommissioning data

	JOBS (JOB-YEARS/MWI)					**SCALE**			**ONSHORE / OFFSHORE**	**LOCATION**	**REFERENCE YEAR**
SOURCE	Direct	Indirect	Direct + indirect	Induced	Total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
(Schallenberg-Rodriguez & Inchausti-Sintes, 2021)	2.655	0.615	3.27	1.005	4.275	40	5	200	Offshore	Gran Canaria	2021
(Kalinina et al., 2020)	0.746	1.186	1.932					798.8	Onshore	Ukraine	2019
(Trypolska et al., 2022)	0.78							3600	Onshore	Ukraine	2050
(Ram et al., 2020)	0.72								Onshore	Global	2015
(Ram et al., 2020)	2.99								Offshore	Global	2015
(Kabayo et al., 2019)	0.6					2599	2	5046	Onshore	Portugal	2015
(Okkonen & Lehtonen, 2016)			0.1	0.02	0.12	31	0.9	27.6	Onshore	Northern Scotland	2009 **

** = only regional impact/job creation/part of job creation, * = values based on Rutovitz et al (2015).

B6: construction phase data

	JOBS (JOB-YEARS/MWI)					**SCALE**			**ONSHORE / OFFSHORE**	**LOCATION**	**REF. YEAR**
SOURCE	Direct	Indirect	Direct + indirect	Induced	Total	Nr. turbines	Turbine capacity (MW)	Total capacity (MW)			
(Schilling et al., 2018)			24.2			365	0.85	310	onshore	northern Kenya	2018

(Corsatea, 2014)	1.25								onshore	EU	2010
(Collins et al., 2012)	2.24					164	2	328	onshore	US, Appalachia	2010
Vasconcellos & Caiado Couto, 2021)	10.03	9.63	19.66	12.27	31.9 3				onshore	Brazil	2023
Vasconcellos & Caiado Couto, 2021)	10.74	2.79	13.53						onshore	Brazil	2023 **
Vasconcellos & Caiado Couto, 2021)	5.18	6.14	11.32	5.6	16.9 2				onshore	Italy	2023
Aldieri et al., 2020)	8.8								nc	Greece	2020
Aldieri et al., 2020)	10.74	2.79	13.53						onshore	Brazil	2017 **
Aldieri et al., 2020)	9.9								nc	Italy	2014
Aldieri et al., 2020)	3.92								nc	Canada	2020
Aldieri et al., 2020)	8.1								nc	Middle east	2050
(Child et al., 2017)	8.6							70	onshore	Aland islands	2030 *
(Child et al., 2017)	18.1							100	offshore	Aland islands	2030 *
(Greene & Geisken, 2013)	0.014	0.286	0.3	0.34	0.63 9	98	1.5	147	onshore	USA, texas	2013 ***
(Esteban et al., 2011)					28.8				offshore	Britain	2009
(Kim & Kim, 2021)	8.6	18.4	27	2.8	29.8	5	2	10	onshore	Korea	2015 *
(Kim & Kim, 2021)	18.1	25.7	43.8	8.2	52	24	5	120	offshore	Korea	2015 *

*** = only regional impact/regional job creation, ** = data from IRENA, * = data from Simas and Pacca, 2015.

B7: other data

	JOBS					ONSHORE / OFFSHORE	LOCATION	REF. YEAR	UNIT
SOURCE	Direct	Indirect	Direct + indirect	Induced	Total				
(Duarte et al., 2022)					0.96	n.d.	Spain	2005	jobs/MW_i
(EL Kinani et al., 2023)					1.2	n.d.	France	2010	jobs/MW_i
(EL Kinani et al., 2023)					13.2	n.d.	Spain	2010	job-years/MW_i
(Heras & Martín, 2020)	9.0					onshore	Spain	2011	jobs/MW_i
(Kandrot et al., 2020)					6.418	offshore	Ireland	2030	job-years/MW_i
(Mu et al., 2018)			26.4			onshore	China	2018	jobs/MW_i

(Behrens et al., 2016)					1.15	n.d.	Portugal	2010	jobs/MW_i
(Şengül et al., 2015)					0.335	n.d.	Turkey	2015	average and person/MW_i
(Roy et al., 2022)					1.1	n.d.	India	2022	jobs/MW_i
(Deloitte, 2021)	0.1	3.7	3.8		3.7	n.d.	Portugal	2021	jobs/MW_i
(Chen & Li, 2021)	15.8	19.3	35.1			n.d.	global south	2021	jobs/US$1 million invested
(Zhou et al., 2020)					30% reduction potential	n.d.	China	2020	30% labor reduction new maintenance schedule
(Lee & Chang, 2018)					0.17	n.d.	Taiwan	2018	jobs/kWh
(Keček et al., 2019)	6	3	9	5	14	onshore	Croatia	2019	FTE/million invested
(Keček et al., 2019)	1	7	8	4	11	onshore	Croatia	2019	FTE/million value produced
(Mikuli et al., 2018)	6.1	3.2	9.3	5	14.3	onshore	Croatia	2018	FTE/million invested
(Mikuli et al., 2018)	0.6	6.5	7.1	3.6	10.7	Onshore	Croatia	2018	FTE/million value produced

B8: local share data

	JOB SECTOR	(SHARE) LOCAL	(SHARE) NATIONAL	TOTAL NATIONAL	LOCATION	ON/OFFSHORE	YEAR
(Gönül et al., 2021)	Manu	0%	0%		Turkey	onshore	2019
(Gönül et al., 2021)	Manu	0%	0%		Turkey	offshore	2019
(Charles Rajesh Kumar et al., 2019)	Manu		40%	40%	India		2018
(Schilling et al., 2018)	O&M		81%	81%	Northern Kenya		2018
(Garsous & Worack, 2022)	Manu		75%	75%	China		2016
(Garsous & Worack, 2022)	Manu		70%	70%	Spain		2016
(Vasconcellos & Caiado Couto, 2021)	O&M	90%	5%	95%	Brazil	onshore	2023
(Vasconcellos & Caiado Couto, 2021)	Manu	50%	30%	80%	Brazil	onshore	2023
(Vasconcellos & Caiado Couto, 2021)	Con	90%	5%	95%	Brazil	onshore	2023
(Kandrot et al., 2020)	Con	local			Ireland	offshore	2030

(Kandrot et al., 2020)	O&M	local		Ireland	offshore	2030
(Kandrot et al., 2020)	Plan	local		Ireland	offshore	2030
(Kandrot et al., 2020)	Manu		0%	Ireland	offshore	2030
(Moldvay et al., 2013)	Manu		66-80%	South Africa	onshore	2013
(Slattery et al., 2011)	Con	24%		US, Texas	onshore	2011
(Slattery et al., 2011)	O&M	72%		US, Texas	onshore	2011
(Slattery et al., 2011)	Con	20%		US, Texas	onshore	2011
(Slattery et al., 2011)	O&M	57%		US, Texas	onshore	2011
(Kabayo et al., 2019)	Manu		0%	Portugal	onshore	2015
(Kabayo et al., 2019)	O&M	local		Portugal	onshore	2015
(Kabayo et al., 2019)	Con	local		Portugal	onshore	2015
(Kabayo et al., 2019)	decom	local		Portugal	onshore	2019

Appendix C: interviews

Interviewee A:

interviewA.docx

Interviewee B:

interviewB.docx

Interviewee C:

interviewC.docx

Interviewee D:

interviewD.docx