SolarPACES 2022, 28th International Conference on Concentrating Solar Power and Chemical Energy Systems Operations, Maintenance, and Component Reliability

https://doi.org/10.52825/solarpaces.v1i.731

© Authors. This work is licensed under a Creative Commons Attribution 4.0 International License

Published: 02 Feb. 2024

DNI Forecast Tool for the Smart Operation of a Parabolic Trough Collector System with Concrete Thermal Energy Storage

Theory, Results and Outlook

Johannes Christoph Sattler¹[https://orcid.org/0000-0001-6796-9439]</sup>, Vikrama Atti¹[https://orcid.org/0000-0002-0777-^{8144]}, Spiros Alexopoulos¹[https://orcid.org/0000-0001-7380-8172]</sup>, Cristiano Teixeira Boura¹[https://orcid.org/0000-0003-1854-1019]</sup>, Ulf Herrmann¹[https://orcid.org/0000-0002-6938-0860]</sup>, Siddharth Dutta²[https://orcid.org/0000-0002-2789-^{5858]}, and Ioannis Kioutsioukis³[https://orcid.org/0000-0002-4653-8442]

¹ Solar-Institut Jülich (SIJ) of the FH Aachen University of Applied Sciences, Germany

² Protarget AG, Zeissstrasse 5, 50859 Cologne, Germany

³ University of Patras, Laboratory of Atmospheric Physics, 26504 Rio, Patras, Greece

Abstract. This work presents a basic forecast tool for predicting direct normal irradiance (DNI) in hourly resolution, which the Solar-Institut Jülich (SIJ) is developing within a research project. The DNI forecast data shall be used for a parabolic trough collector (PTC) system with a concrete thermal energy storage (C-TES) located at the company KEAN Soft Drinks Ltd in Limassol, Cyprus. On a daily basis, 24-hour DNI prediction data in hourly resolution shall be automatically produced using free or very low-cost weather forecast data as input. The purpose of the DNI forecast tool is to automatically transfer the DNI forecast data on a daily basis to a main control unit (MCU). The MCU automatically makes a smart decision on the operation mode of the PTC system such as steam production mode and/or C-TES charging mode. The DNI forecast tool was evaluated using historical data of measured DNI from an on-site weather station, which was compared to the DNI forecast data. The DNI forecast tool was tested using data from 56 days between January and March 2022, which included days with a strong variation in DNI due to cloud passages. For the evaluation of the DNI forecast reliability, three categories were created and the forecast data was sorted accordingly. The result was that the DNI forecast tool has a reliability of 71.4 % based on the tested days. The result fulfils SIJ's aim to achieve a reliability of around 70 %, but SIJ aims to still improve the DNI forecast quality.

Keywords: Direct Normal Irradiance Forecast, DNI Forecast, Parabolic Trough Collector, PTC, Thermal Energy Storage, TES, Cloud Cover, Cloudiness, Weather Forecast, Wind Speed, Wind Direction, Relative Humidity, Smart Operation

1. Introduction

In the current project Smart Solar System (S3), funded by national and regional funding organisations in the European network SOLAR-ERA.NET, the Solar-Institut Jülich (SIJ) is developing a weather forecast tool which can predict direct normal irradiance (DNI) in hourly resolution for the next 48 hours, but in this work only a 24-hour forecast is relevant and discussed. The DNI forecast data is important for optimising the operation of a parabolic trough collector (PTC) system with a concrete thermal energy storage (C-TES) located at the company KEAN Soft Drinks Ltd in Limassol, Cyprus. Fig. 1 shows a photograph of the PTC plant with C-TES which is currently being upgraded with smart features in project S3. The PTC system provides solar generated process steam for KEAN Soft Drinks Ltd.



Figure 1. View of the PTC system and C-TES at KEAN Soft Drinks Ltd (Photograph © Protarget AG).

More details on the PTC system and C-TES are described in [1], [2] and [3]. The DNI forecast data as well as other parameters will be used by a main control unit (MCU), which will be developed and realised in the S3 project by project partner Protarget AG, such that smarter decisions for an optimised control strategy of the PTC plant and C-TES for the next 24 hours can be made (the relevant forecast time is 6 a.m. local time in Cyprus until after sunset). The DNI forecast will be automatically carried out daily at a specific time whereby the forecast data shall be automatically transferred to the PTC's control computer in Cyprus.

With the DNI forecast data and other input parameters, the control strategies shall be applied in a smarter way such that, for example, not only the C-TES can be charged and discharged in a more efficient way, but also the amount of steam production increases. With a smart operation, the energy yield will be optimised for the months of November, February, March and April, which are months with frequent cloud passages (in December and January the PTC system is not in operation due to bad weather and low energy generation possibilities). With the DNI forecast data as one of several inputs, operation strategies for winter/cloudy months shall be realised for the PTC system. For the development of the DNI forecast tool, SIJ is using freely available (or very low-cost) weather forecast data from the internet.

Although a high prediction accuracy is always desirable, this work concentrates more on whether or not the DNI forecast is principally correct with respect to basic pre-defined criteria that are important for selecting the different modes of operation (the criteria are described in chapter 3). Furthermore, it should be noted that DNI forecast data is available commercially with higher forecast accuracy than the DNI prediction presented in this work, but here the aim is to use free or very low-cost weather forecast data.

In this work, the mode selection based on the DNI forecast in hourly resolution shall be realised for a day beginning at sunrise and ending at sunset. It is also considered that steam production at the KEAN factory only takes place until the early afternoon. This means that at a certain time in the early afternoon either the C-TES would be charged or the plant is switched off, i.e. if the DNI is too low for charging.

One example scenario, which highlights the importance of the DNI forecast, is as follows. The DNI forecast shall avoid that the PTC system operates in steam production mode on days with fluctuating DNI due to cloud passages when DNI is <400 W/m². The reason is that on such days the thermal power is insufficient to produce saturated steam at certain pressure and temperature (specified by the consumer, KEAN). In this case, the PTCs boiler would heat up the water but the energy in the boiler would remain unused because KEAN can only accept

saturated steam at a certain specific pressure and temperature. On such days, it would be more energy efficient to store the energy from the PTC system directly in the C-TES in order to then discharge the C-TES at another time for producing steam at the required pressure and temperature e.g. during cloud passages, before sunrise/after sunset.

The DNI forecast is influenced by the variables that are used as input. Zhu et al. (2019) [4] state that clouds and surface meteorological variables have an impact on the DNI. They then used historical measured variables including DNI, wind speed, wind direction, clouds and the relative humidity in their study (both time-series data and images were given as input).

2. Forecast tool development

In the work presented here, a DNI forecast in hourly resolution for the same day from 6 a.m. local time until after sunset is of most importance. The SIJ's approach is to first predict the DNI from cloud cover forecast data in combination with clear-sky DNI reference data and to then optimise the DNI prediction using the typical weather data variables from historical weather data (both forecast and measured). Typical weather forecast variables are the cloud cover, relative humidity, wind direction, wind speed, ambient pressure, ambient temperature and, if available, also fog and dew point. Accordingly, a new forecast tool for predicting DNI was created with the Python programming language. In a first step, the tool automatically downloads weather forecast data and subsequently calculates the DNI forecast values. The used weather forecast data contains cloud cover data for the three altitudes low, medium and high. The relation between the calculated DNI and the described parameters is shown in equation (1).

$$DNI=f(DNI_{cs},K)$$
(1)

where DNI_{cs} is the clear-sky reference DNI [W/m²] and K is the cloud cover [%].

To calculate the DNI via the DNI_{cs} , the cloud cover K and the solar radiation reduction efficiency η for three cloud layers, i.e. low altitude clouds (LAC), medium altitude clouds (MAC) and high altitude clouds (HAC), the following equations (2) to (4) are used by the forecast tool:

$$DNI_{HAC} = DNI_{cs} \left(1 - (K_{HAC} \cdot (1 - \eta_{HAC})) \right)$$
(2)

$$DNI_{MAC} = DNI_{HAC} \left(1 - (K_{MAC} \cdot (1 - \eta_{MAC})) \right)$$
(3)

$$DNI_{LAC} = DNI_{MAC} \left(1 - \left(K_{LAC} \cdot (1 - \eta_{LAC}) \right) \right)$$
(4)

The final value of DNI_{LAC} is the final value for the DNI forecast for a specific hour for which the forecast was carried out. Regarding the values of η_{HAC} and η_{LAC} , values from [5] were taken and for η_{MAC} a value was chosen based trial and error with respect to the effect it had on the DNI prediction. To calculate the DNI when weather forecast data with only a single cloud value is available, then the following shorter equation (5) is used by the forecast tool:

$$DNI=DNI_{cs}\left(1-\left(K_{S}\cdot\left(1-\eta_{S}\right)\right)\right)$$
(5)

where K_S is the single cloud cover value and η_S is the solar radiation reduction efficiency for a single cloud cover value. Another method for calculating DNI from clear-sky reference DNI and cloud cover data is described in [6].

To further improve the quality of the DNI forecast, more parameters from the weather forecast data are used, namely the wind speed, wind direction, relative humidity and final value of DNI_{LAC} is therefore further optimised. The optimisation step is currently carried out with MATLAB[®] but it is foreseen to implement the optimisation algorithms in the Python forecast tool. The optimisation of the DNI forecast quality includes equations that take the change of wind direction (i.e. like a gradient) as well as the magnitude of the wind speed and humidity

into account. The wind direction was simplified by means of rounding the wind direction value to either 0° (i.e. 360°), 90°, 180° or 270°, where 0° is north, which made data analysis and the optimisation process significantly easier. A time delay effect from wind direction onto the DNI was identified in the data and is included in the algorithm in order to increase the forecast accuracy. The correction of the DNI from relative humidity data was partly also made dependent on the wind speed. In the early DNI forecast tool development, also the gradient of the wind speed change over time was taken into account. The wind speed gradient is currently not used but may be included again in a further optimisation process. The relation between the calculated optimised DNI value and the parameters wind speed, wind direction and relative humidity used in this work is shown in equation (6) below:

$$DNI=f(DNI_{cs}, K, v_{wind}, \beta, \chi)$$
(6)

where DNI_{cs} is the clear-sky reference DNI [W/m²], *K* is the cloud cover [%] v_{wind} is the wind speed [m/s], β is the wind direction [°] and χ is the relative humidity [%]. Other weather parameters are not yet included.

3. Reliability of the DNI forecast

Altogether 56 days between January and April 2022 were evaluated, which are months in which cloudy weather conditions occur (data from November and December 2021 could not yet be evaluated). For the forecast tool is it not always essential that the hourly values of the DNI in the forecast perfectly match the measured DNI, e.g. if the forecast predicts a DNI of 600 W/m² but in reality the DNI is 800 W/m² then there is no impact on the operating strategy for the PTC plant (e.g. steam production, charging of C-TES). Rather, it is important to identify in the forecast time spans with sufficient DNI for steam production or for charging the TES (i.e. >400 W/m² for several continuous hours). Therefore, the DNI forecast can be reliable even if the forecast accuracy is not that exact. For the evaluation of the forecast accuracy, three categories were used which are described below. In Figure 2, Figure 3 and Figure 4, examples of days for DNI forecasts of categories (1) to (3) are presented as an orientation with respect to the three described categories. In the legends, "DNI meas" stands for "measured DNI" and "DNI fc" stands for "DNI forecast". The categories (1) to (3) are:

- Category (1): Steam production mode
 - $\circ~$ high measured DNI >400 W/m² and high predicted DNI >400 W/m²
 - steam production from morning until the afternoon and/or charging of C-TES in the afternoon for more than 4 hours possible
- Category (2): PTC plant off mode or charging of C-TES mode
 - \circ predicted and measured DNI is mostly below threshold of 400 W/m²
 - $\circ~$ on some days charging of C-TES possible for a few hours based on real-time DNI measurement
- Category (3): Very low forecast quality
 - o often high overestimation or high underestimation of predicted DNI
 - on some days with highly underestimated predicted DNI, the real DNI would have been sufficient for potential steam production
 - on some days charging of C-TES possible for a few hours based on real-time DNI measurement

The DNI forecast data was compared with the measured DNI for each of the 56 days and the forecast days were sorted into one of the three categories. The results of the evaluation of the reliability of the DNI forecast based on categories (1) to (3) are shown in Table 1. Categories (1) and (2) can be regarded as having a sufficient DNI forecast reliability and comprise altogether 40 days (71.4 %) of the 56 days. Category (3) forecasts can be regarded as bad quality

forecasts, which accounts to 16 days (28.6 %) of the 56 days. This result already fulfils SIJs minimum aim to achieve a DNI forecast that leads to a reliability of 70 %, but SIJ aims to still improve the DNI forecast quality.

Category	No. of days	Share in %
(1)	31	55.3
(2)	9	16.1
(3)	16	28.6
Total	56	100



Figure 2. Six examples of category (1) forecast days showing graphs of DNI vs. local time for the location Limassol, Cyprus.



Figure 3. Four examples of category (2) forecast days showing graphs of DNI vs. local time for the location Limassol, Cyprus.



Figure 4. Four examples of category (3) forecast days showing graphs of DNI vs. local time for the location Limassol, Cyprus.

As seen in Figure 2, Figure 3 and Figure 4, the accuracy of the DNI forecast is in some cases varying greatly and especially for category (3) unsatisfactory. Exemplarily, Table 2 below shows the average DNI deviation between measured and predicted DNI over the day for the days presented in Figure 2, Figure 3 and Figure 4 as well as the cumulative daily solar energy data for the DNI prediction and measurement. The DNI forecast accuracy will be evaluated further within the research project.

Table 2. Evaluation of the average (avg), maximum (max) and minimum (min) deviation in the unit W/m^2 between the measured DNI and the predicted DNI over the day for the presented days in the above Figure 2, Figure 3 and Figure 4. Also, the prediced (E_{fc}) and measured (E_{ms}) cumulative daily solar energy in the unit kWh/m² is shown as well as the difference between the predicted and measured cumulative daily solar energy (E_{df}).

	Category 1: Day #					Category 2: Day #			Category 3: Day #					
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14
Avg	141	132	309	310	137	119	210	258	120	188	225	201	327	434
Max	296	330	520	548	414	344	545	592	258	686	443	484	510	910
Min	2	6	23	10	1	1	14	46	2	12	3	14	6	1
$E_{ m fc}$	5.4	6.1	5.8	8.5	5.5	5.5	2.3	3.2	2.1	1.9	3.8	5.0	7.7	6.4
E _{ms}	4.9	5.4	9.4	4.1	5.3	6.5	3.7	0.7	1.3	0.1	3.3	6.5	3.1	0.3
$E_{ m df}$	0.5	0.7	-3.6	4.4	0.2	-1.0	-1.4	2.5	0.8	1.8	0.5	-1.5	4.6	6.1

4. Outlook for the DNI forecasting tool

Within the scope of the research project, the presented approach shall be further optimised. The optimisation includes, for example, the analysis of potential similarities between forecast days that fall into category (3) such that a method can be developed for improving the forecast quality. Furthermore, other weather forecast parameters such as the air temperature, air pressure and fog may also be included in the algorithm to determine their impact on the DNI forecasting accuracy. Another option to improve the accuracy of the presented DNI forecast tool with respect to predicting DNI for the next 24 hours is to implement satellite cloud image data and by possibly combining that with wind direction forecast data.

Parallel to the ongoing work on developing own algorithms for the DNI forecast, the SIJ also tested several standard regression models from MATLAB in order to assess if standard regression models (amongst others also neural networks) lead to more accurate results. So far, regression models showed a mix of good and bad DNI forecasts for a selection of forecast days that were tested. The SIJ is currently exploring the possibility of DNI forecasting with a Long Short-Term Memory (LSTM) network as well as other deep learning methods, but extensive results are not yet available for publication.

Data availability statement

The detailed and extensive amount of data supporting the results of this paper is only (and even only in parts) accessible to the consortium members of project S3 within legal restrictions bound by a cooperation agreement. For reasons of maintaining intellectual property, the information and data presented in this paper is limited. Weather forecast data from MET Norway was used for the purpose of exemplarily showing the accuracy of the DNI forecast tool.

Author contributions

J. C. Sattler: Conceptualisation, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing;

V. Atti: Conceptualisation, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Writing – review & editing;

S. Alexopoulos: Conceptualisation, Formal Analysis, Methodology, Project administration, Supervision, Validation, Visualisation, Writing – original draft, Writing – review & editing;

C. Teixeira Boura: Supervision, Project administration, Writing - review & editing;

U. Herrmann: Supervision, Writing – review & editing;

S. Dutta: Conceptualisation, Investigation, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing;

I. Kioutsioukis: Conceptualisation, Methodology, Validation, Writing - review & editing;

Project consortium: Funding acquisition

Competing interests

The authors declare no competing interests.

Funding

Project Smart Solar System is supported under the umbrella of SOLAR-ERA.NET Cofund by Projektträger Jülich – Forschungszentrum Jülich GmbH – Energie-Technologie-Nachhaltigkeit (ETN 1) and General Secretariat of Research and Innovation (GSRI). SOLAR-ERA.NET is supported by the European Commission within the EU Framework Programme for Research and Innovation HORIZON 2020 (Cofund ERA-NET Action, N° 691664). Funding from the state of North Rhine-Westphalia on the basis of the directive on the granting of funding from the "Programme for the rational use of energy, regenerative energies and energy saving - progres.nrw - programme area innovation".

Acknowledgement

The project consortium of project S3 would like to sincerely thank the Cyprus University of Technology as well as KEAN Soft Drinks Ltd. for their support given in the project.

References

- J. C. Sattler, S. Alexopoulos, R. A. Chico Caminos, J. Mitchell, V. Ruiz, S. Kalogirou, P. Ktistis, C. Teixeira Boura, U. Herrmann, "Dynamic simulation model of a parabolic trough collector system with concrete thermal energy storage for process steam generation", AIP Conference Proceedings, vol. 2126, p. 150007, Jul., 2019, doi: https://doi.org/10.1063/1.5117663
- J. C. Sattler, R. A. Chico Caminos, N. Ürlings, S. Dutta, V. Ruiz, S. Kalogirou, P. Ktistis, R. Agathokleous, C. Jung, S. Alexopoulos, V. Atti, C. Teixeira Boura, U Herrmann, "Operational experience and behaviour of a parabolic trough collector system with concrete thermal energy storage for process steam generation in Cyprus", AIP Conference Proceedings, vol. 2303, p. 140004, Dec., 2020, doi: https://doi.org/10.1063/5.0029278
- 3. J. C. Sattler, R. A. Chico Caminos, V. Atti, N. Ürlings, S. Dutta, V. Ruiz, S. Kalogirou, P. Ktistis, R. Agathokleous, S. Alexopoulos, C. Teixeira Boura, U. Herrmann, "Dynamic

simulation tool for a performance evaluation and sensitivity study of a parabolic trough collector system with concrete thermal energy storage", AIP Conference Proceedings, vol. 2303, p. 160004, Dec., 2020, doi: https://doi.org/10.1063/5.0029277

- 4. T. Zhu, H. Zhou, H. Wei, X. Zhao, K. Zhang and J. Zhang, "Inter-hour direct normal irradiance forecast with multiple data types and time-series," in J. Mod. Power Syst. Clean Energy, vol. 7, no. 5, pp. 1319–1327, Jul., 2019, doi: https://doi.org/10.1007/s40565-019-0551-4
- 5. D. Matuszko, "Influence of the extent and genera of cloud cover on solar radiation intensity", Int. J. Climatol., vol. 32, pp. 2403–2414, Dec., 2012, https://doi.org/10.1002/joc.2432
- E. Cogliani, "The Role of the Direct Normal Irradiance (DNI) Forecasting in the Operation of Solar Concentrating Plants", Energy Procedia, vol. 49, pp. 1612–1621, 2014, doi: https://doi.org/10.1016/j.egypro.2014.03.170