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Research Paper

Evaluation of a concentrated solar power plant under meteorological and climatological forcing

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ABSTRACT

The performance of renewable energy-conversion systems depends strongly on the background climate and ambient meteorological conditions. However, common approaches to simulating such systems use aggregated climatic data as forcing. Given strong variability in the climate, along with possible future long-term changes, it is important to understand the trade-offs between high-resolution forcing data and representative data. Here we simulate a concentrated solar power plant driven by hourly-resolved reanalysis data using both air and water-based cooling systems. These simulations allow us to analyze plant performance under realistic meteorological variability at two locations. In addition, we simulate the plant under average climatic conditions, where all sub-seasonal and interannual variability has been removed. These simulations are cheaper to run, but do not represent extreme values in the forcing. Our analysis shows that variability in the direct normal irradiance (DNI) is a critical factor for simulating the plant realistically. We show that where (and when) DNI variability is low, average forcing provides a realistic picture of power output. Average forcing can also provide a good estimate of how the plant will perform on average. However, in cases where understanding how robustly the plant performs, it is critical to include realistic variability in the input data.

1. Introduction

Adapting to climate change in the energy sector is an important global goal. Climate change will increase the frequency and severity of extreme weather events that in turn impact the performance of the power sector, causing generation reduction and power outages (Byers et al., 2020; Konisky et al., 2016). In addition, many power plants rely heavily on locally available water resources for cooling purposes (Larsen and Drews, 2019; Petrakopoulou and Olmeda-Delgado, 2019) and rising water temperatures decrease the available quantity of water reserves and deteriorate the quality of the water for power-plant cooling (Murrant et al., 2017; Wang et al., 2017). With increasing air and water temperatures negatively affecting the performance of electricity generation systems, the evaluation of power plants under varying climatic conditions is a topic of primary interest in the energy field (Mekonnen et al., 2016; Petrakopoulou et al., 2020; Totschnig et al., 2017).

Hourly-resolution data of local meteorological variables such as temperature, wind speed and irradiance facilitate the accurate evaluation of the performance of a power plant under varying weather conditions. As such, detailed data are undoubtedly valuable in the field, especially when studying the operation of renewable power plants. However, there are still two challenges to be met. First, transient data at such high temporal resolution in the energy sector has primarily been produced either by private companies, or by complex, high-resolution regional climate models. Thus, they are not always easy to access nor, in most cases, sufficiently transparent to reproduce (Craig et al., 2022). Second, large databases imply numerous simulations, long hours of processing and powerful software.

To circumvent these issues, many studies evaluate the transient operation of power plants using a typical meteorological year (TMY) (e.g., Tambula et al., 2023; Thabit et al., 2022; Ullah et al., 2023). A TMY is calculated as the climatological mean of a set of variables varying over the year, where the averaging time period is typically 30 years. Thus, seasonal cycles in variables are maintained, but all variability related to weather, such as interannual variability, is removed. While TMY forcing is useful to get an overview of the average yearly and seasonal power-plant operation, it does not account for exceptional extreme weather conditions and does not provide information on power generation variability under changing meteorological and/or climatic conditions.

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The advent of open-access, high temporal resolution reanalysis datasets such as ERA5 (Copernicus Climate Change Service (C3S), 2017) has driven recent progress in simulating power-plants with transient datasets. For example, Ramirez et al. (2020) used ERA5-land meteorological reanalysis data for more than one year to generate time series to simulate photovoltaic power plants. The results of the simulations were validated through comparison to real data output from 23 existing photovoltaic plants in Chile, showing satisfactory results (Ramirez Camargo and Schmidt, 2020). Pfenninger and Staffell (2016) used hourly meteorological reanalysis data for a 30-year time period from both the MERRA and MERRA-2 global reanalyses and the CM-SAF SARAH satellite dataset to examine the long-term output of photovoltaic plants across Europe. The simulated output was then validated through a comparison to real data collected from more than 1000 photovoltaic plants across Europe. The study concluded that despite some biases in the simulated output compared to measurements, reanalysis data are a valuable, continuously improving resource for driving transient simulations (Pfenninger and Staffell, 2016).

Several recent studies have also used high-resolution data output from different climate models to examine the impact of long-term changing climate conditions on energy-system performance. For example, Simoes et al. (2021) studied the effects of considering climate variability in energy system models in Europe. For this work, six projections from the regional-climate downscaling experiment EURO-CORDEX were used in the eTIMES-EU model to study technology optimization for the European power sector for the years 2030 and 2050. Conclusions drawn from the study included the important impact of climatic variability on hydro, wind and photovoltaic solar power (Simoes et al., 2021). Meanwhile, Perera et al. (2020) studied the resilience and performance of both power supply and demand under 13 different climate change scenarios. The meteorological data used for such scenarios was mesoclimate-scale data with hourly temporal resolution obtained from a regional climate model, from which three 1-year data sets were synthesized: one for the typical down-scaled year, one for the extreme cold year and one for the extreme warm year. The results showed a drop in supply reliability of the power sector caused by extreme weather events (Perera et al., 2020). To study the effects of climate change on capacity expansion decisions across the Southeast US, Fonseca et al. (2021) used weather data from 1979 to 2015 in a reference scenario, combined with output from Global Circulation Models to project air temperature, air humidity and air pressure data from 2015 to 2050. The study confirmed the importance of taking climate change effects into account in the decision-making process of energy planners across the U.S. (Fonseca et al., 2021).

Even though it is clear that the use of high temporal resolution data provides more accurate information, the level of detail of data necessary to produce trustworthy solar power-plant operation over a large number of years is still not clear. In this work, we aim to address this challenge by comparing the results of the 41-year (1979–2019) hourly transient operation of a concentrated solar power plant to its hourly operation throughout a representative year (TMY) approach. The main input data are air and cooling water temperature, as well as solar irradiance. The transient simulation over the 41-year time period includes 359.400 simulation points, i.e., hours of operation, while the simulation of the TMY only requires 8.760 points.

In addition, to evaluate the impact of data resolution for different climatic conditions, the same system is simulated in two chosen locations, Dubai in United Arab Emirates, and Fuentes de Andalucía in Spain. The plant is also simulated with two different cooling systems to evaluate the impact that future water restrictions may have on the plants and to test what the impact of data detail is for different cooling technologies. The two cooling systems considered included a conventional water-based (once-through cooling system) and an air-cooled condenser that eliminates the need for water use in power plant cooling.

2. Methods

Data from the European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis ERA5 (C3S, 2017) was used as climatic input for the simulations performed here. ERA5 assimilates meteorological observations into an operational weather forecasting model to produce estimates of global weather at hourly temporal resolution on a 31 km-resolution spatial grid. The time series of the near-surface air temperature, total incident solar irradiance at the top of the atmosphere and direct solar irradiance at surface were extracted for each location. Simulating a concentrated solar power plant also requires the hourly direct normal irradiance at the surface (DNI, $I_{d,n}$), which is not available directly as an output of the ERA5 reanalysis dataset. However, it can be calculated from the direct solar irradiance (I_d) and the zenith angle of the sun (z) as:

$$I_{d,n} = I_d \quad / \cos(z) \tag{1}$$

With hourly-resolution data, it has been shown that an effective zenith angle ($z = z_e$) can be calculated for a given time to provide a good estimate of DNI (Blanc and Wald, 2016). We use algorithm A3, as described by Blanc and Wald (2016), where the effective zenith angle for a given hour is the integral of the zenith angles over the daylight time over the last hour divided by the total daylight time of the last hour (see Eq. 6 in their paper).

For the purpose of this study, a reference concentrated solar power (CSP) plant without storage was simulated using the commercial simulation software EbsilonProfessional. The design point parameters of the power plant are representative of a real solar-power plant. A schematic of the plant is shown in Fig. 1, with example output simulated for Dubai for the spring equinox of the arbitrarily chosen year 1992 at 08:00. The ambient temperature for the cited date and time is 26.4 °C and the DNI is 620.7 W/m^2. The heliostat field reflects the sun's rays on the solar tower, with a calculated incident power in the receiver aperture area of 55,801.3 kW. The thermal fluid is water/steam with a flow rate of 20 kg/s, which absorbs 49,509.7 kW of thermal energy. The temperature of the steam increases from 245.4 °C at 115 bar (Stream 1) to 565 °C at 100 bar (Stream 2) and it is led to the high-pressure steam turbine. The steam then exits the turbine at 16.5 bar and 309.5 °C (Stream 6) and is split into Streams 7 and 38. Stream 7 is sent to the low-pressure steam turbine and exits at 32.9 °C and 0.05 bar. The condenser of the once-through cooling system uses 944.8 kg/s of cooling water (Stream 18) to condense the steam of the Rankine cycle of the plant (Fig. 1b). The inlet hourly cooling water temperature is estimated by multiplying the air temperature by a factor of 0.7 (Morrill et al., 2005). The difference between steam inlet (Stream 17) and cooling water outlet in the condenser (Stream 19) of the reference simulation is 4 °C. The cooling water exits the condenser at 26.5 °C and is released to the environment (Stream 19). The steam of the plant is condensed at 32.9 °C and 0.05 bar (Stream 20). The water (Stream 21) at 0.05 bar passes through a pump that increases its pressure up to 6.15 bar and then a series of heat exchangers, where it is heated up to 122.4 °C (Stream 30). It is then led through the deaerator, pump and two more heat exchangers, reaching 245.4 °C and 125.1 bar (Stream 39). Stream 1 is then heated up once again by the solar tower, repeating the cycle.

When water resources are limited, dry cooling systems provide a possible alternative for cooling in power plants (Ehsan et al., 2018). Dry cooling systems use air as the cooling fluid, avoiding the vast amounts of water usually required in conventional water-based cooling systems. However, dry cooling systems are less efficient than water-based systems and highly dependent on relatively higher air temperatures (Thopil and Pouris, 2016). To evaluate the option of a dry cooling system, an alternative configuration of the solar plant with an air-cooled system is also considered here (Fig. 1c). In this plant, the water-cooled condenser of the reference plant is replaced by a simple air-cooled condenser. The air enters the condenser at ambient conditions. The air-based cooling

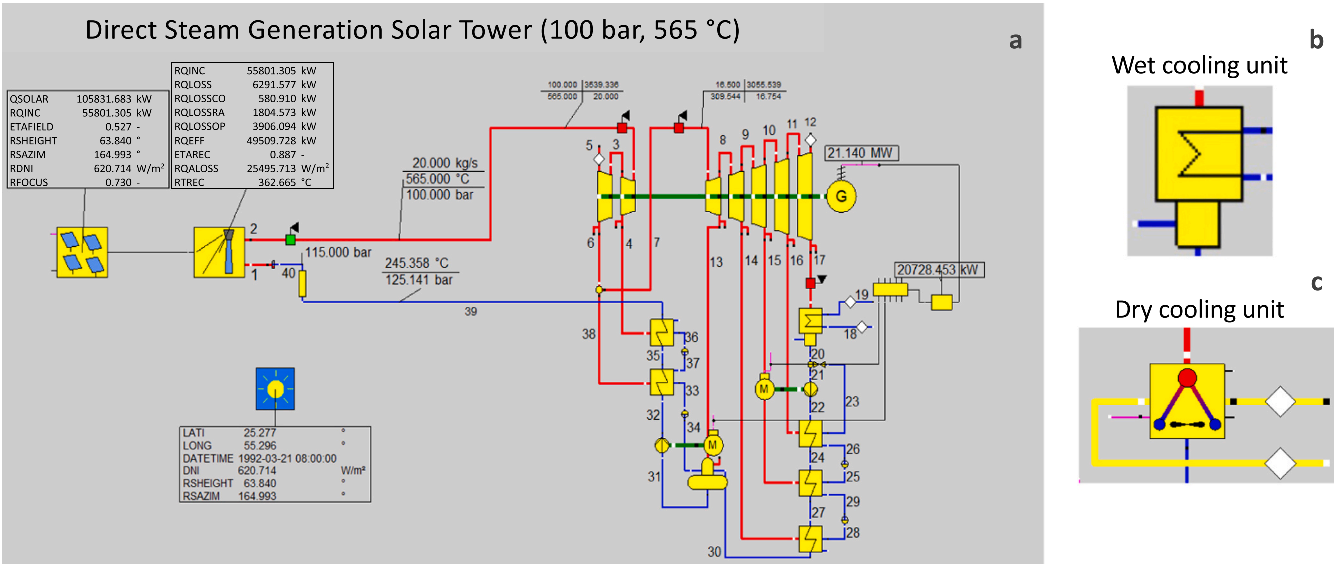

Fig. 1. Reference plant schematic as defined in Ebsilon Professional (panel a). A once-through wet cooling system is used in the default configuration (panel b), while a dry cooling system is tested as an alternative (panel c).

system does not require water to operate but it needs a fan to drive the air through the component. The power needed for the fan, in addition to the relatively higher air temperatures, cause an efficiency reduction when compared to the reference water-cooled plant. Higher temperatures of the cooling medium result in a less efficient cooling process that then results in an increase of the pressure at the exit of the steam turbine (pressure and temperature are interdependent at that point). This reduces the power generation.

Simulations are performed for two different locations: Dubai (25.3 N, 55.3 E) and Fuentes de Andalucía (Southern Spain, 37.3 N, 5.3 W). These locations were chosen because of their relatively high irradiance values, appropriate for good performance of concentrated solar plants. At the same time, the warm climate in both locations is suitable for evaluating the effect of high ambient temperatures on these plants with water- and air-based cooling systems throughout the years.

In total, four CSP power-plant configurations are simulated: in two locations (Dubai and Fuentes de Almería) operating with two cooling systems (wet and dry cooling). Each of the four simulations is then run under two scenarios, one using fully transient data and one using TMY data as forcing. The first scenario is transient over 41 years (1979–2019) and captures the full variability in the climatological forcing (359.400 total simulation hours). This scenario provides insight into all factors that cause changes in the power plant's performance. The second scenario is driven by the TMY forcing that was calculated as the mean hourly values over the time period 1981–2010 (8.760 total simulated hours). This scenario is, therefore, significantly cheaper computationally, as only one year is simulated instead of 41 years. However, the extremes in the variability of the forcing are eliminated here through the averaging process. The goal of these simulations is to evaluate to what extent the TMY forcing is representative of the performance of the plant when forced by the real 41-year meteorological dataset. All power-plant simulations are performed with hourly time resolution using the TimeSeries tool in Ebsilon Professional.

It should be noted that a CSP plant as studied here is not actually operational during the night-time hours, since no thermal storage is included in the design. To facilitate the analysis, temporal averaging is performed to obtain daily, monthly, and annual values that only account for the daytime potential operation of the plant. To this end, the total incident solar irradiance at the top of the atmosphere obtained from the ERA5 data is used to diagnose when the power plant could be expected to be operational. A daily, monthly, or annual average represents the average only over the hours that sunlight is present at the top of the atmosphere.

2.1. Climatic conditions

Fig. 2 presents the time series of the ambient temperature and DNI for Dubai and Fuentes de Almería. There is a clear positive trend in ambient temperatures in both locations over the 41-year period. Both locations also present a strong seasonal cycle in temperatures throughout the year. The annual mean temperature in Dubai over the time period 1981–2010 is 31°C, while that of Fuentes de Almería is much cooler at 22°C. In summer months, both locations are substantially warmer, averaging to 37°C and 31°C, respectively. The ambient temperature can affect the performance of the plant, in particular when it comes to cooling methods, thus it is interesting to compare the seasonal operation of these two locations.

DNI is highly variable year-by-year, and it shows strong seasonal variability as well. The seasonal variability in DNI is much less regular than that of temperature, and this is due to the fact that DNI is strongly affected by the meteorological conditions at any given moment, with cloudiness being a key factor. Both locations present a relatively similar magnitude of annual mean DNI (552 and 515 W/m^2 in Dubai and Fuentes de Almería, respectively). However, no trend in DNI is present in Dubai, while there is a marked positive trend in DNI in Fuentes de Almería. DNI is the primary energy input to the plant, which implies that both its variability and possible trends can be expected to be important for the performance of CSP plants.

3. Results

3.1. Transient versus TMY forcing

Fig. 2c presents the mean power output of the plant with wet cooling at both locations given transient meteorological forcing. The power output in Dubai is generally more stable month-by-month, as well as annually, compared to that of Fuentes de Almería. In Fuentes de Almería, the power output for several individual months can average 10 MW, which is around 30% lower than the overall average power output of about 14 MW. It is immediately apparent that strong reductions in output appear to be correlated with the variability in DNI (Fig. 1b).

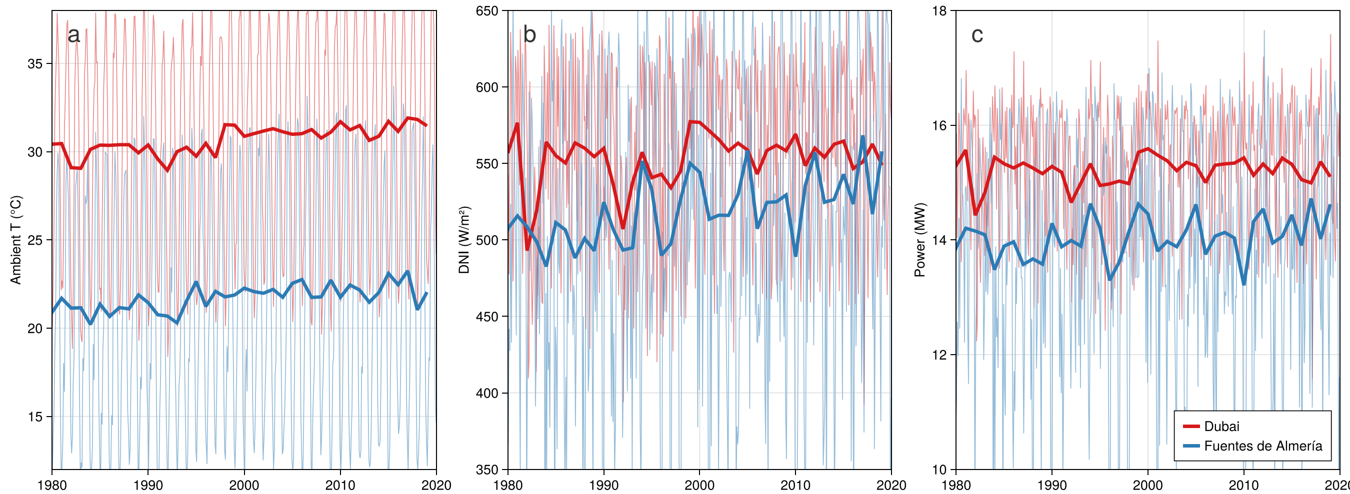

Fig. 2. Monthly (thin lines) and annual (thick lines) average values for (a) ambient temperature (°C), (b) DNI (W/m^2) and (c) power output for simulated power plants with wet cooling in Dubai (red lines) and Fuentes de Almería (blue lines).

This can be seen more clearly by looking at the seasonal cycle of power output over each month, first in Dubai (see Fig. 3). The seasonal cycle of temperature follows the classical pattern of warmer temperatures in summer months and colder temperatures in winter months, with variation between the seasons of about 15°C. In contrast, the mean DNI received in Dubai each month is relatively stable. However, somewhat more variability in DNI can be seen for winter months. The power output in the winter months is also more variable compared to the summer months and is otherwise relatively stable. The standard deviation of power output in June is 0.64 MW (4%), while in January it reaches 3.31 MW (20%). Fig. 3 also shows a much higher number of hours of operation of the plant in the summer than in the winter. This means that the same capacity of the plant would result in higher daily electricity production in the summer than in the winter (see Fig. 3e). The highest monthly electricity generation of the plant is estimated to occur in May, when the mean DNI is at its highest, and the plant operates for a relatively high number of hours each day. It should be noted that the impact of the temperature that is close to its maximum value (~35°C) that month seems to have a negligible impact on the overall operation of the plant.

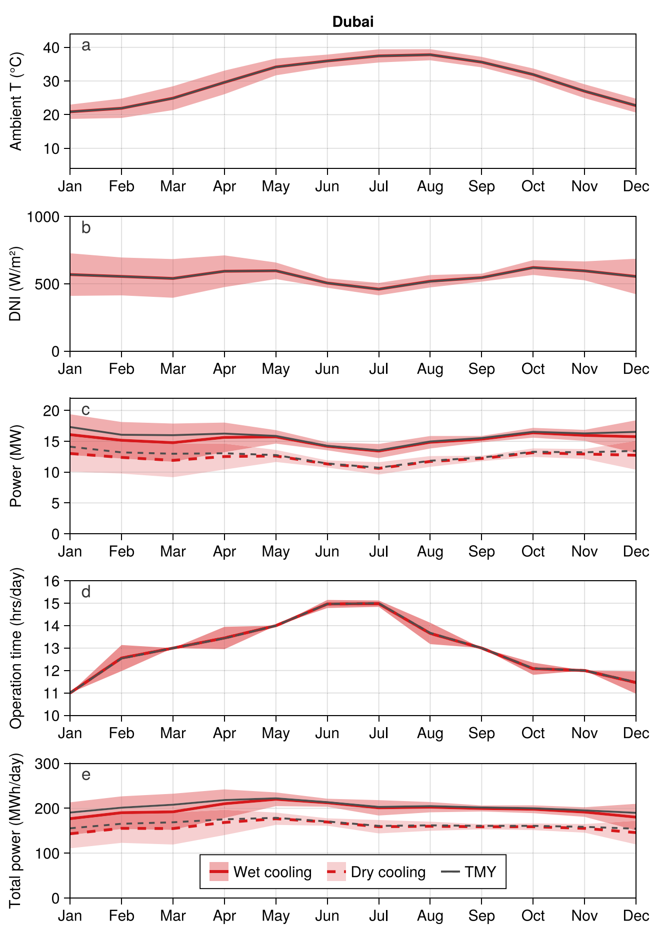

Fig. 3. Monthly values of (a) ambient temperature (°C), (b) DNI (W/m^2), (c) daily power output rate (MW), (d) daily operation time (hrs/day) and (d) total daily power output (MWh/day) for simulated power plants with wet cooling (solid lines) and dry cooling (dashed lines) in Dubai using transient data. The monthly mean and standard deviation around the mean are shown with the red lines and light red shading, respectively. The dark grey lines (solid and dashed) show values that correspond to the simulation forced with TMY data.

When forcing the simulation with the TMY data, the power output is generally equal to or higher than the mean of the transient simulation over the same time period. In particular, given that variability in DNI (and temperature) is lower in summer, the power output of the TMY simulation corresponds well to the mean. In the wintertime, the power output in the TMY case remains significantly higher than in the transient simulation, since this heightened variability is averaged out in the TMY case.

The same picture emerges in the case of Fuentes de Almería, but with more climatic variability resulting in less reliable power generation (Fig. 4). The mean temperatures are lower than in Dubai, while mean DNI levels are similar. The seasonal cycle of temperature variability is also similar to that of Dubai, however DNI shows more variability throughout the year overall. The winter months again are more variable than the summer months, and this appears to have a direct effect on the variability of the power output of the plant. As in the case of Dubai, there is a very close link between the mean monthly capacity of the plant (Fig. 4c) and the DNI of the region. The highest electricity production is achieved in the summer months and, specifically, in July, when the DNI values are highest (see Fig. 4e). It should also be noted here that ambient temperatures reach their highest annual levels for the region in the month of July. This means that here as well, as in the case of Dubai, the power reductions from the increase of the outlet steam pressure due to the increase in ambient temperature of air and water have only a small impact on the final operation of the plant.

While the previous figures give a good overview of the statistical variability of the climatic forcing and the impact on power output,

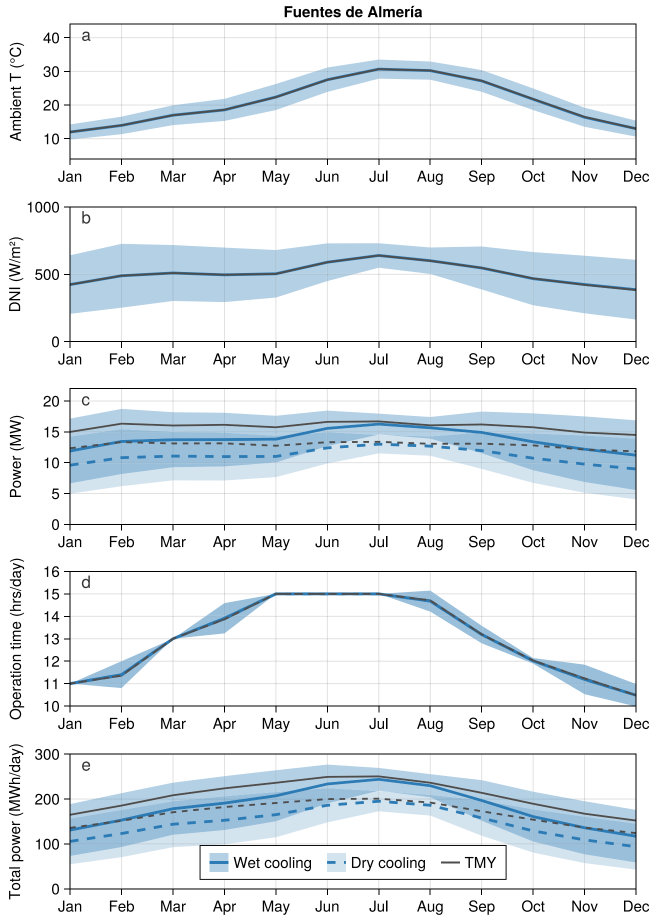

Fig. 4. Monthly values of (a) ambient temperature (°C), (b) DNI (W/m^2), (c) daily power output rate (MW), (d) daily operation time (hrs/day) and (d) total daily power output (MWh/day) for simulated power plants with wet cooling (solid lines) and dry cooling (dashed lines) in Fuentes de Almería using transient data. The monthly mean and standard deviation around the mean are shown with the blue lines and light blue shading, respectively. The dark grey lines (solid and dashed) show values that correspond to the simulation forced with TMY data.

Figs. 5 and 6 show the direct, transient response of the power plants to changes in temperature and DNI for specific days in Dubai and Fuentes de Almería, respectively. We compare output from the first week in February of each year, as representative of a typical week in winter, and likewise for the first week in July, as representative of a typical week in summer.

In Dubai, variability in temperature and DNI is especially present in winter rather than summer, and this can be seen directly in the strong variability in power output in the week in February. Some days experience enough of a reduction in DNI for a long enough period to drive power output down near zero. However, such an extreme reduction is rare. The mean of the transient simulation over the period 1981–2010 shows that the mean power output is near to, but below, that of the simulation forced by the TMY with no interannual variability. While the TMY forcing does not exhibit as high of DNI values as for a few specific years, the averaging process used to create the TMY removes the low extremes as well. In the representative summer week, variability in both temperatures and DNI is significantly reduced, and this is reflected in the power output from the plant as well. In this case, results from the TMY simulation match any given individual year and the mean very well.

In Fuentes de Almería, a similar picture emerges but with amplified variability impacting the results even more. Here in February, it is possible that power output is driven to near zero for any given day. This appears to be driven most strongly by variability in DNI, likely as storm systems pass through the region. By contrast, all extremes are removed from the TMY forced simulation, which ensures, unrealistically, that a reasonable level of power is always generated. Here we see there is a large discrepancy in the power output estimated by the TMY simulation and the 1981–2010 average of the simulation with individual-year forcing. The variability is again, greatly reduced in the summer, and so this discrepancy is largely absent in the week in July.

Figs. 5 and 6 also show the variation of the pressure at the exit of the steam turbine of the plants because of changes in water temperature. The steam turbine outlet pressure increases as a result of an increase in the temperature of air and water, thus it follows a clear daily cycle, as well as being on average higher in summer than in winter. Strong variability in pressure can be seen on individual days, as a function of ambient conditions, though on average the simulated outlet steam pressure compares well with that simulated with TMY data. Even though relatively important pressure decreases are caused due to the increase of the ambient temperature of air- and water-cooling mediums, they do not decisively impact the final power output of the plant.

3.2. *Wet cooling versus dry cooling*

Simulations using dry cooling were very similar in nature to those using wet cooling, with the main difference being that using dry cooling results in lower power output overall (see Figs. 3 and 4). A similar reduction in power output of about 20% was found in both simulated locations when using dry cooling. Specifically, in Dubai the air-cooled power plant resulted in 18% lower power output in the winter and 21% lower power output in the summer than the water-cooled plant. In Fuentes de Almería, this percentage was in the range of 18–20%, again with the higher reduction calculated in the summer months. Furthermore, this reduction in power output was largely constant over the course of the simulations – i.e., variability in ambient temperatures and/or DNI do not seem to play a large role.

Dry cooling systems work less efficiently than water-cooled systems because they require fans to move high mass flow rates of air (approximately four times higher air mass flow than water) and they are more affected by high temperatures, as the temperature of the air tends to be higher than that of water. In places with an extreme scarcity of water and/or a high price of water, such a penalty in power output may balance with the benefit of reduced water use. In addition, environmental restrictions related to maximum allowed temperatures of cooling water from power plants to avoid environmental contamination can cause significant reductions in the power output of water-cooled plants. Accounting for such measures could lead to poorer performance of the water-cooled systems, and thus would favor air-cooled systems. This is especially true in the summer months, when the ambient temperatures increase significantly. Analyzing these trade-offs is specific to regional policies and outside of the scope of the current work.

4. Discussion

The time series of ambient temperature, DNI and power output shown above all indicate that DNI variability impacts power output much more than temperature variability for a CSP plant. In fact, there is a strong linear relationship between power output and DNI (Fig. 7) – the higher the DNI, the more power output can be expected (up to the capacity of the plant). In contrast, no clear relationship between power output and ambient temperature can be discerned over a wide range of temperatures. Overall, a small reduction in the power output is noted with increasing temperatures, which can only be identified when forcing with the detailed data (Figs. 5 and 6), while with the TMY as forcing, no reduction whatsoever can be recorded. Nevertheless, this power output reduction is mostly minor when the plants receive a considerable amount of irradiance. In such instances, the plants operate close to their full capacity.

It is important to note that there is a nonlinear relationship between

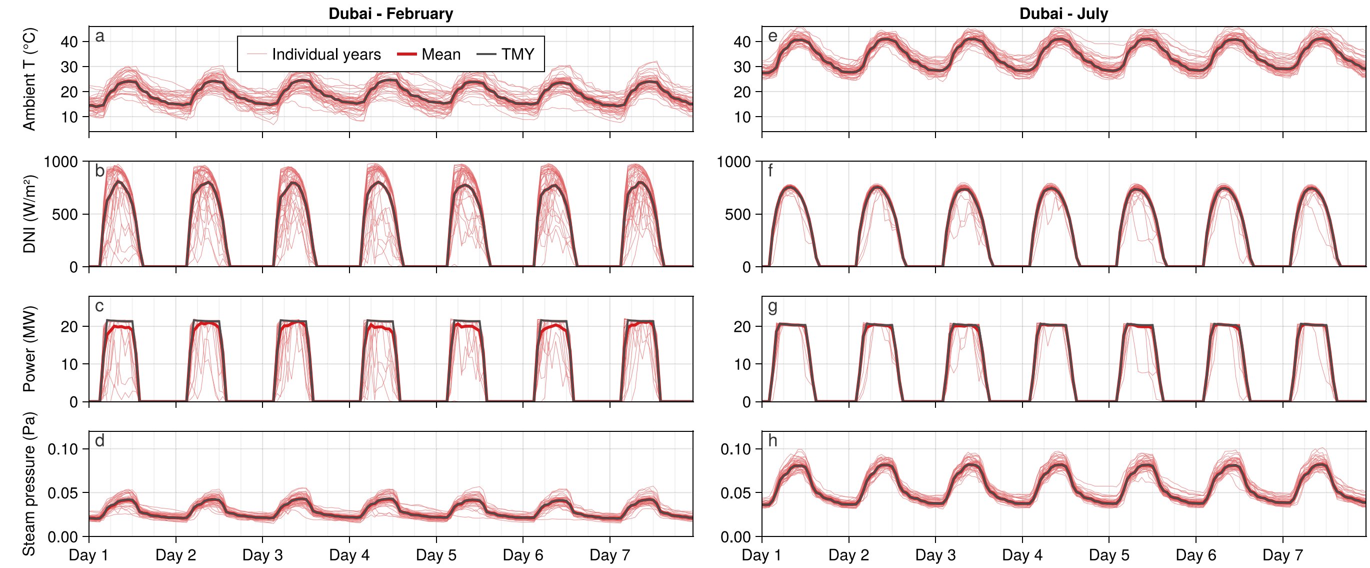

Fig. 5. Ambient temperature (a, e), DNI (b, f) power output (c, g) and turbine steam pressure (d, h) for the first week in February (left column) and the first week in July (right column) for simulated power plants with wet cooling in Dubai. Thin red lines show the time series of individual years, the thick red line is the average over the years 1981–2010, and the black line gives the corresponding TMY forcing data and simulation results.

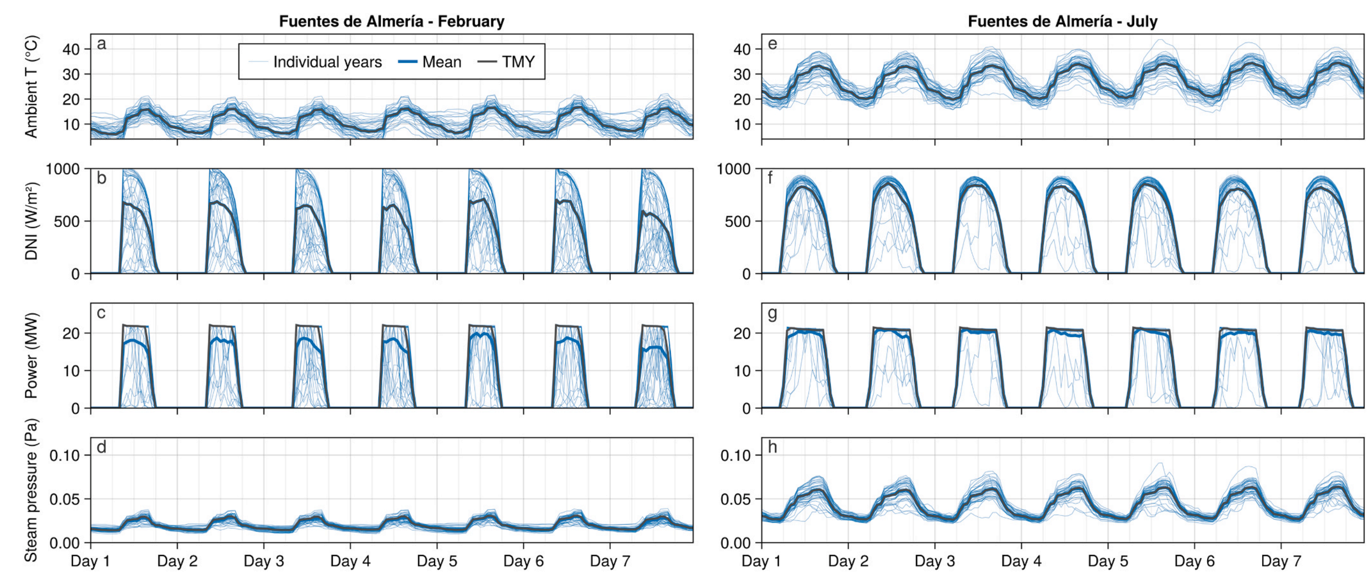

Fig. 6. Ambient temperature (a, e), DNI (b, f) power output (c, g) and turbine steam pressure (d, h) for the first week in February (left column) and the first week in July (right column) for simulated power plants with wet cooling in Fuentes de Almería. Thin blue lines show the time series of individual years, the thick blue line is the average over the years 1981–2010, and the black line gives the corresponding TMY forcing data and simulation results.

power generation *variability* and DNI *variability* above and below the mean. Low values of DNI generally result in a stronger reduction in power output relative to the mean than high values lead to an increase (Fig. 8). This explains why the mean power output from the transient simulation over a month is never higher than the power output from the TMY simulation, and when DNI is more variable, the mean is even lower. For a range of medium to high DNI values, near maximum power output can be expected (see Fig. 7), and the TMY-averaged DNI values fall in this range. In contrast, as DNI gets lower (e.g. below about 400 W/m^2), there is a steep reduction in power output. For this reason, it is clear that the use of detailed transient forcing data becomes more important in locations and times when DNI variability is high.

In the two locations analyzed here, it is seen that the plant operates more effectively and generates a higher power output in Dubai, which can be linked to the lower variability of the DNI in the region. Furthermore, low DNI variability allows TMY forcing here to more closely reflect the dynamic operation of the plant under real conditions (Fig. 8). When the DNI variability increases, however, detailed data are necessary to depict the operation of the plant accurately. For example, in the case of Fuentes de Almería, forcing with the detailed data frequently results in power output deviations from the TMY forced simulations of 10% to up to 100% (on days when real DNI is very low due to meteorological conditions) – see Fig. 8b.

Results of the simulations using dry cooling are also included in Fig. 7 for comparison. The same strong correlation between power output and DNI is found, with little correlation to ambient temperature. The air-cooled power plants perform somewhat worse than the water-cooled alternatives, because they rely on ambient air temperatures and the air has a higher temperature than the water. However, the dry cooling method does not appear to be limited in efficacy over a wide

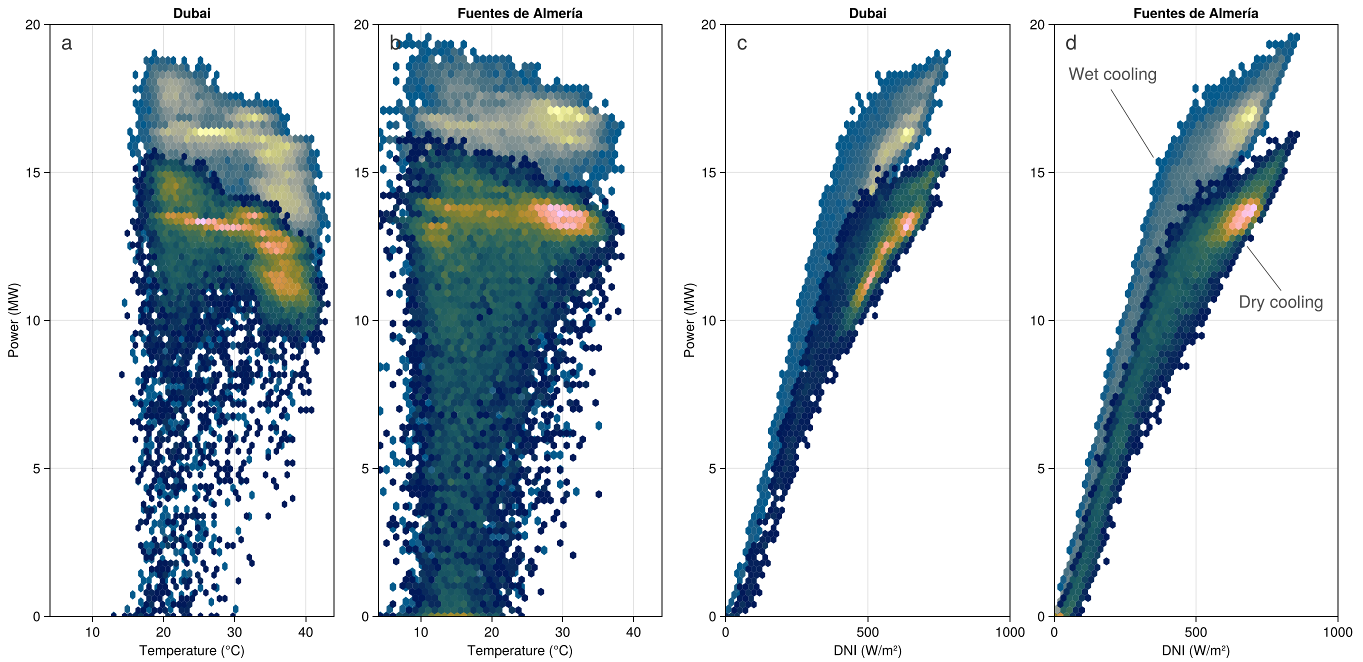

Fig. 7. Daily power output versus temperature and DNI in Dubai (a, c) and Fuentes de Almería (b, d) for the case of the power plant using wet cooling (lighter shading) and dry cooling (darker shading). Individual points were aggregated into hexagonal bins, with the shading showing the density of points (darker, bluer shading within each palette corresponds to the minimal density of points and lighter, whiter shading corresponds to the maximum density). I.e., values corresponding to the light-colored bins occur much more frequently in the simulations.

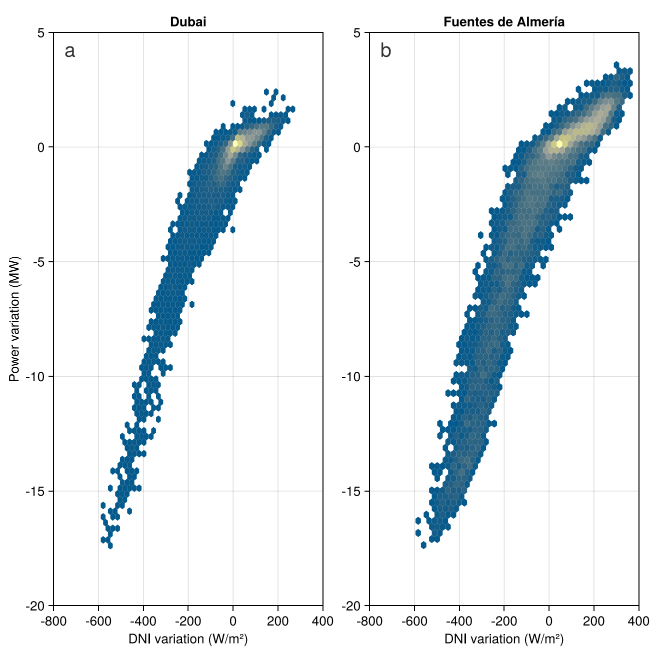

Fig. 8. Deviation in daily power output versus the deviation in DNI in Dubai (a) and Fuentes de Almería (b) for the case of the power plant using wet cooling, in terms of the full simulation with interannual variability relative to the simulation using TMY forcing. Individual points were aggregated into hexagonal bins, with the shading showing the density of points (darker, bluer shading within each palette corresponds to the minimal density of points and lighter, whiter shading corresponds to the maximum density). I.e., values corresponding to the light-colored bins occur much more frequently in the simulations.

range of temperatures, as the plant performs quite analogously to the wet-cooling plant.

In general, an important factor that explains the operation of the plants close to their full capacity at high ambient temperatures is that no further operational restrictions, like maximum-allowed water temperature at outlet or quantity of water withdrawal in times of water scarcity, have been imposed in this work. If such measures were applied, water-cooled power plants, in particular, would not be able to cover the cooling water demand required to operate at full capacity. For the water temperature to remain below a specific limit and for the plant to comply with given regulations, significant power reductions would have to be imposed. This would lead to a significant reduction of the power output gap between the two technologies. Such issues should be considered when the choice between the two systems is considered in water-restricted areas.

5. Conclusion

This study explores the relationship of the simulated power output from a concentrated solar plant to the meteorological data used for driving the simulations. Temperature and DNI data over a 41-year historical period are used to force a power plant with both wet- and dry-cooling in two locations, Dubai and Fuentes de Almería. Both locations are good candidates for a large-scale facility of this kind, but both exhibit different weather patterns. Simulations are also performed with data averaged over the time period 1981–2010 as a representative TMY dataset.

In both locations, power output from the plant follows the seasonal cycle of the forcing data. Higher total power output is obtained during summer months when DNI is consistently higher and there are more daylight hours available for the plant to operate. Forcing with TMY data consistently overestimates the power output of the plants, although it is more accurate as a forcing method when meteorological variability, and particularly that of DNI, is low.

It was found that local DNI variability is an important factor to decide whether TMY is accurate enough for dynamic numerical simulations or detailed data will be necessary. For the two locations analyzed here, detailed data are seen to be more important for winter when we have higher variations in DNI, while TMY is mostly suitable in the summer months. In regions with more weather variation that expect future changes in weather patterns due to long-term trends, TMY might become even less reliable. Before performing detailed simulations over many years, it is recommendable to diagnose the DNI range that gives reliable power output, and compare this to the range of variability seen in the DNI forcing data.

The use of climate data from the past is not only necessary for understanding how climate change has affected the performance of solar power plants, but it also serves as the first step to predict the future of such technology under increasing global warming conditions. As such, the level of detail in the data used is very important to save engineering time and computational cost. As more detailed data becomes available in the future, effort should be made to balance the cost of direct simulation with its benefit.

CRediT authorship contribution statement

Fontina Petrakopoulou: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Alexander Robinson:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Formal analysis.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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