ACCELERATING THE DECARBONIZATION OF ISLANDS' ENERGY SYSTEMS

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INDIVIDUAL RENEWABLE SUPPLY GENERATION FORECAST MODELS

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Change Control

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2 ABBREVIATIONS

Short Name	Meaning
RLM	Real-Load-Metering
WRLM	Without Real Load-Metering
CHP	Co-generation units
W	Watt
PV	Photovoltaic
H2	Hydrogen
ESPS	Emergency Standby Power Systems
DC	Direct Current
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NMAE	Normalised Mean Absolute Error
API	Application Programming Interface

3 EXECUTIVE SUMMARY

Task 4.2 of ISLANDER was dedicated to develop individual renewable supply generation forecast models. The present work was focused on photovoltaic and wind turbine power generation forecasting. The objective was to develop a 2-days ahead forecast (lead time from +0 to +48hours) with an hourly granularity for the PV and wind turbine production, with the further aim of computing the global production of the island of Borkum.

In a first main step of the study, historical data was collected from 3 main sources: (i) a wind farm; (ii) a large PV park (iii) 2 small PV parks.

More than 4 years of historical data (from January 2017 to January 2021) was collected from Borkum's utility company. The pre-treatment and analysis of this input data was very time consuming as data quality was poor (inconsistency, missing data, false data). Many filtering or altering processes had to be applied to the collected data. At this point a first study consisted in analysing the in-situ measurements measured on the Borkum island, and improving data quality to be able to test models on the data was carry out.

In order to deliver forecasts of renewable production, this study proposed a physical approach using asset characteristics and weather forecast as inputs. In the final test, these models were tested on data from 2017 to 2020.

The forecasts are used as inputs of the global production forecast model, and will be used in the future to predict individual PV production of households and businesses.

4 INTRODUCTION

This deliverable aims to explain the development of wind turbine and photovoltaic park production forecasting models, i.e. the intermittent renewable electricity sources located in Borkum.

Forecasting individual renewable energy power production becomes crucial in the context of smart grid technologies at a household or business level. By accurately predicting the amount of renewable energy that will be generated, the energy consummed and stored by households and businesses can be effectively managed. With precise forecasts, a smart IT platform can optimize the utilization of self-generated power, ensuring efficient use and minimizing reliance on the grid. This enables greater control over energy costs and promotes sustainability by maximizing the use of clean energy sources. Accurate forecasts also facilitate effective battery storage management, allowing excess energy to be stored for later use during periods of low generation or high demand. Furthermore, forecasting empowers users to make informed decisions about energy usage, enabling them to align their activities with periods of abundant renewable energy supply. Ultimately, forecasting individual renewable energy power production promotes energy self-sufficiency, cost savings, and environmental sustainability at the household or business level [1].

This deliverable will begin by providing an overview of the context and objectives. Subsequently, the methods employed will be described, followed by a presentation of the forecast results and subsequent discussions. Data forecasts will be sent daily to the smart IT platform through communication protocols developed in the context of the WP4. The section about industrialisation and communication protocols is detailed in deliverable 4.5 [2], as identical procedures have been applied to make the PV and wind production forecasting algorithms operational.

5 CONTEXT AND OBJECTIVES

5.1 Objective of the task and deliverable

As detailed in the Grant agreement of the project, Task 4.2 aims at developing a "module [that] will deliver estimations about the production of the renewable assets within the grid". The module combines fundamental physics data and manufacturer information to accurately depict the product of renewable energy units. By integrating these sources, the module can effectively derive power production based on weather forecasts.

5.2 Value of the task in the rest of the project

The short (a few hours) to medium-term (a few days) forecast of power production from individual renewable assets (PV and wind farms) is required as an input for the energy management system (the smart IT platform) in order to optimize energy flows and storage on the island. The underlying objective of task 4.2 is to maximise the accuracy of the power production forecasts: the better the forecast performances the better the energy management decisions. Notice that the optimization will, in the long-term, be made more efficient by an increased forecast accuracy as well as a higher forecast update frequency (the latter being limited by the availability of new weather forecast as well as near "real-time"

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production measurement feedback).

5.3 Problem statement

The specific objective of the task is to provide a software module that forecasts power production from each renewable production unit on the island that is monitored in the smart IT platform, i.e. the following assets:

- The 2 wind turbines production farm (3.6 MW total capacity);
- The large (1.4 MWp) PV field and 2 small PV fields (40 kWp and 80 kWp)
- The individual households (30 units planned) and buildings (3 planned) PV production units (notice that, since these assets are not operational at the time this deliverable is written, no forecast has been made available nor tested for these systems).

In agreement with the requirements expressed by WP3 (Smart IT platform development), the power production forecasts will be delivered with the following specifications for each renewable asset:

- Hourly forecast of the average power production;
- A forecast horizon of 2 days (from +1 to +48 hours, i.e. 49 data points) for short term optimization and potentially valuing energy on the market ;
- The forecast will be made available each day at 9am.

5.4 Background

During the previous NETfficient project held in Borkum, the consortium worked on global consumption and production forecasts. This project ended in 2018. BCM contacted the partner in charge of the models and discussed the issues encountered and the strategies chosen. However, it was not possible to have access to the NETfficient data nor to the model created. Therefore, BCM built global consumption and production models from scratch.

5.5 State of the art

5.5.1 Photovoltaic power forecasting

To introduce the problem of forecasting power plant production, the needs of this prediction must be assessed first. In their article, Brancucci Martinez-Anido et *al.* [3] conclude that having a reliable power prediction system significantly reduces the energy production cost in a multi-technology ecosystem by optimising the start and shutdown of other energy sources as a function of the solar energy forecast.

Antonanzas et *al.* [3] gives an overview of the state-of-the-art knowledge about solar power forecasting, studying various time horizons (from a few seconds to days or weeks ahead) and spatial horizons (from a single site to regional forecasts). It also includes the usual metrics used for evaluating time series models. It is valuable information to decide on the best solution for Borkum. It confirms the value and relevance of a physical model and how other types of models could complement it.

Dolara et *al.* [5] and De Soto et *al.* [6] offer in-depth analyses of physical models and present how a solar panel can be modelled with a finite set of parameters, computed for each panel model at reference conditions and enable the forecast of power generation in any operating conditions.

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Interestingly, a recent paper [7] has demonstrated that while properly trained machine learning algorithms outperform first principles in terms of power production forecasts for individual assets or portfolios with up to 100 systems. However, when evaluating the same models in terms of financial performances on the day-ahead electricity market (the study focuses on The Netherlands) the physical model outperforms all machine learning approaches.

5.5.2 Wind power forecasting

Wind turbine forecasts have been widely studied from the early beginning. Output power modelling has been a major focus because of the central role of this information within the development and operational lifetime of wind power plants. This particular part of the study can be split into two different domains:

- Production scenarios reconstitution (historical or not) industrially implemented to compute power plant performances without having any realised signal. This part does not integrate the scope of the proposed study.
- Production forecasts over a determined time horizon (from 30 minutes to months). This point is the main interest of this work package for which day-ahead forecasts are required for Borkum wind turbine plants.

Different models can be implemented with varying degrees of complexity to provide reliable forecast signals for Borkum's wind turbines. Literature proposes interesting papers with complete descriptions of the most widely used implementations [8], [9].

A power-curve-based implementation is proposed for this work package as a first development step, as described in [10]. This choice is motivated by:

- The relatively low modelling error level that can be reached.
- The integrated physical modelling that allows the integration of machine parameters such as power curves and global performance ratio directly.
- The integration of the weather forecast work package provided in this project (task 4.3) aims to enhance the weather prediction and the input of this model.

5.6 Hypothesis – assumptions

The physical laws govern the response of the installations to the prevailing weather conditions. In simpler terms, they determine the amount of electricity generated as a function of the input features. By coding those physical laws and machine characteristics, the model can be implemented.

As first approximations we hypothesize that the power production depends on a limited number of weather variables depending on the technology:

- Photovoltaic electricity production: PV power depends principally on solar irradiance on the system (with air temperature and wind cooling effects as "corrective" variables to account for module temperature efficiency dependence [11].
- Wind electricity production: Wind power depends on the kinetic energy of the air incident on the turbine blades: the produced power depends mainly on wind speed as well as air pressure and temperature (that modulate air density) [12].

With the assumption that the physical laws can be correctly transcribed into code, the model is independent of any learned parameter, unlike machine learning models.

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6 METHODS

6.1 Data analysis

This section aims to analyse the raw data sent by the Borkum utilities and explain the work carried out to clean this data.

6.1.1 PV power production data

Three photovoltaic (PV) plants produce energy on the island. Their production has been metered in real-time on a fifteen-minute time step, from 2017/01/01 for the main park and from 2018/01/01 for the two smaller parks and plotted in Figure 1 and Figure 2. Solar production follows a yearly bell shape with higher production in summer, up to 40 kW, 80 kW and 1300 kW, respectively. Scale errors in raw data in 2019 for the smaller parks and 2020 for the main park were detected due to a pre-processing issue when converting data from a one-hour granularity to a fifteen-minute one. Therefore, the related power neededs to be multiplied by a correction coefficient of four. Also, data were missing in the production of photovoltaic systems 0095 and 0054 towards the end of 2019. Whether this is just a case of missing data, the result of breakdowns or a voluntary cut-off for maintenance is unknown. In order to predict further missing values, it would be crucial to collect a calendar of the performed and planned maintenance and set up a warning system.

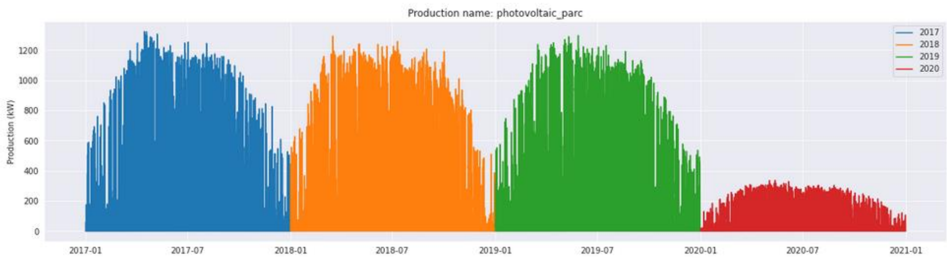

Figure 1: Production load curve of the main photovoltaic park, before data cleaning

Figure 2: Production curves of the two smaller photovoltaic parks before data cleaning

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Finally, a discontinuity of the production of the photovoltaic plant 0054 was noticed: production fell from 70 to 60 kW during the summer of 2020. This drop is unexplained.

6.1.2 Wind turbines production data

The two wind turbines of Borkum – wind turbines 2513 and 2510 as numbered in Figure 3 - are producing up to 1755 kW. During periods of 2019 and in 2020, the production seems to be curtailed under 1500 kW, with different behaviors for each turbine. It is unknown if there is a physical explanation for these lower values or if they are due to data pre-processing artefacts. Besides, the load curve of the wind turbine 2510 has missing data from 2018/01/01 to 2018/01/06.

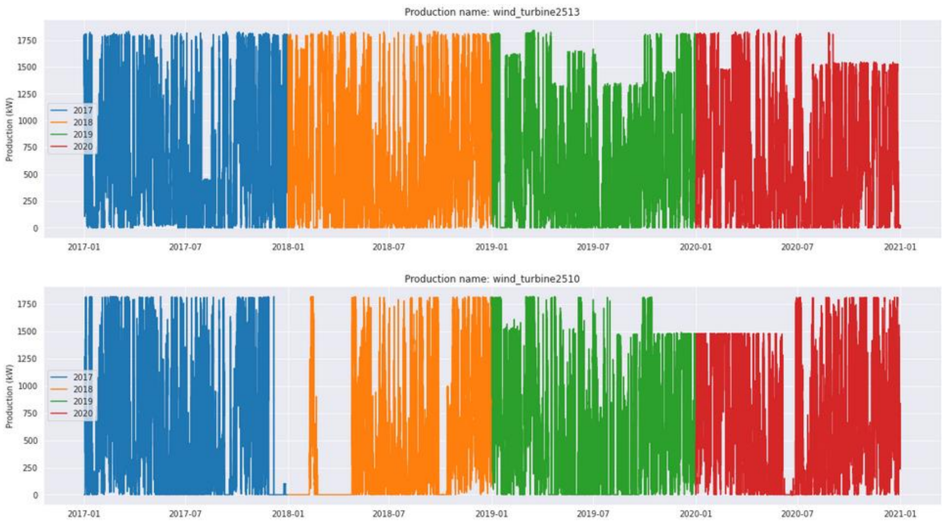

Figure 3: Production curves of the wind turbine energy production from 2017 to 2020.

6.2 Forecast module development

6.2.1 Wind turbine model

Introduction to wind turbines

The first version of the forecast model provided in this task is based on the physical modelling of wind turbines. Since the early beginning of wind turbine development, numerous models have been proposed helping scientists to reach a valuable degree of fidelity from a comprehensive simulation framework.

The flowchart of the wind power forecast is illustrated within the Input/Output figure presented in Figure 4. As one can see, four main components are depicted:

- The core numerical simulator introduced as the *'Wind Power Forecast Model'* aims to transform weather forecasts into power forecasts.
- The simulation parameters, regrouping the variables and specific fields used to adapt the model to the asset of interest.
- The weather forecast database can be composed of several sources depending on the simulation goals.

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- The production Forecast Database to store simulation results.

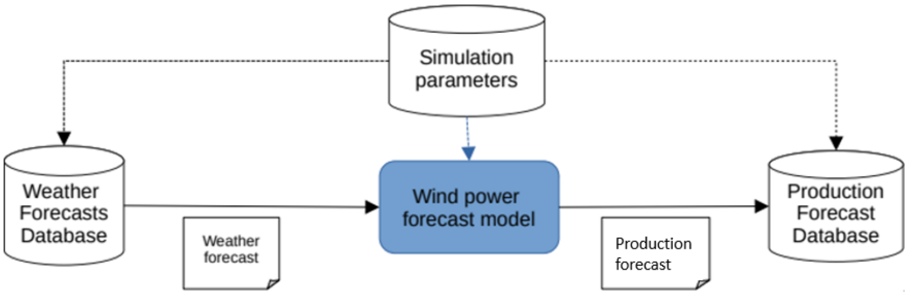

Figure 4: Flowchart of the wind power forecast

The following proposes specific explanations to ease pipeline and model comprehension. An illustration of the performances of this pipeline is then proposed based on real condition simulations adapted from Borkum wind turbine installations.

Wind power forecast model

To ease comprehension, the first component of the physical pipeline to be described is the core forecast model. Wind turbines can be assumed to be mechanical transformers that convert wind power into electrical power. As a result, their behaviour can be described as transfer functions mapping wind speed to electrical power. These latter are usually called «power curves» and globally represent the deterministic behaviour of the mechanical assembly. As an illustration, Figure 5 depicts the power curve of the Enercon wind turbine model.

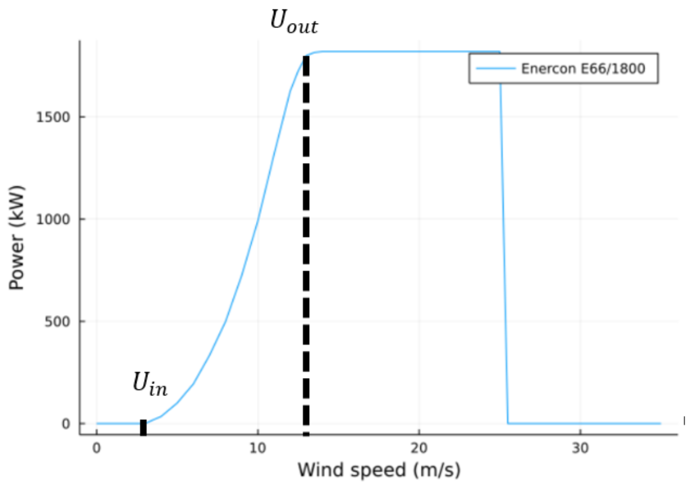

Figure 5: Power curve of the Enercon E66

Three domains are distinguishable:

- The low wind speed zone from 0 to U_{in} for which the turbine does not output any power.
- The operational domain for wind speeds between U_{in} and U_{out} corresponding to production to the grid.

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- The high-speed domain for wind speeds upper than U_{out} where the turbines stall for safety reasons.

The physical model is implemented based on these physical considerations. First, the temperature, wind speed and pressure are extracted from the weather forecast database. A pre-processing stage is integrated into the power forecast model to adapt these parameters to the model requirements. This step stands on physical modelling to provide an adapted wind speed at hub height. This wind speed becomes then the input of the power-curve projection, and a power forecast is deduced.

Additionally, to be as close as possible to the machine behaviour, this step only proceeds for wind speeds between U_{in} and U_{out}.

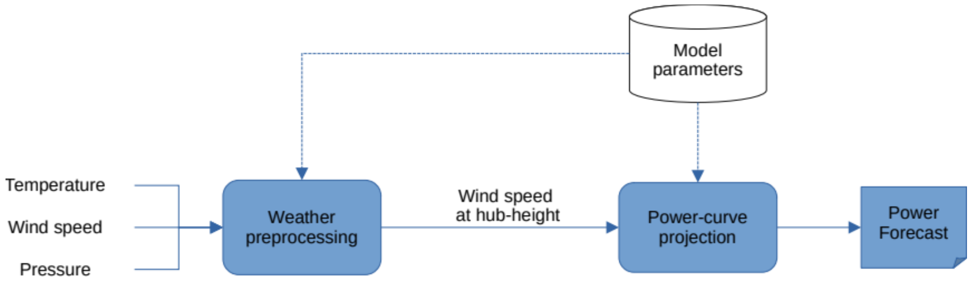

Figure 6: Flowchart of the wind turbine power forecast in an operational configuration

Weather forecasts as input sources of the pipeline

The physical modelling of wind turbines is based on weather solicitations of various types. In the proposed model, several weather parameters are taken into account:

- The temperature.
- The pressure.
- The wind speed.

To provide an accurate input for the physical model, these environmental parameters are extracted from weather forecast models (see Fischer et *al.* [13] on this topic). Depending on the data source, these parameters must be adapted to reach model requirements.

6.2.2 PV model

Introduction to photovoltaic system

A photovoltaic system consists of numerous solar cells mounted together in a system, as described in Figure 7. A group of solar cells creates a solar module, and several solar modules are solar panels. A PV system is a framework of solar panels together with additional components. This renewable production system is used to transform solar energy into electricity.

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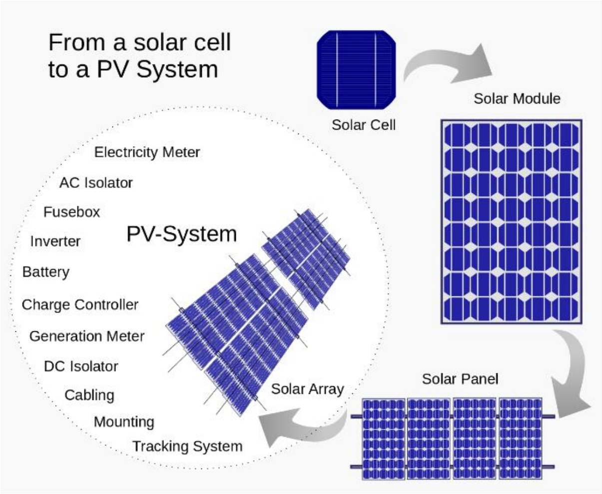

Figure 7: Photovoltaic system

To model and predict the power production of a photovoltaic system, two types of inputs are needed:

- The characteristics of the installation
  - Coordinates data
  - Array angles of the panels and tracking data
  - Soiling data
  - Losses data
- The weather previsions
  - Irradiance (Watts per square meter W/m²)
  - Time of day
  - Temperature
  - Wind speed (as meters per second, m/s)

Physical model

The process of predicting the power production can be divided into two main parts:

1. The irradiance computation: compute the exact irradiance received by the panels depending on the time of day, location, array angles, tracking of the panel, and weather predictions.
2. The power computation: compute the power created from this irradiance from the physical characteristics of the panels.

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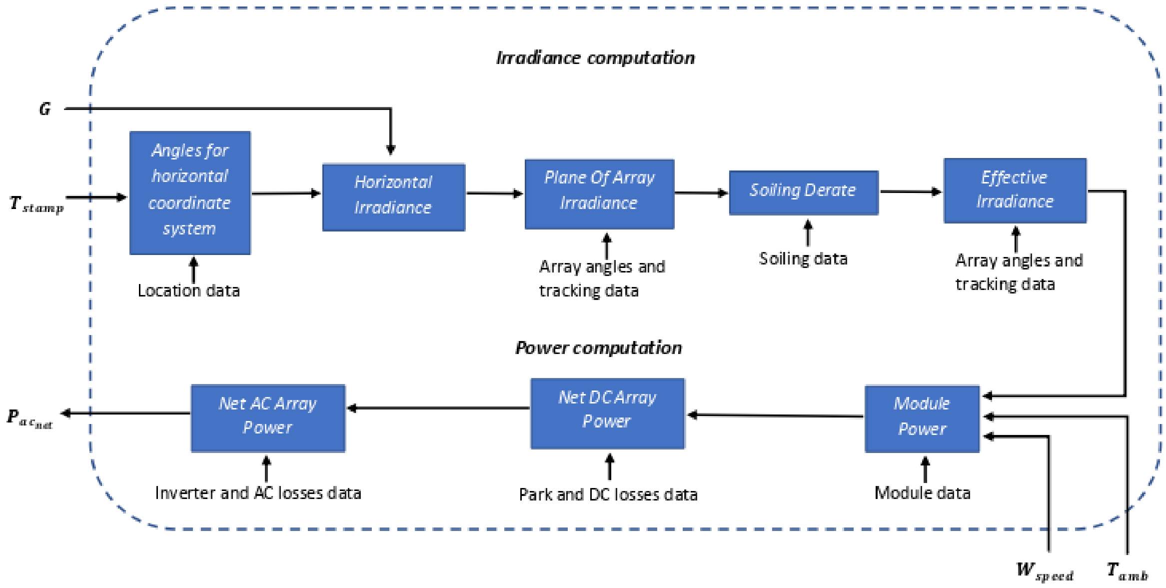

Figure 8: Irradiance computation

The irradiance computation:

1. The first module computes the localisation of the system in the world and what will be the incidence of the Sun's radiation at this location. It depends on the day of the year, the time of the day (and thus the location of the Sun compared to the Earth at this time of year). This module uses several types of coordinates and computes angular relations to output the sun angles at the location and time of prediction.
2. The second module is in charge of predicting the horizontal beam irradiance and diffuse horizontal irradiance received from those Sun's angles at this location. It takes into account the air mass and atmospheric transmittance and uses several mathematical models to determine the irradiances.
3. The next module applies those irradiances to the panels, introducing the angles and tilt of each panel with the ground. It computes the angles of incidence and the diffused and reflected irradiance.
4. Next, the soiling module considers the self-soiling of the panels and how it affects the irradiance received by each module.
5. Finally, the effective irradiance module sums everything above to output the watt per square meter received by each panel.

The power computation:

1. After that, the model has to transform the watt per square meters of solar power data to watts of electrical power taking into account the losses of the array. The power computation starts by computing the energy for each power cell which depends upon the installation model. It then multiplies this by the number of cells per panel to get the power at the output of each PV panel.
2. The next module computes the net DC power for each array, being the sum of the power of its panels. This is the gross power as it computes and applies the DC losses, which are, to the only name a few: the wiring losses, the nameplates losses, etc.
3. Finally, everything is put together to get the power prevision of the installation.

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6.3 Performance metrics

Error metrics used in the following parts of this document have been defined in detail in deliverable 4.5 of the project [2], only the formulas will be reminded here for the convenience of the reader.

Let $y_1, y_2, \ldots, y_n$ be the observations of the target at time steps $t_1, \ldots, t_n$ and $y_{hat_1}, y_{hat_2}, \ldots, y_{hat_n}$ the forecasts made for the same period. For i in $\{1, \ldots, n\}$ the prediction error is computed by the formula $\varepsilon_i = y_{hat_i} - y_i$.

- Bias : $BIAS = \frac{1}{n}\sum_{i=1}^{n} \varepsilon_i$
- Mean absolute error: $MAE = \frac{1}{n}\sum_{i=1}^{n} |\varepsilon_i|$
- Mean absolute percentage error: $MAPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left|\frac{\varepsilon_i}{y_i}\right|}$
- Normalized mean absolute error: $nMAE = \frac{MAE}{\frac{1}{n}\sum_{i=1}^{n} y_i}$

7 RESULTS & DISCUSSIONS

7.1 Wind turbine model

A performance analysis has been proposed to evaluate the reliability of the proposed forecast model. The parameters of this study are displayed in Table 1.

Begin date	2021-01-01
End date	2021-12-31
Power turbine	Enercon E66/1800
Number of turbines	2
Turbine efficiency	95%
Weather forecast model	00:00 UTC ARPEGE RUN

Table 1: Information on the back-testing conducted for the wind turbine production

The forecast analysis is proposed to cover the two days ahead production period based on the D-1 ARPEGE run of 00:00 UTC. The study showed that the physical model based on the power-curve implementation is reliable. Table 2 sums up the analysis results from metrics, and Figure 9 proposes an illustrative comparison between the forecast and the realised production over January 2021.

Bias	323.28 kW
MAE	616.89 kW

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NMAE	51 %
Data coverage	98%

Table 2: Results obtained with the physical model on the MAE (Mean Absolute Error) and NMAE (Normalized Mean Absolute Error) for the wind turbine park

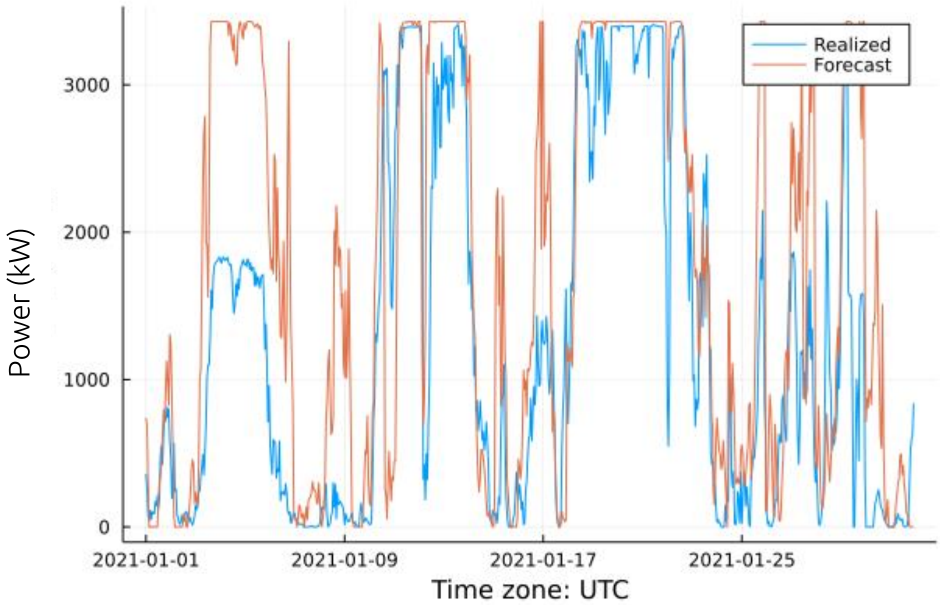

Figure 9: Power produced during an hour by the wind turbine expressed in kW– the blue plot is the realised production, whereas the orange plot is the prediction. The forecast has been evaluated for the wind turbine park composed of the 2 turbines.

The power-curve modelling used in this study to forecast Day Ahead production shows an industrially admittable error with a mean bias of 323 kW (power produced during an hour) and an MAE of 616 kW. The nMAE remains high with a value of 51%, mainly explicable by the lack of information concerning the production state of the turbines.

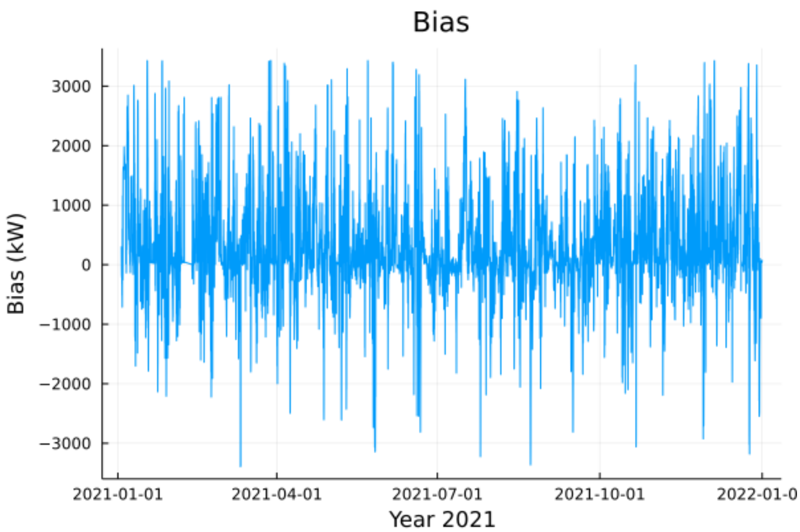

Figure 10: Overall bias of the wind power forecasted versus the realised data during 2021

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The results are analysed by looking at the bias over time at different scales. The 2021 bias is presented in Figure 10. However, studying the mean bias over the hour of day and month of the year did not lead to valuable conclusions. Indeed, the bias is higher in correlation with the production volumes during the nights and winters. To have an overview of the impacts of the hour of the day and season, the heatmaps of the bias and nMAE are compared as a function of the hour and month presented in Figure 11 and Figure 12.

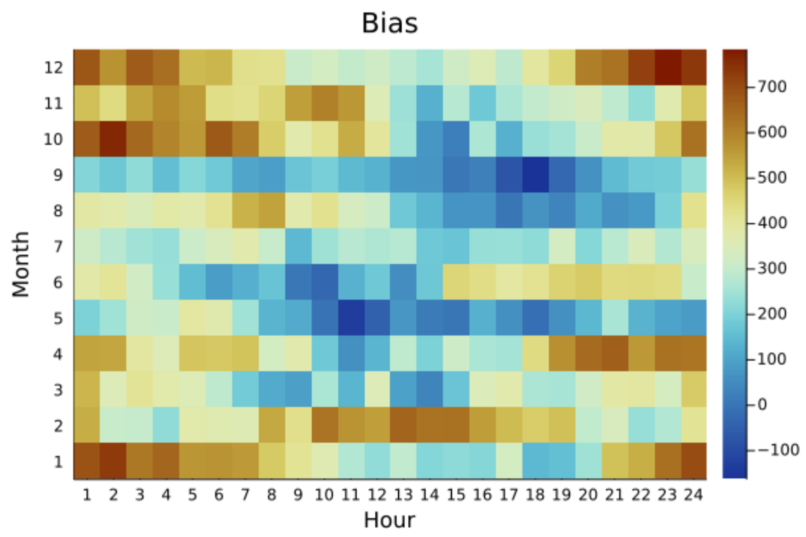

Figure 11: Heatmaps of the bias as a function of the hour and the month (expressed in kW)

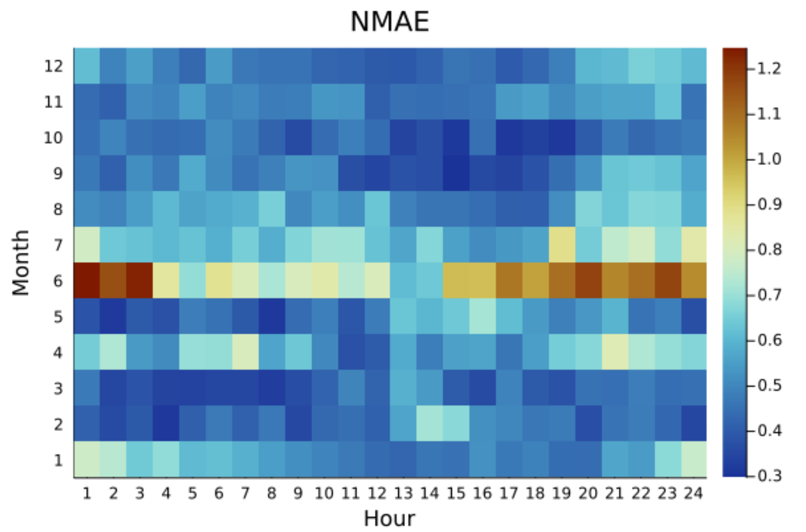

Figure 12: Heatmaps of the nMAE as a function of the hour and the month

What can be concluded is that the nMAE seems to be weighed down in June, which represents only 4% of the year's production. As stated above, the highest bias is during the winter nights, even though the nMAE is quite low at those times.

To enhance these models, precise information on the state of production could be added, such as maintenance, regulations due to weather conditions, or fault modes. To do so, the metric was calculated only when the power of the two turbines did not differ by more than 10%.

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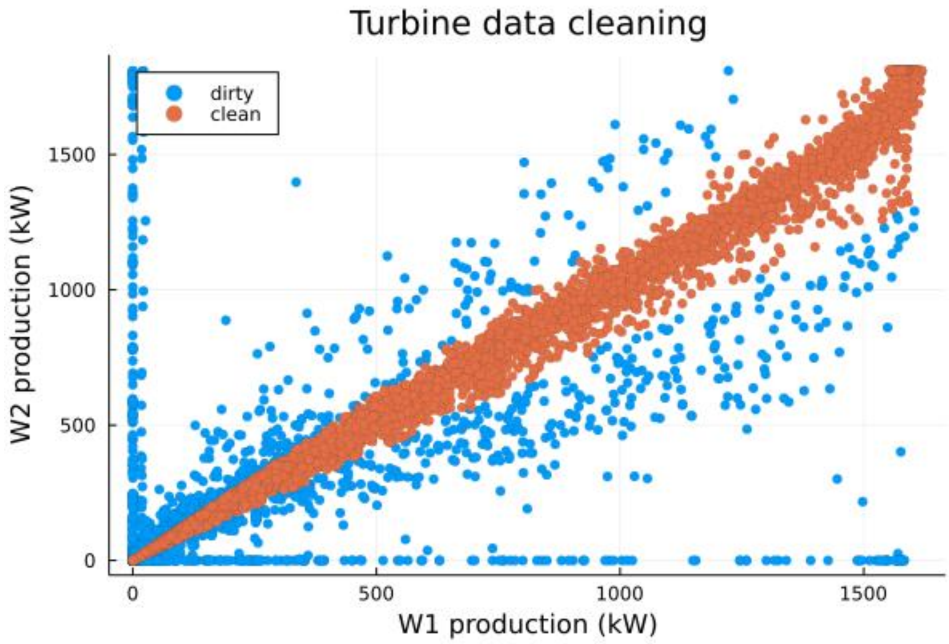

Figure 13: Graph of the production of wind turbine 1 versus wind turbine 2. The blue points represent the raw data, whereas the orange only the data on which the power produced by the 2 turbines does not differ more than 10%.

Cleaning the data allows to improve the nMAE by 10%, showing the importance of having "on the spot" data.

Bias	258 kW
MAE	655 kW
NMAE	40 %

Table 3: Results obtained with the physical model on the MAE (Mean Absolute Error) and NMAE (Normalised Mean Absolute Error) for the wind turbine park using cleaned data

Finally, this physical model can be improved by implementing statistical approaches, which have shown relevant enhancement over traditional approaches, as illustrated by Barbosa de Alencar et *al.* [8].

7.2 Solar powerplant model

The performance of the photovoltaic forecast is evaluated with the same metrics as above. The parameters used in the analysis and the results are presented in Table 4.

Begin date	2021-01-01
End date	2021-12-31
Photovoltaic installation	Borkum 1400 kW
Weather forecast model	00:00 UTC ARPEGE RUN

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Data coverage	92 %
Bias	1.36 kW
MAE	60.0 kW
NMAE	34 %

Table 4: Results obtained with the physical model on the MAE (Mean Absolute Error) and NMAE (Normalised Mean Absolute Error) for the PV park

First, looking at the bias and MAE, it can be concluded that, regarding the overall Borkum balance, the photovoltaic production forecast would not induce a significant error compared to the total island energy. As the bias is small compared to the MAE, it can be concluded that the model error is centred - the chance of predicting higher or smaller energy is quite equivalent.

The MAE of 34% is acceptable considering the condition of this study. A lot of information was indeed missing, and data had to be interpolated when possible. To give some examples of possible reasons explaining the nMAE :

- As the exact characteristics of the parks were unknown, it was not possible to properly tune the hyperparameters (shading, etc.).
- The maintenance and stops of the park are unknown and thus not taken into account.
- The park losses efficiency over time.
- The island has specific weather due to its conditions which are hard to analyse.

In Figure 19, the behaviour of the nMAE over time is further highlighted.

Below are plotted side-by-side the forecasted and realised load curves. Because of the scale, Figure 14 cannot be directly analysed, but it gives an overview of the production over one year.

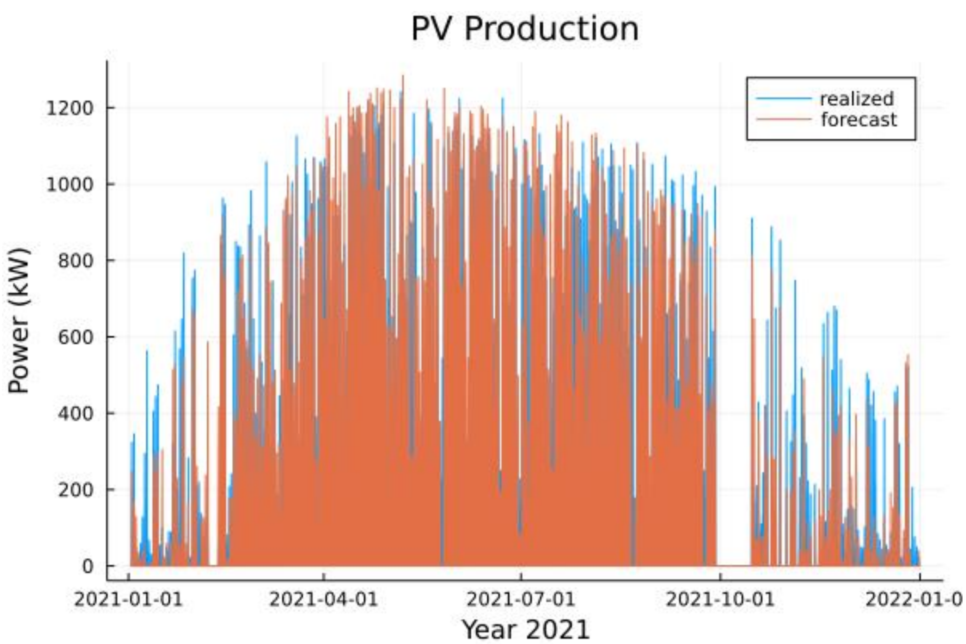

Figure 14: Realised and forecasted load curve over 2021 for the photovoltaic installation

The following Figure 15 shows the bias over 2021. As stated above, it confirms that the bias is

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centred and typical of a photovoltaic forecast model.

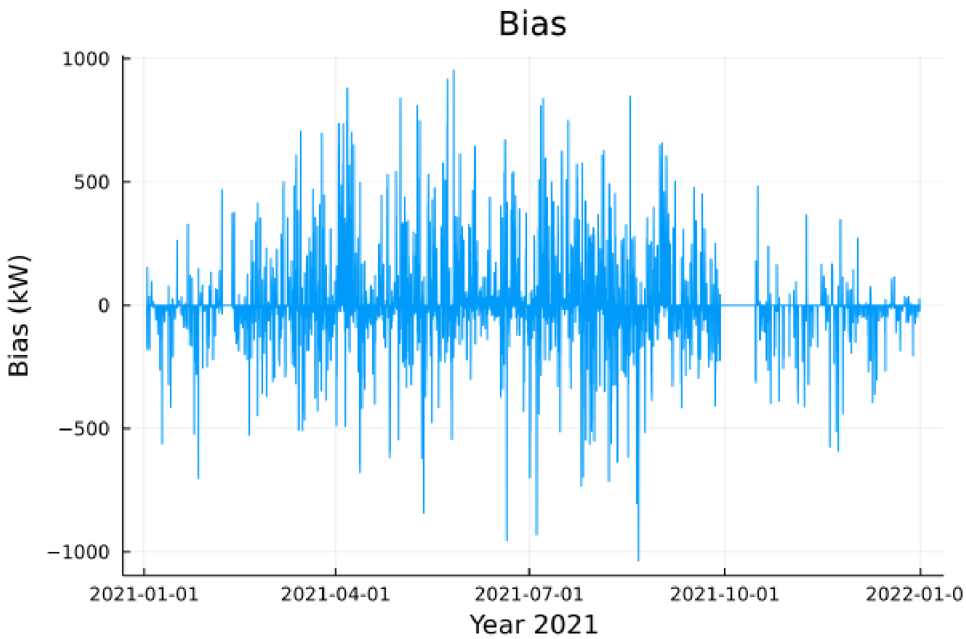

Figure 15: Bias (realised - forecast) of the photovoltaic model over 2021 expressed in kW

To further analyse and understand the behaviour of the model, several plots were outputted to examine the performance (particularly the bias) according to the hour of the day (Figure 16) and on the month of year (Figure 17).

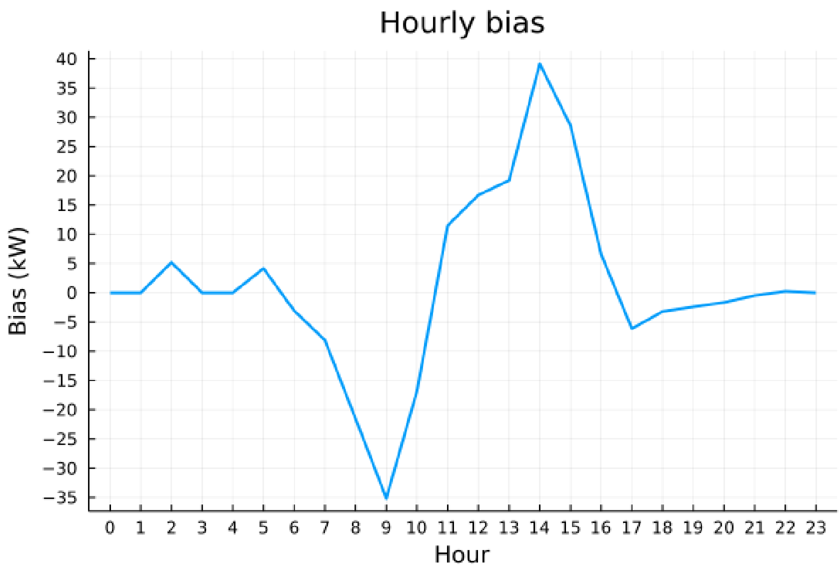

Figure 16: Mean hourly bias (realised - forecast) of the photovoltaic model

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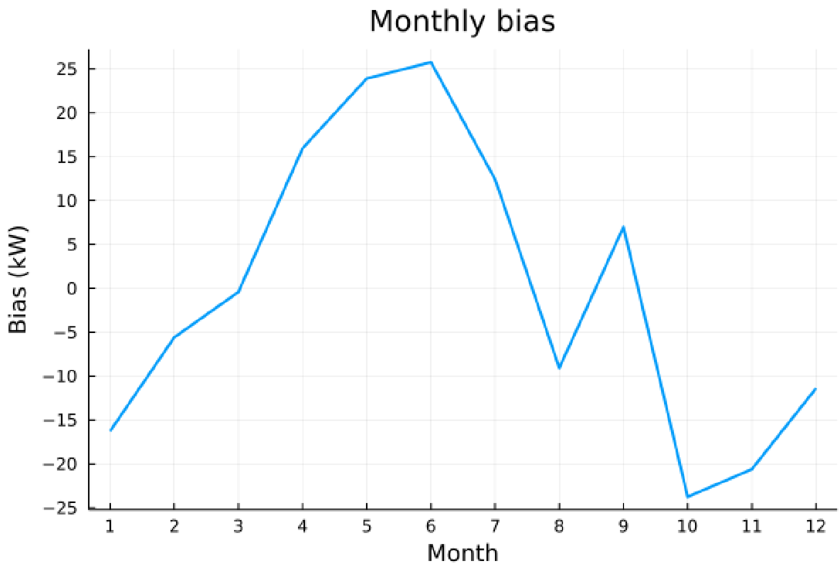

Figure 17: Mean monthly bias (realised - forecast) of the photovoltaic model

Figure 16 is interesting as it highlights a distinct behaviour: the bias is negative on mornings and positive on afternoons, the transition occurring around noon. Figure 17 was more predictable as it shows a higher bias in the middle of the year – during the summer when the irradiance is significant – and a negative bias over the fall and winter when the irradiance is lower, and the sky tends to be cloudy.

With these plots, it is possible to conclude that the model tends to overpredict when the irradiance is high (for example during afternoons, or summer) and underpredict when the weather is more uncertain (during mornings or winters for example).

Most importantly, these graphs need to be compared with the bias of the weather models presented in deliverable 4.3 of the WP4 of the ISLANDER project [13]. It can be noted that the error of the irradiance forecast has the same shape for both variables. As the photovoltaic model depends mostly on the irradiance forecast, it is significantly subordinated to it and the error of the irradiance will lead to a bias in the photovoltaic model.

Finally, an explanation for the nMAE considering the bias and time is given to point out the hours that badly weight in the final result. The heatmaps of the bias and nMAE are showed in Figure 18 and Figure 19.

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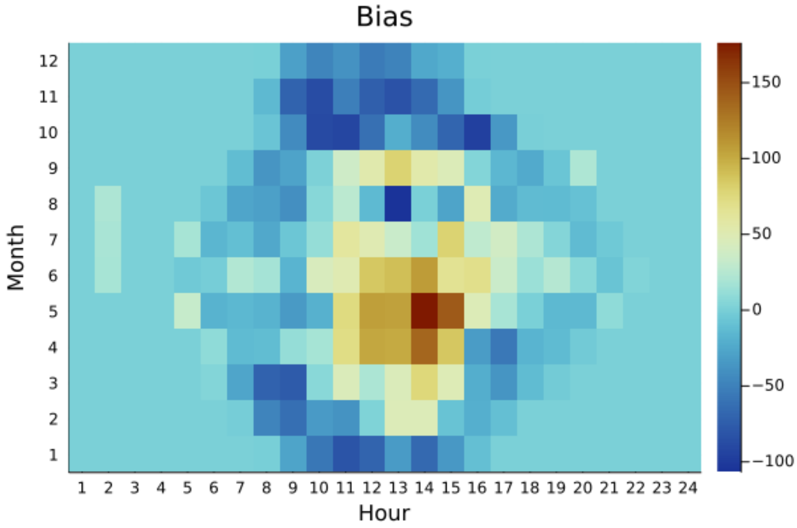

Figure 18: Heatmap bias of the photovoltaic model

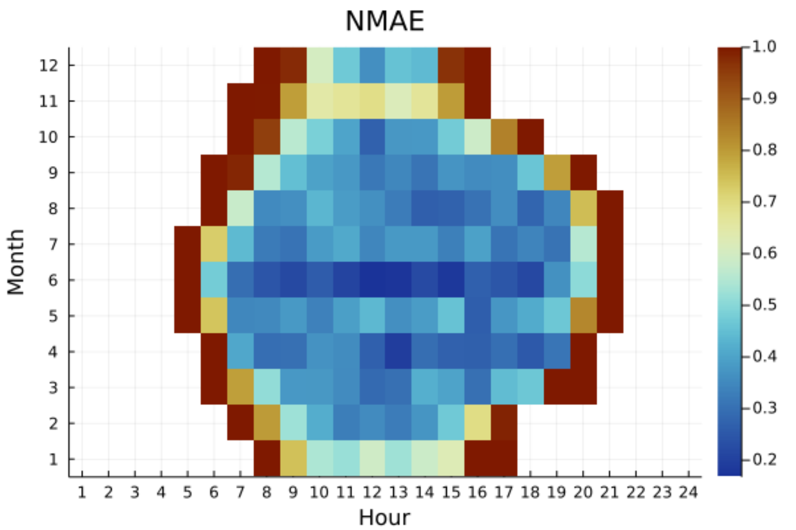

Figure 19: Heatmap nMAE of the photovoltaic model

These graphs highlight that the nMAE is weighted up by the first and last hours of the days all year round: the nMAE is around 100% at those times. Looking at the corresponding bias, which is low, it can be concluded that the nMAE is badly influenced by the hours when production is low. Although it is important to achieve a reasonable nMAE, the focus should be set on times when production volumes are significant as it when the photovoltaic installation will have a major role in the island electricity balance.

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8 MAIN CONCLUSIONS

This study describes and analyses a system to forecast the production of renewable sources on the island of Borkum in Germany in the frame of the European ISLANDER research project. Physical models have been developed and tested to forecast wind and photovoltaic power production. Currently, the forecasts have been evaluated on the wind farm and PV park as the individual PV pannels are not installed yet. Forecasted data is used as inputs of the global production model (see deliverable 4.5 [2]).

It can be concluded that it is very difficult to reach high model performances if the data quantity is low, the data quality is poor, and it is not reliable. Models' performance achieved are equal to 34% and 40% in terms of nMAE for the PV and wind production, respectively.

It would be relevant to test new approaches such as combined machine learning and physical models to reach higher performances and compare the two approaches.

9 DEVIATIONS

Delivery of the content is in time and to full satisfaction, without any deviations to actions planned.

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