

Environmental value function model / D3.3

WP3, T3.3

Authors: Samuel Kainz, Annamaria Scherzl,
Abhinav Anand, Adrien Guilloiré



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Executive summary

The energy transition is pivotal in mitigating climate change, and wind energy plays a crucial role in this shift due to its low carbon footprint compared to fossil fuels. However, wind energy infrastructure still carries lifecycle emissions that must be minimized as the sector expands. Furthermore, it is important to consider the time-varying environmental value of wind energy in displacing as much fossil fuel-based emissions as possible in the connected electrical grid to effectively achieve the goals of the energy transition. This deliverable, developed under the SUDOCO project, presents two innovative tools created by the Technical University of Munich to assess the carbon footprint and environmental value of most common European wind energy systems.

The first tool, DETECT, quantifies the carbon footprint of typical European offshore wind farms using Life Cycle Assessment. It evaluates the entire lifecycle of wind farm components, from cradle to grave, allowing for a detailed understanding of the emissions linked to different design configurations and site characteristics. DETECT is showcased by means of a scaled version of the HKN offshore wind farm for which a carbon footprint of 11.17 kg CO₂eq/MWh is determined, with a large share resulting from steel component production and from vessel operations over the plant's lifecycle.

The second tool focuses on the environmental value of wind energy in the connected grid, specifically by estimating the marginal displacement of emissions due to changes in wind farm power output following a machine learning approach. A case study of the German electrical grid demonstrates the large potential for wind energy to displace grid emissions far exceeding its own carbon footprint. Furthermore, the environmental benefit of wake steering-based wind farm control strategies to maximize power production is demonstrated by means of the German Wikingen offshore wind farm, allowing to displace grid emissions equivalent to a quarter of the plant's own life cycle emissions through the additionally generated electricity.

The presented tools enable the integration of environmental impact and value consideration into control strategy formulation and co-design optimization of future wind energy systems. This will be achieved by SUDOCO's "Control Room of the Future" framework, enabling more sustainable and economically viable wind energy solutions.



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Acronyms

AEP Annual Energy Production

ANN Artificial Neural Network

COE_€ Levelized Cost Of Energy

COE_{CO2} Environmental Cost of Energy

DETECT Design and Evaluation Toolchain with Eco-Conscious Targets

LCA Life Cycle Assessment

MDF Marginal Displacement Factor

O&M Operation & Maintenance

TLCE Total Life Cycle Emissions

TUM Technical University of Munich



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1 Introduction

The energy transition plays a critical role in reducing the global greenhouse gas emissions and mitigating climate change. Wind energy generation is among the least pollutant energy sources but still features a certain carbon footprint due to the infrastructure and logistics required over the entire lifecycle of the wind turbines and farms. Considering the ambitious growth targets of the worldwide wind energy sector, assessing and subsequently minimizing the lifecycle emissions related to wind energy system design is crucial to most effectively accomplish the mitigation of climate change.

In the connected energy system, wind energy is displacing other, mainly fossil fuel-based power plants. Among other objectives, wind farm control provides the possibility of regulating the power output of wind farms such that power plants with high emissions in the connected grid are displaced to the greatest possible extent. On the other hand, the power output of wind farms can be reduced in times of high share of renewable energy generation in the connected system. This leads to reduction in consumed health as well as the lifetime of individual components, which can be used to operate with the aim of maximizing the environmental value of the system.

As part of the SUDOCO project, the Technical University of Munich (TUM) has developed two tools that allow (a) to quantify the carbon footprint linked to most common European offshore wind farm designs using Life Cycle Assessment (LCA), and (b) to determine the displaced grid greenhouse gas emissions in the connected energy system through marginal changes in power output of a wind farm using a data-driven machine learning approach. Both tools are described and showcased in this deliverable. The models are developed in a generic way, allowing them to be adapted and applied to many existing and future European wind farms and connected energy systems. Among other applications, the tools presented here will be used in the SUDOCO project to optimize wind farm control strategies and conduct co-design activities considering climate change impacts, energy yield, fatigue loads, reliability, or economic revenue. Pareto-optimal trade-offs between the economic and environmental performance will be explored. This will be achieved by integrating the presented tools into a holistic toolchain for control and layout co-design optimization as part of SUDOCO's "Control Room of the Future".



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2 Methods

In the following two sections, the methods to determine the carbon footprint of most common European offshore wind farm configurations, and to evaluate the displaced grid greenhouse gases in the connected grid for a given time series are presented. The models have been developed following a generic and parameterized approach, which allows their adaption and application to a large variety of wind farm configurations and electricity grids in Europe.

2.1 Life cycle assessment

2.1.1 Introduction to DETECT

To automatically calculate the greenhouse gas emissions linked to the generation of electricity in offshore wind farms over their whole life cycle, TUM has developed the Design and Evaluation Toolchain with Eco-Conscious Targets (DETECT) as part of the SUDOCO project. DETECT couples existing, augmented and newly developed wind farm design tools and cost & value analysis methods. The toolchain covers all components of most common European offshore wind farm configurations up to and including the onshore substation. All life-phases from cradle to grave are considered: material extraction & processing, transport to manufacturing plant, manufacturing, transport to port, installation, Operation & Maintenance (O&M), decommissioning, and End-of-Life including recycling and disposal.

The approach of linking LCA to the design of wind energy systems was first presented in (Canet et al., 2023), although limited to the turbine level. A full wind farm-level version of DETECT has been introduced and demonstrated in a recent publication (Kainz et al., 2024) where details about the method can be found. In the following, a summary of the method relevant for the assessment of the carbon footprint of a wind farm is provided. A future journal publication (currently under development) will give further insights into DETECT and showcase the multi-objective optimization capabilities of DETECT in concurrently optimizing economic and environmental performance of offshore wind farms.

Figure 2.1 illustrates the data and model flows that support the forward analysis functionalities of DETECT. To approximate a studied wind farm of interest, the turbine, farm, and site properties are set in the toolchain parameters. Then, the masses of all components involved in the wind farm are determined, either as specified in the inputs or estimated by means of scaling models. Subsequently, the



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component masses are broken down into up to 33 materials. Installation and O&M models allow to determine the required vessel activities over the lifetime of the studied wind farm. Energy harvest models assess the Annual Energy Production (AEP) of the studied wind farm considering wake and other losses. All information is then processed to determine economic and environmental cost and value metrics linked to the studied wind farm. The determined cost metrics are the economic Levelized Cost Of Energy ($COE_{\text{€}}$), and the Environmental Cost of Energy (COE_{CO_2}) which is also termed carbon footprint. The calculated value metrics are the economic Net Value Of Energy ($NVOE_{\text{€}}$) for profit, and the environmental Net Value Of Energy ($NVOE_{\text{CO}_2}$) for grid avoided greenhouse gases. In the following, the focus lies on the determination of COE_{CO_2} (carbon footprint) for fixed wind farm designs, but it is emphasized that later in the SUDOCO project (a) the parallel environmental and economic approach will be used to determine synergies and trade-offs between economic and environmental aspects, and (b) the ability of DETECT to optimize designs will be used to conduct control co-design activities.

2.1.2 Carbon footprint calculation

The LCA method is applied to calculate the carbon footprint of the studied wind farms. LCA is a well-proven, widely accepted, and standardised method that allows to quantify the environmental impacts of processes or products occurring in each of their life stages. The LCA implementation in DETECT follows the standardization frameworks ISO 14040 and ISO 14044, and the guidelines provided by (Hauschild et al., 2018). The parameterized and automated model quantifies the global warming potential over 100 years associated to the production of electricity from the wind farm, expressed in $kgCO_2eq/MWh$ following the IPCC life cycle impact assessment guidelines (IPCC, 2014). Only the impact on climate change is evaluated, whereas other environmental impact categories are disregarded for now, although they will

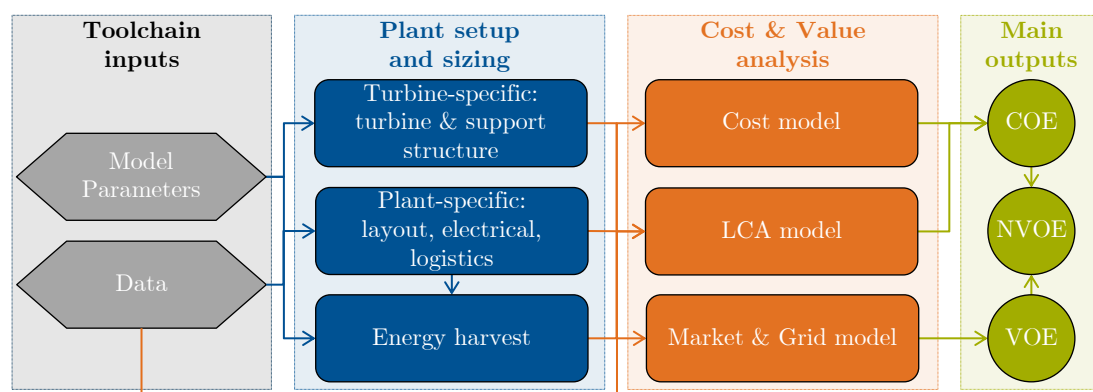


Figure 2.1: Forward analysis mode of the DETECT code, adapted from Kainz et al., 2024.



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be included in future releases of DETECT.

Due to limited access to sector-specific supply chain datasets, more than 60 reference activities from the *ecoinvent* database v3.8 (Wernet et al., 2016) are used for approximating the life cycle of all wind farm components from cradle to grave. The *ecoinvent* system model ‘Allocation cut-off by classification’ is chosen, implying that the production of a primary material is always allocated to the primary user of the material. However, the circular footprint formula (European Commission, 2021) has been implemented to better capture the benefits and burdens of recycling and recyclability from a design perspective. To determine the allocated burden for upstream impact of recycled material input, the necessary activities for the extraction of the respective virgin material are taken from the *ecoinvent* database (Wernet et al., 2016). Similarly, materials that are recycled at the end of life provide a certain credit, which corresponds to the burden due to the extraction of the virgin material that is allocated to the next user of that same material. The allocation is determined by means of burden and credit factors between supplier and user of each recycled material, as recommended in (European Commission, 2021).

In the following, the approach taken to model each life phase of a wind farm’s lifetime is described briefly. The emissions of each life phase sum up to the plant’s Total Life Cycle Emissions (TLCE). Finally, COE_{CO_2} (carbon footprint) in $kgCO_{2eq}/MWh$ is calculated as a function of the total life cycle emissions, AEP , and design lifetime Y :

$$COE_{CO_2} = \frac{TLCE}{AEP \cdot Y} \quad (2.1)$$

Material extraction, processing, and transport to manufacturing

To model the first life stage *Material extraction, processing, and transport to manufacturing* for each material in the plant’s material bill, reference market activities have been selected in the *ecoinvent* database to approximate the inventory of the materials used in offshore wind farms. Where available, Europe has been chosen as the geographic scope, otherwise global datasets have been selected. The market datasets include average transport distances to the users of the raw materials. Therefore, transport to the manufacturing site is not regarded as a separate life phase.

Manufacturing

To approximate the manufacturing stage of the individual wind farm components, generic reference market activities have been selected in the *ecoinvent* database to approximate the life cycle inventory of the involved materials. Due to limited dataset availability, mainly global markets for metal working are regarded in this life stage.



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Transport to port

To model the transport of components from manufacturing to port, *ecoinvent* market datasets for freight transport by land and sea have been selected. The transport distances associated with individual components are taken from (Razdan and Garrett, 2019).

Installation

The impact of all the installation activities as modelled with DETECT is calculated through the fuel consumption (Arvesen et al., 2013) of the involved vessel types in three different operating modes (idling at port, transit, operational on site). Furthermore, the life cycle impact of the vessels is modelled via generic *ecoinvent* datasets for vessel production and maintenance.

Operation & Maintenance

Similar to the foregoing life phase, the impact of all vessel activities required for component reparation, replacement, and turbine service as modelled with DETECT is calculated through fuel consumption and life cycle impact of the involved vessels. Furthermore, spare parts for component replacement are modelled from cradle to grave. Life stages aside from spare part installation - which falls into the current phase - are modelled the same way as original components.

Decommissioning

Decommissioning is modelled as reversed installation with the exemption of scour protection material assumed to be left at the seafloor. Subsequently, all components are assumed to be transported 200 km by truck to a regional recycling or disposal operator, as suggested by (Razdan and Garrett, 2019). This is modelled with a corresponding *ecoinvent* market dataset for truck transport in Europe.

End-of-Life

Different end-of-life options are considered in the analysis. Components that have been replaced in the last five years of the operation time are assumed to be resold (DNV GL, 2017), and 80% of the linked emissions up to component manufacturing are assumed to be transferred to the buyer. Recycling is modelled using the circular footprint formula (European Commission, 2021), with allocation of burdens between the successive users of the materials as described earlier. Recycling rates are taken from (Razdan and Garrett, 2019). Waste components are either incinerated or landfilled, which is modelled with corresponding end-of-life *ecoinvent* datasets. The



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ratios for incineration and landfilling are taken from (Razdan and Garrett, 2019) and, for components and materials that they do not specify, directly from the *ecoinvent* datasets.

2.1.3 Uncertainty Quantification

The results as calculated with DETECT feature uncertainties resulting from uncertainties in the inputs and model parameters. To propagate these uncertainties throughout the toolchain, a classic Monte Carlo approach is taken, allowing to calculate the confidence level of the calculated carbon footprint. Due to the low computational cost of the DETECT analysis, a classic Monte Carlo approach is sufficiently fast for a case study evaluation. However, when coupling DETECT with a co-design platform for stochastic optimization activities later in the SUDOCO project, surrogate-creating approaches such as polynomial chaos expansion will be used to speed up the uncertainty quantification of the analysis. For this purpose, UQ-Lab (Marelli and Sudret, 2014) has been coupled to DETECT. Since the exact configuration is dependent on the setup of the optimization platform, a detailed description will be provided in the corresponding future deliverable. For the current analysis, the classic Monte Carlo simulation is used, where DETECT is called once for each iteration.

If the actual distributions in the inputs and model parameters are unknown, quantiles for the confidence intervals around the deterministic baseline values are defined to fit normal distributions describing the associated uncertainties. Next, N random configurations are sampled from the uncertain inputs and model parameter distributions, and DETECT is executed for each of the N samples. The distribution of the N model results describes the uncertainties propagated by the inputs and model parameters. To plot these uncertainties, a normal distribution is fit to the model results, and the values at the quantiles of the desired confidence interval are computed. This approach allows to add error bars to the deterministic toolchain results.

2.1.4 Sensitivity Analysis

To quantify the uncertainties in the inputs and model parameters that have the largest influence on the model estimates, variance-based sensitivity analysis as suggested by (Saltelli et al., 2008) is applied. This method measures the sensitivity of the inputs and model parameters over their full range by the amount of variance they cause in the outputs by means of sensitivity indices, and determines interactions among them. The two main sensitivity indices of interest are the first-order sensitivity index S , and the total effect index S_T . Both indices are calculated for each input variable, and are strongly linked to the respective predefined range of variation.



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The first-order sensitivity index S measures the main effect of the respective input on the the output variance: “ S_i indicates by how much one could reduce, on average, the output variance if x_i could be fixed” (Saltelli et al., 2008). The second index, the total effect index S_T , measures the total effect that an input variable has on the output variance, including interactions with other variables: “ S_{Ti} accounts for the total contribution to the output variation due to factor x_i , i.e. its first-order effect plus all higher-order effects due to interactions” (Saltelli et al., 2008).

The numerical method to derive the two sensitivity indices is applied as suggested by (Saltelli et al., 2008) and (Saltelli et al., 2010), requiring an extended Monte-Carlo-Simulation. First, a $n \times 2m$ input matrix is generated, with n being the number of samples, and m the number of analysed inputs or model parameters with uncertainty distributions. For variables with unknown distributions, normal distributions with predefined quantiles are created, analogous to the approach for uncertainty quantification described earlier. To fill the input matrix, Sobol's quasi-random sequences in the interval $[0,1]$ are created, representing sample values for cumulative probabilities of the input and model parameter distributions, that are then translated into sample points with actual values for the individual variables by means of their respective distributions. Then, the input matrix is split in two parts: the first m columns are defined as matrix **A**, the rest as matrix **B**. Both serve as independent input matrices to the Monte-Carlo-Simulation, containing n samples for the m analysed input factors. Next, m further input matrices \mathbf{A}_B^i of dimension $n \times m$ are created, where all columns are taken from **A**, except the i -th column which is equal to the i -th column of **B**. This results in $m+2$ input matrices to the Monte-Carlo-Simulation which is now conducted for each of them. I.e., DETECT is executed $n \cdot (m+2)$ times. The results are stored in the output vectors $f(\mathbf{A})$, $f(\mathbf{B})$, and m times $f(\mathbf{A}_B^i)$, each of dimension $1 \times n$.

Finally, both sensitivity indices can be determined via numerical estimators as suggested by Saltelli et al., 2010:

$$S_i = \frac{\frac{1}{n} \sum_{j=1}^n f(\mathbf{B})_j (f(\mathbf{A}_B^i)_j - f(\mathbf{A})_j)}{\text{Var}(Y)} \quad (2.2)$$

and

$$S_{Ti} = \frac{\frac{1}{2n} \sum_{j=1}^n (f(\mathbf{A})_j - f(\mathbf{A}_B^i)_j)^2}{\text{Var}(Y)} \quad (2.3)$$

where $\text{Var}(Y)$ is the variance of the vector Y containing all entries of $f(\mathbf{A})$ and $f(\mathbf{B})$. When coupling variance-based sensitivity analysis with a co-design platform later in the SUDOCO project, the UQ-Lab framework will be used to reduce computational costs as described earlier.



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2.2 Grid emissions displacements

In this section, a data-driven model to investigate the temporal marginal displacement factors for wind energy generation in European energy systems is proposed. The displaced grid emissions due to wind energy generation at a given time instant depend on the emissions of the generator operating at the margin at that instant, i.e. the last generation technology in the merit-order of the affected market adapting its output to meet the rapid change in demand. Identifying the generator at the margin is a complex task, it is highly market-dependent, and requires consideration of the relevant regulations, policies, and mechanisms. A data-driven approach can rather be more effective and straightforward, as all relevant driving phenomena from markets and grid are implicitly considered through the data. In fact, a data-driven approach can statistically capture all relevant markets for a given region and predict the most likely displacement factor associated with wind energy generation, for a given operational state of the connected energy system.

2.2.1 Time series of emissions

To create a data-driven model that predicts the emissions displaced through wind energy generation, the time series of the total emissions occurring in the regarded energy system needs to be determined first. In this study, the scope of an energy system is defined to correspond to the boundaries of a country. However, the approach is more general and can be applied to regions with lower or higher granularity (e.g., control areas or bilateral market zones).

Since the European electricity grid is characterised by a high level of inter-connectivity, it is not sufficient to consider emissions associated solely with the generation internal to the country (Thomson et al., 2017). In reality, cross-grid transfers due to energy imports and exports need to be considered explicitly (Oliveira et al., 2019, Tang et al., 2022). Thus, the total emissions E^{tot} for the different operational states of an energy system at a given time instant t

$$E^{tot}(t) = E^{int}(t) + E^{imp}(t) - E^{exp}(t) \quad (2.4)$$

includes emissions due to electricity generation within the country E^{int} , emissions due to electricity import E^{imp} , and emissions due to electricity export E^{exp} . The emissions at a given time instant due to N_{tech} generational technologies operating within the country can be calculated as

$$E^{int}(t) = \sum_{tech=1}^{N_{tech}} e^{tech} \cdot P_{gen}^{tech}(t). \quad (2.5)$$

Here, P_{gen}^{tech} denotes the aggregated power production from a particular generation



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technology $tech$ at a given time instant, and e^{tech} denotes the technology-specific emission intensity.

The emissions at a given time instant due to electricity import from N_{nc} neighbouring countries can be calculated as

$$E^{imp}(t) = \sum_{nc=1}^{N_{nc}} e_{nc}(t) \cdot P_{nc}^{imp}(t). \quad (2.6)$$

Here, P_{nc}^{imp} denotes the electricity imported from a given neighbouring country, and e_{nc} denotes the average emission intensity of that neighbouring country at a given time instant t , calculated as

$$e_{nc}(t) = \frac{\sum_{tech=1}^{N_{tech}^{nc}} e^{tech} \cdot P_{gen}^{tech}(t)}{\sum_{tech=1}^{N_{tech}^{nc}} P_{gen}^{tech}(t)}. \quad (2.7)$$

N_{tech}^{nc} denotes the number of generation technology in the neighbouring country nc .

The emissions at a given time instant due to electricity export to N_{nc} neighbouring countries can be calculated as

$$E^{exp}(t) = e_{int}(t) \cdot \sum_{nc=1}^{N_{nc}} P_{nc}^{exp}(t). \quad (2.8)$$

Here, P_{nc}^{exp} denotes the electricity exported to a given neighbouring country nc , and e_{int} denotes the average emission intensity due to production inside the country under consideration, calculated as

$$e_{int}(t) = \frac{\sum_{tech=1}^{N_{tech}} e^{tech} \cdot P_{gen}^{tech}(t)}{\sum_{tech=1}^{N_{tech}} P_{gen}^{tech}(t)}. \quad (2.9)$$

2.2.2 Artificial Neural network for emission prediction

An Artificial Neural Network (ANN) is trained to predict, for a given set of operational states of the considered energy system at a certain time instant, the corresponding total grid emissions E^{tot} . The architecture of the neural network is inspired by the discussions in (Mayes et al., 2024). The input layer is followed by two hidden layers with 512 and 256 neurons each. The activation function of both the hidden layers is a hyperbolic tangent. All other layers have a linear activation function. During the ANN development phase, multiple generation-specific, demand-specific, and temporal parameters were considered as inputs to the ANN. The aim was to assess the significance of different grid operational variables and their impact on the prediction from ANN. The performance of the ANN was quantified using the R^2 score, where



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an R^2 score of one signifies perfect predictions. The model is trained for 500 epochs with a learning rate of 0.01. Both the inputs and the target datasets are normalized so that all the values are in between 0 and 1.

Table 2.1 lists the final set of input variables of the ANN. Here, imports and exports are considered as summed net imports and summed net exports over all neighbouring countries, respectively. This is different than the approach to calculate the ANN target emissions, where a more accurate formulation is considered, as shown in Eq. (2.6) and Eq. (2.8). The time series data for demand, electricity generation, imports and exports are taken from the ENTSO-E Transparency Platform (ENTSO-E, 2024). Table 2.1 also shows the respective tags on the ENTSO-E data platform corresponding to each input variable. Each dataset has been downloaded at the highest available frequency and is then resampled to quarter-hourly time steps.

Emission intensities of the considered technologies are taken from the Ecoinvent database v3.7.1 (Wernet et al., 2016). The system model ‘Allocation cut-off by classification’ has been chosen. Germany has been selected as geographic scope and is considered being representative for emission intensities in the studied European countries. The emission intensities of each technology have been adapted such that only operational emissions are considered, whereas life-cycle emissions due to infrastructure are omitted since only the former can be considered to be displaced in real-time on the electrical grid.

ANN input variable	ENTSO-E dataset	Column in dataset
Demand	Total Load - Day Ahead / Actual	Actual Total Load
Wind power generation	Actual Gen. per Production Type	Wind Offshore, Wind Onshore
Solar power generation	Actual Gen. per Production Type	Solar
Power gen. from lignite	Actual Gen. per Production Type	Fossil Brown coal / Lignite
Power gen. from hard coal	Actual Gen. per Production Type	Fossil Hard coal
Power gen. from oil	Actual Gen. per Production Type	Fossil Oil
Power gen. from gas	Actual Gen. per Production Type	Fossil Gas
Nuclear power generation	Actual Gen. per Production Type	Nuclear
Hydro power generation	Actual Gen. per Production Type	Hydro Pumped Storage, Hydro Run-of-river and poundage, Hydro Water Reservoir
Other renewable power gen.	Actual Gen. per Production Type	Marine, Other renewable
Other conventional power generation	Actual Gen. per Production Type	Other, Fossil Coal-derived gas, Fossil Oil shale, Fossil Peat
Electricity imports	Cross-Border Physical Flow	Neighbors to studied country
Electricity exports	Cross-Border Physical Flow	Studied country to neighbors

Table 2.1: Input variables of the artificial neural network and specifications of data sources (ENTSO-E, 2024).



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2.2.3 Marginal displacement factors for wind energy

The artificial neural network predicts the overall emissions in the considered system as a function of the previously listed system parameters, referred to as function Y in the following. The Marginal Displacement Factor (MDF) for wind MDF_{wind} can be obtained via the partial derivative of Y with respect to the wind power production $P_{\text{gen}}^{\text{wind}}$ in the system (considering that all other system states remain constant):

$$MDF_{\text{wind}}(t) = - \frac{\partial Y(t)}{\partial P_{\text{gen}}^{\text{wind}}} \quad (2.10)$$

Since in this case Y is predicted by a neural network and not an analytical function, the partial derivative is approximated using the central finite differences method:

$$MDF_{\text{wind}}(t) = - \left(\frac{Y(P_{\text{gen}}^{\text{wind}}(t) + \Delta P_{\text{gen}}^{\text{wind}}) - Y(P_{\text{gen}}^{\text{wind}}(t) - \Delta P_{\text{gen}}^{\text{wind}})}{2\Delta P_{\text{gen}}^{\text{wind}}} \right). \quad (2.11)$$

$\Delta P_{\text{gen}}^{\text{wind}}$ is set to 0.001 in the normalised mode, which corresponds to an absolute value of 100 MW for the following case study.



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3 Results

3.1 Life cycle assessment

3.1.1 Case study description

The fully parameterized LCA implementation in DETECT allows to determine the carbon footprint of most common European wind farms by approximating site and design configuration in the toolchain input parameters. DETECT will be used to calculate the reference carbon footprint of the baseline case studies analysed in the SUDOCO project, and to evaluate the performance of varying design configurations as output by control co-design activities. For demonstration purposes in this report, DETECT is applied on one of the main SUDOCO case studies: the rotor diameter scaled version of the HKN wind farm with 69 IEA 22-MW turbines. The main characteristics of the case study are listed in Table 3.1. No wind farm control strategy is applied. The case study is specified and described in more detail in the SUDOCO Deliverables D1.1 (Andersen et al., 2024) and D3.1 (Gebraad et al., 2024) with the following modifications:

1. The 11MW Siemens turbines (SG 11.0-200 DD) have been replaced with IEA 22-MW turbines. The layout of the wind farm has been scaled such that the turbine distances in rotor diameters remain constant, with the offshore substation position serving as reference point. Similarly, the bathymetry, originally extracted from (EMODnet Bathymetry Consortium, 2022), has been stretched such that the water depth at the turbine positions remains unchanged. Layout, cabling plan and bathymetry of the scaled HKN wind farm are plotted in Figure 3.1.
2. Turbine parameters, component masses, and performance data are taken from the IEA 22-MW turbine report (Zahle et al., 2024). To scale the support structure mass (tower and monopile) with the water depth of the individual turbine positions, the surrogate mass model as described by (McWilliam et al., 2022) is executed by DETECT.
3. To avoid parallel array cabling sections, the array voltage level has been upgraded to 110kV, whereas the cabling plan remains unchanged. TUM's offshore cabling database based on (ABB, 2010) has been used to assign the cable with lowest possible active power capacity to each array cabling section,



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Table 3.1: Main characteristics of the case study.

Parameter	Baseline	Parameter	Baseline
Rated turbine power	22 MW	Distance to installation port	230 km
Rotor diameter	284 m	Distance to service port	40 km
Hub height	170 m	Power train type	Direct drive
Number of turbines	69	Offshore platform height	15 m
Support structure type	Monopile	Significant wave height	5.6 m
Array voltage level	110 kV	Significant wave period	9.0 s
Export voltage level	220 kV	Coating material	Epoxy
Lifetime	25 years	Sacrificial anode material	Aluminium

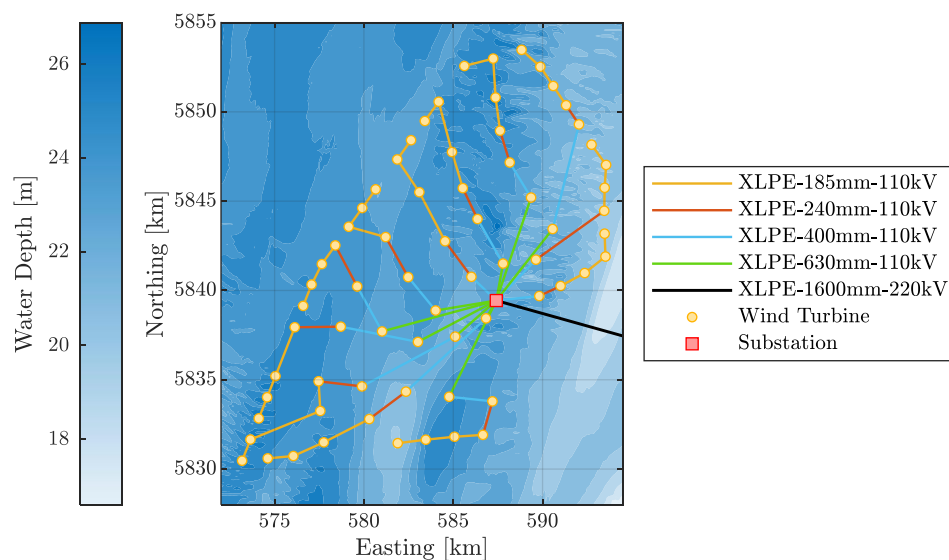


Figure 3.1: Layout, cabling plan and bathymetry of the scaled HKN wind plant. Coordinates refer to the UTM zone 31U.

considering the summed rated power of the supplied turbines. Reactive power demand has been neglected due to the relatively short section lengths.

4. The export cable type has not been upgraded. Therefore, four export cables are required to transfer electricity from the scaled HKN wind farm to shore. Cable properties are taken from (TENNET, 2022), and reactive power demand has been considered via the indicated charging current.
5. An energy storage facility is not included in the scope of DETECT and therefore disregarded.
6. The long-term wind speed and wind direction time series in the wind zone center of HKN, provided in the official site assessment report (Node 1 described

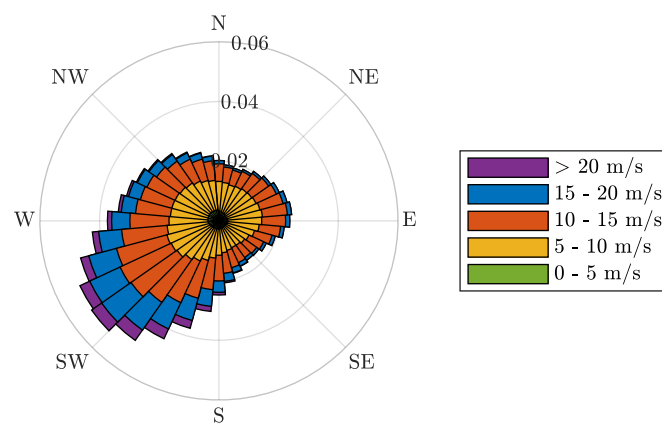


Figure 3.2: Wind rose at the HKN wind farm zone center, created with data from (Oldbaum, 2019).

in Oldbaum, 2019), is used to determine the wind rose of the site. Wind speed is scaled to turbine hub height by means of the power law with the power law coefficient being calculated for each time stamp using the data of 160 m and 200 m height. Wind direction is taken at the height of 100 m. The resulting wind rose is plotted in Figure 3.2.

7. Pywake (Pedersen et al., 2024) is used to calculate wake losses in the wind farm. The Jensen wake model with a wake decay coefficient of 0.05 is chosen for demonstration purposes. Other losses (such as cable or transformer losses) are calculated as specified in the SUDOCO Deliverable 3.1 (Gebraad et al., 2024).

3.1.2 Carbon footprint assessment

The total life cycle emissions of the scaled HKN wind farm regarding climate change (global warming potential) sum up to 1,703,555.5 tCO₂-eq. The annual energy production of the farm is determined as 6102.4 GWh, which corresponds to a capacity factor of 0.459. As a result, the carbon footprint of the scaled HKN wind farm is found to be 11.17 kgCO₂eq/MWh, which is similar to values reported in the literature for other European offshore wind farms with monopile foundations (Reimers et al., 2014; Kouloumpis and Azapagic, 2022).

In Figure 3.3 and Table 3.2, the results for carbon footprint are broken down by life phases. Additionally, the impacts of materials and logistics - mainly due to vessel fuel emissions - are distinguished. Figure 3.4 and Table 3.3 present the breakdown of carbon footprint by components and materials / logistics. Materials with a contribution of less than 0.5% to the carbon footprint are bundled as "Other Materials". Since the total life cycle emissions are independent of the annual energy



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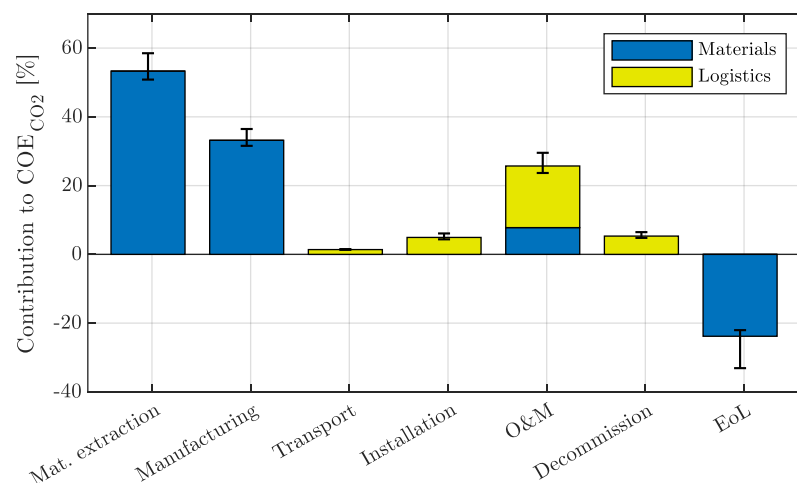


Figure 3.3: Carbon footprint of the scaled HKN wind farm broken down by life phases and materials / logistics. The error bars correspond to the 95% confidence interval of the results, caused by the uncertainties in the inputs as defined in Table 3.4 and propagated through DETECT.

production, the presented relative contributions to the carbon footprint are the same as those to the total life cycle emissions.

The energy-intensive material extraction and manufacturing processes, especially related to structural steel, contribute the most to the life cycle emissions. However, a significant credit for material extraction is achieved at the end of life due to recycling. The relative contribution of logistics to COE_{CO_2} reaches almost 30%. Most of these emissions result from vessel fuel consumption in the O&M phase and are linked to repair and replacement activities of nacelle components. In fact, the nacelle contains the most impactful components, followed by tower and monopile due to their massive steel content, and in turn followed by cabling.

The error bars in the plots correspond to the propagated uncertainty of six inputs as defined in Table 3.4. The table also reports the corresponding first order and total effect sensitivity indices. The inputs with their respective normal distributions have been selected to demonstrate the implemented uncertainty quantification and sensitivity analysis methods in DETECT, and might be updated later in the SUDOCO project if data regarding uncertainty of the toolchain inputs and model parameters becomes available. The 95% confidence interval of the calculated carbon footprint lies within the boundaries of 9.57 and 12.04 $\text{kg CO}_2\text{eq/MWh}$.

The same input distributions feed into the variance-based sensitivity analysis. The resulting first order and total effect Sobol indices are reported in Table 3.4. The similar values for the two sensitivity indices imply little interaction between each variable with other input factors. Among the defined uncertain inputs, the distribution of



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Component	Material extraction	Manufacturing	Transport to port	Installation	O&M	Decommissioning	End-of-Life
Materials							
Blades	3.54	1.12	-	-	<0.1	-	0.49
Hub, Pitch and Nose	1.76	1.02	-	-	0.15	-	-0.93
Generator	7.76	5.42	-	-	6.99	-	-4.76
Electronics	3.94	-	-	-	0.16	-	<0.1
Nacelle	4.63	2.65	-	-	0.42	-	-2.26
Tower	13.07	11.16	-	-	-	-	-7.99
Monopile	7.62	6.51	-	-	-	-	-4.66
Transition Piece	0.90	0.77	-	-	-	-	-0.55
Scour Protection	0.28	-	-	-	-	-	-
Array Cables	1.67	0.82	-	-	-	-	-0.60
Export Cables	5.00	2.23	-	-	-	-	-1.69
Offshore Substation	1.64	1.29	-	-	-	-	-0.87
Onshore Substation	0.24	0.12	-	-	-	-	>-0.1
Support structure corrosion protection	1.26	<0.1	-	-	-	-	<0.1
Logistics							
Blades	-	-	<0.1	0.20	0.26	0.22	-
Hub, Pitch and Nose	-	-	<0.1	<0.1	1.16	0.11	-
Generator	-	-	0.15	0.41	7.58	0.47	-
Electronics	-	-	<0.1	<0.1	1.64	<0.1	-
Nacelle	-	-	<0.1	0.26	6.28	0.29	-
Tower	-	-	0.51	1.19	0.22	1.29	-
Monopile	-	-	0.30	0.89	0.13	0.95	-
Transition Piece	-	-	<0.1	0.10	<0.1	0.11	-
Scour Protection	-	-	-	0.63	0.55	0.89	-
Array Cables	-	-	<0.1	0.64	<0.1	0.44	-
Export Cables	-	-	<0.1	0.32	<0.1	0.34	-
Offshore Substation	-	-	<0.1	0.13	<0.1	0.14	-
Onshore Substation	-	-	<0.1	-	<0.1	<0.1	-
Support structure corrosion protection	-	-	<0.1	<0.1	<0.1	<0.1	-

Table 3.2: Relative contribution (in %) of components and life phases to carbon footprint and total life cycle emissions of the scaled HKN wind farm, provided as percentage, and distinguished by material impact (upper table) and logistics impact (lower table).



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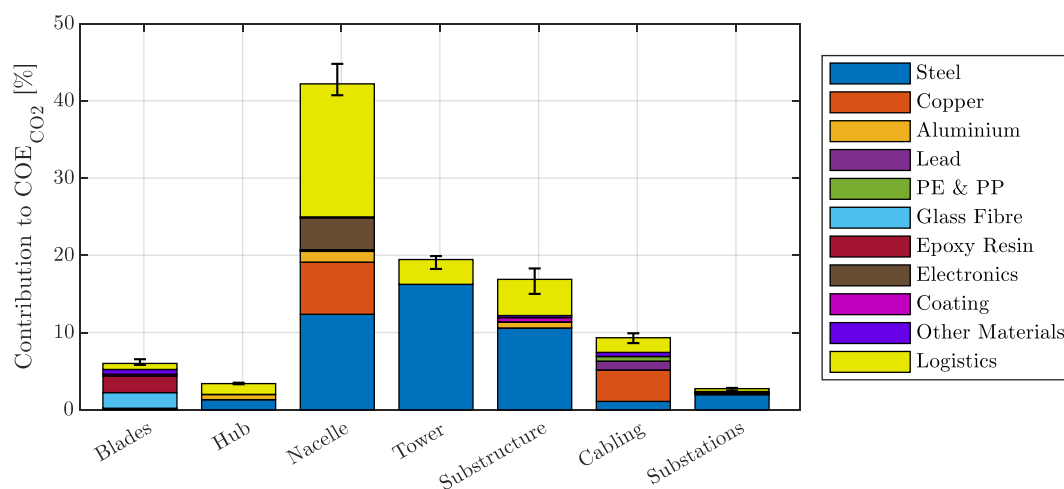


Figure 3.4: Carbon footprint of the scaled HKN wind farm broken down by components and materials / logistics. The error bars correspond to the 95% confidence interval of the results, caused by the uncertainties in the inputs as defined in Table 3.4 and propagated through DETECT.

	Steel	Copper	Aluminium	Lead	PP+PE	Glass Fibre	Epoxy Resin	Coating	Electronics	Logistics	Other Materials
Blades	0.12	-	<0.1	-	-	2.02	2.17	0.21	-	0.78	0.62
Hub, Pitch and Nose	1.32	-	0.68	-	-	-	-	-	-	1.40	-
Gearbox and Shaft	<0.1	<0.1	<0.1	-	-	-	-	-	-	<0.1	-
Generator	9.12	6.30	-	-	-	-	-	-	-	8.61	-
Electronics	-	-	-	-	-	-	-	-	4.11	1.70	-
Nacelle	3.25	0.45	1.40	-	-	0.10	0.11	<0.1	-	6.92	<0.1
Tower	16.24	-	-	-	-	-	-	-	-	3.21	-
Monopile	9.48	-	-	-	-	-	-	-	-	2.26	-
Transition Piece	1.12	-	-	-	-	-	-	-	-	0.27	-
Scour Protection	-	-	-	-	-	-	-	-	-	2.07	0.28
Array Cables	0.36	0.75	-	0.43	0.18	-	-	-	-	1.13	0.17
Export Cables	0.73	3.32	-	0.71	0.43	-	-	-	-	0.76	0.36
Offshore Substation	1.83	<0.1	<0.1	-	-	<0.1	<0.1	<0.1	-	0.36	<0.1
Onshore Substation	0.13	<0.1	<0.1	-	-	<0.1	<0.1	<0.1	-	<0.1	<0.1
Corrosion protection	-	-	0.79	-	-	-	-	0.55	-	<0.1	-

Table 3.3: Relative contribution (in %) of components and materials / logistics to carbon footprint and total life cycle emissions of the scaled HKN wind farm, provided as percentage. Materials with less than 0.5% contribution are bundled in the category "Other Materials".



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Table 3.4: Definition of uncertainties in the inputs, and first order and total effect Sobol indices resulting from the variance-based sensitivity analysis. Uncertainties are defined via the quantiles for the 95% confidence interval associated with the assumed normal distribution in the input parameters. The same distributions feed into the variance-based sensitivity analysis.

Parameter	Q _{2.5%}	Q _{97.5%}	Unit	S _i	S _T
Water depth at each turbine position	95	105	%wrt baseline	0.10	0.10
Wind farm lifetime	23	27	years	0.47	0.47
Distance to installation port	90	110	%wrt baseline	<0.01	<0.01
Distance to service port	90	110	%wrt baseline	<0.01	<0.01
Vessel engine load factor	90	110	%wrt baseline	0.25	0.25
Recycling rate	70	100	%	0.18	0.19

the wind farm lifetime contributes the most to the variance of the carbon footprint. This underlines the importance of properly modelling the lifetime of the studied wind farm, which is another focus of the SUDOCO project. Other significant uncertainties in carbon footprint result from the input distributions of the vessel engine load factor and recycling rates. The former demonstrates the strong impact of vessel activities on carbon footprint and highlights the importance of less polluting solutions in the future marine sector. The latter underlines the significant positive impact of high recycling rates with respect to climate change. Furthermore, the impact of water depth plays a significant role in the evaluation of carbon footprint, mainly linked to the sizing of the monopile support structures and the concomitantly required steel mass. In contrast, the distances to the installation and service ports feature negligible influence on carbon footprint, which can be explained by the relatively small share of vessel transfer from port to site with respect to total vessel operating hours.

3.2 Grid emissions displacements

3.2.1 Model performance evaluation

Germany is selected as case study to demonstrate the methodology and evaluate the performance of the tool predicting the displaced grid greenhouse gas emissions through marginal adjustment of the power output of a wind farm, MDF_{wind} . Data for the years 2022 and 2023 is used to describe the most current state of the energy system. Data from 2022 is used for training the ANN while data from 2023 is used for evaluation of the proposed methodology. The corresponding R^2 score for training and testing are found to be 0.94 and 0.9, respectively. These values show that the formulated ANN can successfully learn the complex relations between system operational states and grid emissions, and perform accurate predictions.

Figures 3.5 and 3.6 show the output obtained using the developed model for two



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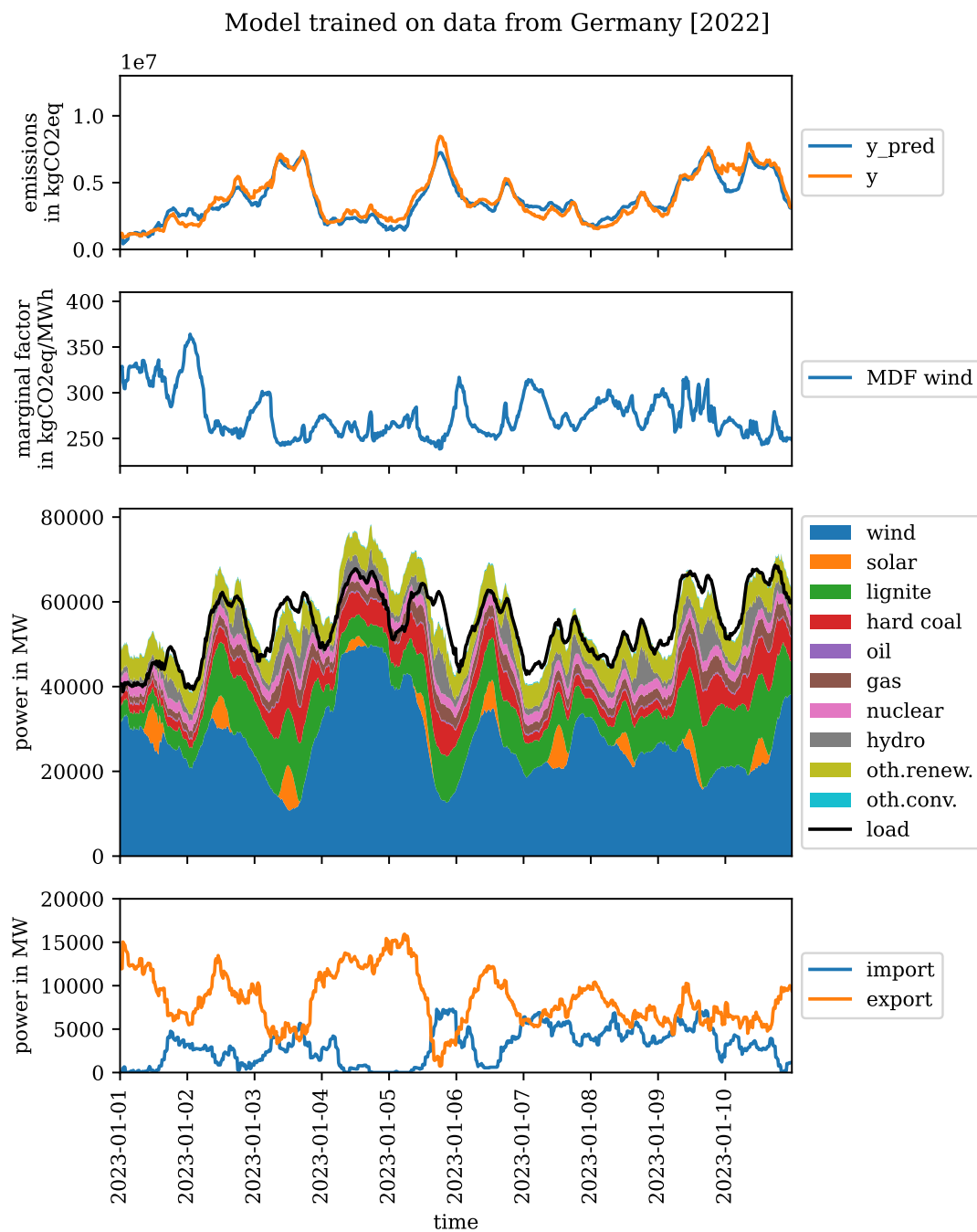


Figure 3.5: Results of the proposed model in winter (trained on data from Germany, 2022; tested with data from Germany, 2023), from top to bottom: emissions (calculated vs. predicted), absolute value of calculated MDF for wind, input variables regarding generation and demand, input variables regarding import and export.



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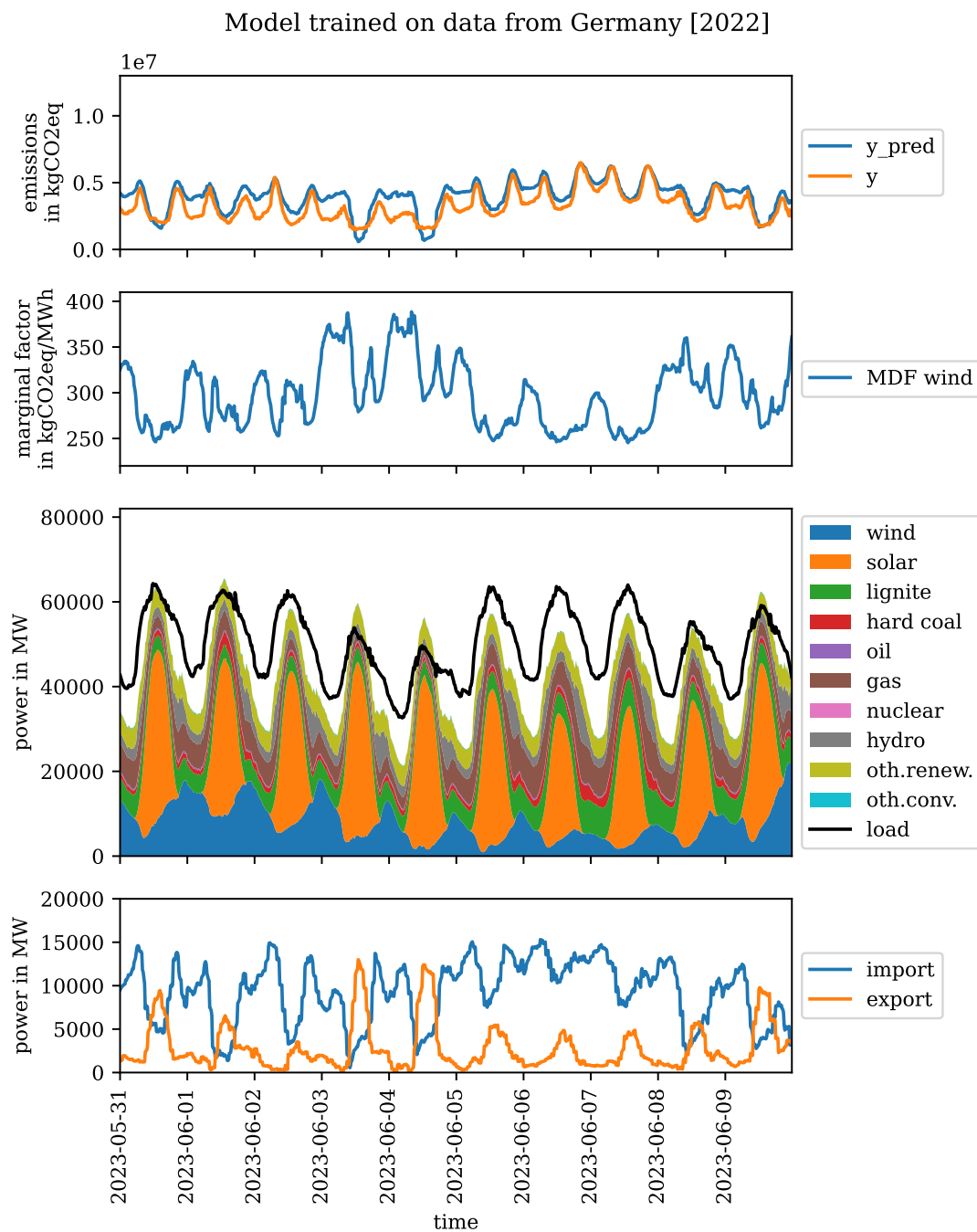


Figure 3.6: Results of the proposed model in summer (trained on data from Germany, 2022; tested with data from Germany, 2023), from top to bottom: emissions (calculated vs. predicted), absolute value of calculated MDF for wind, input variables regarding generation and demand, input variables regarding import and export.



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exemplary weeks of the year 2023, considered to be representative of the winter and the summer weeks, respectively. In both the figures, going from top to bottom, the subplots show the time series of calculated (labeled as y) and predicted (labeled as y_{pred}) total grid emissions in Germany, the corresponding time series of MDF_{wind} derived using the approach discussed in Sect. 2.2.3, technology-specific generation as stacked plots as well as the total demand (labeled as 'load') within Germany, and finally the total imports and exports with all the neighboring countries of Germany, respectively. The next paragraphs highlight several key observations for the exemplary time series. Generic conclusions are difficult to draw since MDF_{wind} appears to strongly depend on the operational state of the grid.

For the representative week in winter (Fig. 3.5), the total grid emissions predicted by the ANN match well with the actual values. Furthermore, a large share of demand is being met by wind energy. A strong negative correlation can be observed between wind energy generation and total grid emissions, which can be explained by the required compensation of power generation through fossil fuel-based power plants in times of low wind. Furthermore, in this winter week, the electricity export from Germany appears to be strongly correlated to wind generation. On the other hand, Fig. 3.6 shows that, for the exemplary summer week, the prediction of the total grid emissions by the ANN seems to have a noticeable error. This can be due to a higher fluctuation in load compared to the winter week and a higher share of electricity imports, which can induce uncertainties in the model.

The exemplary time series also show that in Germany, the MDF_{wind} is expected to lie in the range of 250 to 350 kg CO₂eq/MWh in the winter week. In the summer week, the MDF_{wind} goes up to 380 kg CO₂eq/MWh. Compared to the life cycle carbon footprint of the scaled HKN wind farm of 11.17 kg CO₂eq/MWh estimated by the DETECT tool (Sec. 3.1), this estimated MDF_{wind} is thus expected to be 22 to 34 times larger. This demonstrates the huge potential of emissions displacements that can be achieved by increasing the wind energy production in the German electricity grid.

Another observation is the strong dependency of MDF_{wind} on time with variations of up to 50%. This demonstrates the application potential of the presented model: it appears crucial to not only expand wind energy generation in general, but also to increase power production through wind farm control when it is most needed to displace a maximum of emissions on the electrical grid level. On the other hand, fatigue loading could be decreased when MDF_{wind} is low. The balancing of displaced emissions with the structural fatigue loads of turbines will be further explored in the SUDOCO project through development and application of the *Control Room of the Future*, considering also other aspects such as energy yield, fatigue loads, reliability, or economic revenue.

Furthermore, the exemplary time series also indicate that the MDF_{wind} tends



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to be higher when the total wind generation in the grid is low. This highlights the potential benefit of producing at low wind speeds when other wind generators cannot produce, which can, for example, either be achieved through wind farm control or through the design of wind turbines with low specific power.

Finally, it can be observed that the MDF_{wind} does not strictly follow the total absolute grid emissions. This justifies the need to consider marginal emissions in order to properly assess the potential of grid emissions savings through marginal changes in the power output of wind farms.

3.2.2 Use case “Wikinger” wind farm: displaced emissions through wind farm control

The following use case aims to assess the application potential of the developed model in the context of wind farm control. Specifically, the objective is to quantify the displaced emissions by an offshore wind farm when operated under a wind farm control strategy that aims to maximize the AEP.

The proposed model, including the neural network and the MDF calculation approach, is applied on the Wikinger offshore wind farm (Iberdrola, 2024) located in the Baltic Sea near the island *Rügen* in Northern Germany. The wind farm was commissioned in 2017, consists of 70 turbines, and has a total nominal power of 350 MW. The farm layout is suitable for improving total power output by yaw-optimized wake steering. The effect of wake steering within a wind farm is investigated using the simulation software FLORIS (NREL, 2024) and hourly wind data from ERA5 (Munoz Sabater, 2019) for the year 2023. This results in optimal yaw-offsets for each turbine that maximizes power for the given input wind condition. As the baseline operation, the wind farm operates under a ‘greedy’ control strategy, where each turbine within the farm maximizes its own output. The difference in power output between the two strategies at each point in time is calculated and multiplied by the corresponding MDF for wind at that time instant. This results in a time series of emissions that can be displaced by wake steering at each time instant. The sum of the emission time series results in the total possible emission savings for 2023. The maximum observed power gain was found to be approximately 50 MW. This value is within the step length $P_{\text{gen}}^{\text{wind}}$ of the central finite difference method used to calculate the MDF of wind, as shown in Eq. (2.11). This validates the applicability of the proposed approach to calculate MDF_{wind} for this use case.

Figure 3.7 provides two exemplary time series of the additional power generation through wake steering, and the associated additionally displaced grid greenhouse gas emissions. Similar trends are observed for both quantities, resulting from relatively low variations in MDF_{wind} (see Figure 3.5 and Figure 3.6). For the whole year of 2023, the optimal increase of power by wake steering is estimated to yield an extra 47,123 MWh for the Wikinger wind farm, which corresponds to 3.03% of the



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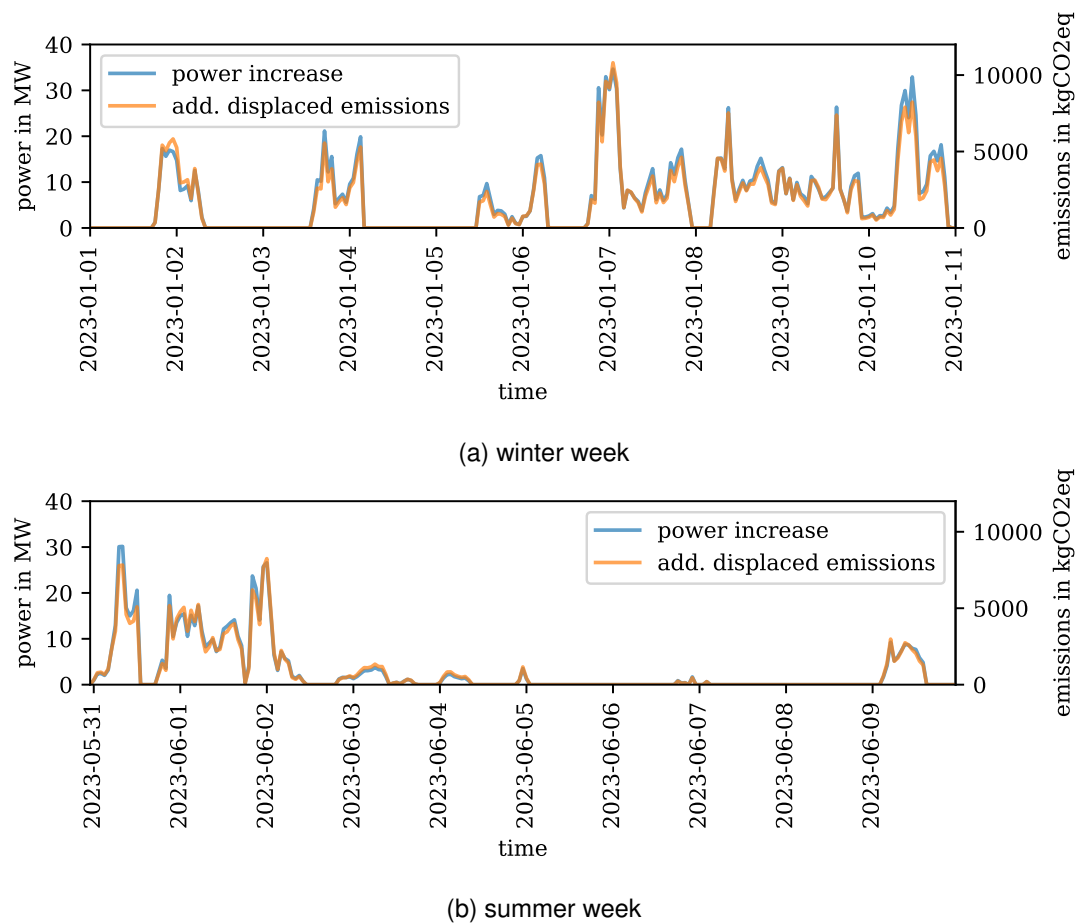


Figure 3.7: Exemplary time series of increased power production through wake steering and the associated additionally displaced grid greenhouse gas emissions for the Wikingen wind farm (a) in winter, and (b) in summer.

annual baseline production. Linking the time series of power gained by wake steering with the predictions for MDF_{wind} , the related total additional displaced emissions in 2023 are found to be 13,474 tCO₂eq.

To put these values into perspective, the displaced emissions are compared to the life-cycle emissions of the Wikingen wind farm itself. Applying DETECT on the wind farm, the total greenhouse gases emitted over the whole life cycle are determined as 1,343,600 tCO₂eq. The potential additional displaced emissions due to power increase through wind farm control in the year 2023 then have a share of 1% of the total wind farm emissions. Assuming that 2023 is an average representation of the wind resource and electrical grid condition over a 25-year lifetime of the wind farm, 25% of the plant's life cycle emissions can be displaced solely by increasing power generation with wind farm control. This estimation assumes a fixed lifetime



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and no additional emissions due to extra maintenance induced by wind farm control actions. Future work in the SUDOCO project will investigate the trade-offs between energy yield, fatigue loading, economic revenue, and displaced emissions.



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4 Conclusion

This deliverable has presented the methodological development of two tools developed at TUM that quantify the environmental cost and value linked to the design and control strategies of wind farms. The tools have been showcased by means of case studies to demonstrate their capabilities and evaluate their performance.

The first tool, DETECT, allows for holistic and automated evaluation of the carbon footprint (COE_{CO_2}) linked to most common European wind farms based on their design configurations and site characteristics. Using Life Cycle Assessment, all life phases of the individual plant components are modeled from cradle to grave. Furthermore, DETECT includes the capabilities of uncertainty quantification and sensitivity analysis in order to identify the drivers of emissions linked to the design of wind farms. To showcase the tool's capabilities, DETECT has been applied on a rotor diameter scaled version of the HKN wind farm featuring 69 IEA 22-MW turbines. The carbon footprint (COE_{CO_2}) of the wind farm is calculated as 11.17 kg CO₂eq/MWh. A detailed breakdown of the emissions by components, materials, logistics, and life stages has been presented. The results show that the production of steel components and the vessel operations with associated fuel consumption contribute the most to the overall emissions. Within the SUDOCO project, future work will explore the potential of reducing the carbon footprint of offshore wind farms through control strategy optimization and control co-design activities.

Beyond the quantification of the carbon footprint of a wind farm, its environmental value can be determined via the associated displacement of fossil energy emissions in the connected electrical grid. To achieve this, the second tool introduced in this deliverable is designed to estimate a time series of the marginal displaced emissions through wind energy generation in dependency of the operational state of the electrical grid. Following a data-driven approach, an artificial neural network first predicts the instantaneous total emissions of the grid. The marginal displacement factor of wind is then defined as the partial derivative of these grid emissions due to an incremental change in wind power generation. The model is designed to be adaptable to any desired control zone, country, or (bilateral) market zone in the European Union.

To demonstrate the capability of the data-driven approach to predict grid emissions displacements, the case of the German electrical grid has been selected as a case study. The model is trained using data from 2022 and applied to predict results for the year 2023. The developed model is able to properly predict the time series of total grid emissions, especially in winter when the wind energy generation has a



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large share of the total load. In this case, the MDF_{wind} lies in the range of 250 to 380 kg CO₂eq/MWh, which is 22 to 34 times larger than the carbon footprint of typical offshore wind farms in Europe. This demonstrates the large potential for alleviating net emissions by increasing wind energy production. Another important takeaway is that the MDF_{wind} is strongly time-dependent, owing to the complex interactions on the whole electrical grid. As a consequence, it is crucial to not only increase wind energy generation, but to do so when it is most needed to displace a maximum of emissions on the electrical grid level. Finally, the Wikingen offshore wind farm has been selected as a wind farm control application case in order to quantify the potential additionally displaced emissions by utilizing wake steering-based wind farm power increase strategies. In this scenario, the wind farm is estimated to additionally displace 13,474 tCO₂eq for the year 2023 due to the application of wind farm control. To put into perspective, this would correspond to 25% of the plant's own life cycle emissions (considering fixed lifetime and O&M activities).

In future work, the two presented models will be further developed and applied to other application cases. The DETECT tool will be used to conduct multi-objective design optimizations of wind farms to quantify possible trade-offs between economic profit and environmental value. The grid emissions displacement tool will be further validated and applied to new case studies for estimating the potential of emissions displacements using wind farm control. Both tools will be integrated into SUDOCO's *Control Room of the Future* aiming to consider the environmental cost and value linked to wind energy generation in wind farm control optimization and co-design applications next to energy yield, fatigue loads, reliability, and economic revenue.



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