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Systematic bias in reanalysis-derived solar power profiles & the potential for error propagation in long duration energy storage studies

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HIGHLIGHTS

- Evidence suggests MERRA-2 exhibits a significant overestimation of solar resource.
- Overestimation bias proliferates in cloudier climates for both MERRA-2 and ERA-5.
- Low round-trip efficiency of long-duration storage allows propagation of bias error.
- Error propagation could heavily distort total energy requirement of such storage.
- For modelling solar resources, ERA-5 is recommended over MERRA-2.

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ABSTRACT

This study consolidates the literature relating to the systematic bias of model-derived irradiance data and further characterises the same for ERA-5 and MERRA-2, two reanalysis datasets that are frequently used to model renewable power in energy system modelling studies. The bias errors yielded when modelling Solar PV generation for solar parks in Australia and Northern Ireland are compared under the optics of typically clear versus typically cloudy respective climates. Evidence is presented that MERRA-2 exhibits a significant global overestimation bias, contrary to some literature that suggests local variation and underestimation in some locations. Based on the trends identified, it is proposed that overestimation bias proliferates in more cloudy climates for both reanalysis datasets. The implications of such bias for studies involving long-duration energy storage with low round-trip efficiency are investigated and an unfortunate mechanism for error propagation is highlighted. A simplified power system consisting of wind, solar, and energy storage is modelled to demonstrate this effect with solar power profiles derived from metered generation, ERA-5, and MERRA-2. It shown that greater systematic bias of MERRA-2, in combination with the opportunity for error propagation through low-round trip efficiency, has the potential to significantly distort the charging & discharging pattern, overall utilization, and total energy requirement of long duration energy storage infrastructure. ERA-5, despite also exhibiting systematic bias, was better able to reproduce the simulated results of the metered generation scenario. Finally, it is recommended that energy modellers using MERRA-2 data to simulate solar PV outputs should now migrate to ERA-5 if reanalysis data is to be used.

1. Introduction

Reanalysis datasets, such as MERRA-2 [1] and ERA-5 [2], are increasingly used to model meteorologically driven renewable power sources in energy system modelling studies. Pfenninger & Staffell [3,4] provide the backbone to the renewables.ninja tool which employs the MERRA-2 dataset (amongst others) and allows the user to simulate wind and solar power timeseries data across the globe. The Open Power System Data platform [5] provides an interface for downloading selected MERRA-2 data in addition to country-level MERRA-2 derived solar PV & Wind capacity factor timeseries from the renewables.ninja tool along with other useful energy-system related data. With regards to the modelling of solar energy resources specifically, satellite data is also widely used. The National Solar Radiation Database (NSRDB) [6] is

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generally considered the “gold standard” of freely available resources for modelling Solar PV across its domain and has been reasonably well validated [6–8]. The NSRDB irradiance variables are derived principally from satellite data but also incorporates MERRA-2 reanalysis aerosol data. Pfenninger & Staffell [3] also explore the use of the satellite-derived SARAH dataset [9,10] for modelling solar PV timeseries data. However, both SARAH and the NSRDB are limited in their geographic domains, as is typical of any one satellite derived irradiance dataset. In this instance, the global domain common of reanalysis datasets offers a particular advantage. For example, Brinkerink et al. [11] use the renewables.ninja framework to model worldwide wind and solar power profiles with MERRA-2 data for input into a detailed global electricity model. Ruggles & Caldeira [12] also leverage MERRA-2 data to simulate both wind and solar PV power profiles for electricity systems in France and different regions across the U.S.

A second attractive feature of reanalysis datasets is the multitude of meteorological variables they offer. This allows for co-examination of different renewable power drivers and their relationships. Bett & Thornton [13] examined the climatological relationships between wind and solar power supply in Britain using the ERA-interim reanalysis dataset [14,15]. Based on their analysis, the authors find an optimal ratio of wind and solar nameplate capacity that minimises seasonal balancing requirements with respect to an arbitrary static load. Strikingly, this is found to consist of a mix consisting of approximately 70 % solar and 30 % wind capacity. Similarly, Jurasz et al. [16] used the ERA-5 reanalysis to examine the complementarity of wind and solar energy in Poland and present an analysis of periods of “drought” in renewable power production. As in Bett & Thornton [13] the authors find a general complementarity between the two power sources but note spatial variability in the strength of this trend.

As exhibited by the sample of works discussed above, reanalysis datasets can be seen to be enabling of important work that examines topics which are vital to the energy transition and the agile integration of variable renewable power sources into power grids globally. However, reanalysis datasets are not without their limitations. The occurrence of significant biases in solar radiation data derived from numerical weather and earth system models is well documented across the literature. Xie et al. [17] remark “a dramatic and unexpected bias is found in the routine computation of DNI” (Direct Normal Irradiance). Mathieson et al. [18] found significant positive bias in the forecast global horizontal irradiance (GHI) from both the Global Forecasting System (GFS) and the North American Mesoscale Forecast System (NAM) over the continental United States. Sianturi et al. [19] compared both the ERA-5 and MERRA-2 reanalysis datasets to radiation observations made on the ground over Indonesia. The authors find a systematic overestimation of surface incoming shortwave radiation by ERA-5 and a systematic underestimation by MERRA-2. However, we note that in conducting their analysis the authors have compared the Shortwave Solar Radiation Downward (SSRD) variable of ERA-5 and the Surface Net Downward Shortwave Flux (SWGNT) from the MERRA-2 dataset to the ground observations. It is suggested that the Surface Incoming Shortwave Flux (SWGDN) from the MERRA-2 dataset would be a more appropriate comparison. In this case it is hypothesised that the MERRA-2 data would also yield a significantly positive bias contrary to the authors’ analysis. Khatibi et al. [20] make a similar observation with regards to the use of the SWGNT variable in [19], however they explain that SWGNT is “not global irradiance, but the sum of direct and diffuse irradiance”. For clarity, it should be noted that global irradiance is itself the sum of direct and diffuse incoming irradiance. The SWGNT variable is, more specifically, the sum of all incoming sources of shortwave radiation less the sum of the outgoing shortwave radiation. Hence, it is the net downward shortwave radiation (such that radiation incoming towards the surface assumes the positive sign convention)[21,22]. The same apparent conflation between the net downward shortwave radiation flux and the surface incoming shortwave radiation flux of the MERRA-2 dataset is made in Urraca et al. [23] wherein an analysis of the performance of several reanalysis datasets and the SARAH satellite dataset is presented through comparison to ground observations of global irradiance. This is concerning given that the authors found the MERRA-2 dataset exhibits a strong positive bias. If this strong positive bias has indeed been derived of MERRA-2’s net downward solar radiation variable, it is likely that the actual bias when analysing the surface incoming radiation is significantly worse. For context, one might expect the SWGDN variable to be about 33 % greater than the SWGNT variable on average when considering a surface albedo of approximately 0.25. Encouragingly however, the authors also found that the ERA-5 dataset significantly reduced the quality gap between reanalysis data and satellite data with ERA-5 exhibiting a similar bias to the satellite data over less cloudy inland regions. This is an interesting observation and is similarly reflected in the findings of [19] who noted a strong variation in the overall bias on a basis of the observation-estimated clearness index whereby the reanalysis datasets had a lesser tendency to overestimate global surface irradiance when the actual conditions were clear. Clarke et al. [24] also compared ERA-5 and MERRA-2 data to weather observations. The authors found a tendency for overestimation bias on incident shortwave radiation across both datasets which was more significant in the case of MERRA-2. In agreement with [19], the authors also highlight a bias trend that varies with cloudiness.

Polo et al. [25] give a useful summary of the need to correct model-derived irradiances for systematic bias considering both satellite and reanalysis datasets. Indeed, Pfenninger & Staffell [3] highlight the same need for bias correction of model-derived irradiance under the context of modelling solar PV outputs. Notably, the authors find multiplicative scaling factors to correct the average capacity factor biases observed when modelling PV outputs using the MERRA-2 and SARAH datasets. Li et al. [26] similarly find multiplicative corrective factors for MERRA-2 when modelling solar PV in China, however these are applied to MERRA-2 GHI data based on observed bias at meteorological stations and geospatially interpolated to account for geographic variation. It is also necessary to consider the extent to which a static correction factor truly improves the overall model if the model biases are dynamic in nature and vary strongly with the cloudiness or clearness at any one time. For example, if a significant monthly trend in cloud cover is typical at any one location or area, the overall profile of monthly modelled generation could be distorted, which may have implications for energy system studies involving solar power generation.

Recently, the role of storage and hydrogen has attracted attention in future-looking studies of renewable power systems, in which these reanalysis datasets are commonly used. Hydrogen and its derivatives have been proposed as one possible solution for long-duration energy storage. Conceptually speaking, hydrogen storage could allow for a 100 % renewable power-grid through the conversion of renewable electricity to hydrogen (or a derivative) during periods of high renewable generation, and reconversion to electricity during periods of ‘drought’ in renewable production. Similar power system pathways, with the addition of other technologies such as pumped-hydro storage, are explored in the likes of Jacobsen et al. [27], Steinke et al. [28], Colbertaldo et al. [29] and Maruf [30] for example. In discussing hydrogen or other potential long duration storage technologies, it is important to consider the concept of round-trip efficiency. In the conversion of electricity into hydrogen and the subsequent generation of electricity using the stored hydrogen, the conversion processes incur significant losses due to the limited efficiencies of the fundamental processes involved. These losses lead to a low ‘round-trip efficiency’, the percentage of the input power consumed in filling the storage that is recoverable later when the storage discharges. For long-duration hydrogen storage, the round-trip efficiency depends on the precise technologies involved, but a value of 30 % could be considered typical [31,32]. Consequently, where an overestimation bias on a renewable power profile leads to a corresponding underestimation in the required delivery of stored power, the underestimation on the total energy requirement of the scenario will be even larger. More simply, if more electrical energy must be delivered by the long duration storage than originally estimated, it follows that additional energy must also be lost in the conversion processes. This is true for technologies of any round-trip efficiency (less than 100 %) but is far more pronounced for those of low round-trip efficiencies where a greater proportion of input energy is lost in a storage cycle.

To illustrate this, consider Fig. 1. Part 1 is a simple diagrammatic representation of a hypothetical hydrogen-based long duration energy storage unit with a round-trip efficiency of 30 % as per above. Consider the scenario where, due to a shortfall of available renewable power during a given period, it is modelled that 60 MWh of electrical energy must be discharged from the (initially full) storage unit in order to meet demand. Consider further that, due to error associated with the renewable power profiles, the error on the shortfall of available renewable power during the period in question is arbitrarily ± 6MWh. This is represented by part 2 of Fig. 1 where 60 ± 6 MWh is discharged from the storage unit to the grid. Subsequently, as per part 3, 200 ± 20 MWh of electrical energy would be required to fully refill the storage unit. In this case, the original error of 6 MWh has propagated to become an error of 20 MWh on the total energy requirement due to losses in the storage cycle. To this end, it is hypothesized that the bias that is documented to arise on reanalysis-derived renewable power profiles could undergo significant propagation in certain energy systems modelling scenarios.

Kies et al. [33] examined the implications that different model-derived renewable generation datasets might have for European power system modelling studies. It was found that differences in levelized cost of 10 % could occur and the choice of dataset could therefore impact policy advice. In the context of energy system planning and optimisation models, this raises important questions. Indeed, the European Network of Transmission System Operators for Electricity (ENTSO-e) leverage reanalysis data for the Pan-European Climate Database (PECD) [34] which is used for loss of load expectation calculations in the European Resource Adequacy Assessment (ERAA) studies [35]. With the European Commission's Hydrogen Strategy [36] targeting 40 GW of electrolysers in Europe by 2030, future studies incorporating this growth in Power-to-X (P2X) technology could potentially experience amplified error propagation that could distort important metrics, such as loss of load expectation. Between the documented bias on reanalysis-derived solar irradiance and the rapid growth in European solar PV capacity, it is considered that there is particular potential for solar PV to exacerbate this.

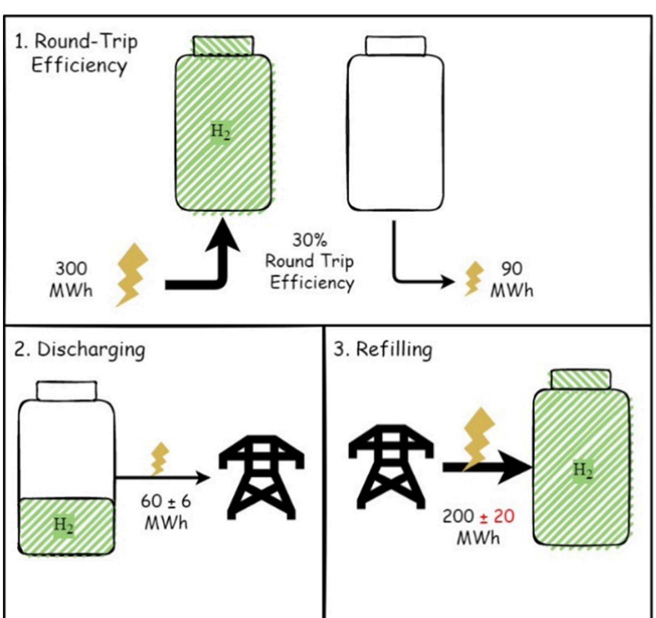

Fig. 1. Error Propagation Through an Energy Storage Cycle.

In the current work, an approach like that of Pfenninger & Staffell [3] is taken in that the output of multiple PV installations is simulated using hourly reanalysis data and compared to actual generation data. In doing so, the expected typical bias when modelling PV output is quantified, rather than that of the reanalysis irradiance variables through comparison to ground-based measurements. Given the documentation of significant bias on model-derived irradiances across the literature, it is hypothesized that these are the primary driver of bias in the subsequent modelling of PV output using such data. Nonetheless, it is also likely that the intermediate modelling work in estimating PV output from the meteorological inputs introduces some bias. In any case, it is deemed useful to quantify the net resulting biases when good or best practice is followed in simulating PV output using reanalysis datasets, given the increasing number of studies that do so. In this paper, we further examine the extent to which the occurrence of bias is dynamic. Rather than examining the net annual or indeed multi-annual bias that arises, a closer look is taken at intra-annual variation in bias as well as the variation in bias with the modelled clearness index as per each reanalysis dataset. Each of these aspects are characterised across two different locations representing different climates. In rather loose meteorological terms, these two locations, Northern Ireland and Australia, represent a distinctly cloudy and a typically clear climate respectively.

We aim to place context around the potential implications of any biases found on prospective power system studies with large solar buildouts. Specifically, we examine the effects of biased solar profiles with respect to the topical issue of seasonal or long-duration energy storage, such as green hydrogen or its derivatives, where low round-trip efficiencies could amplify the influence of any intra-annual bias and distort patterns or trends in charging and discharging. It is further aimed to provide some indication as to whether any potential implications found are of equal concern in clearer climates or more relevant to cloudy climates where reanalysis datasets are seen to suffer in terms of accurately resolving the effects of cloud on surface irradiance. It must be noted, however, that rather than attempting to precisely quantify any potential impacts for a specific region or power system with a complete and representative power system model, the intention behind this work is to highlight one potential mechanism by which the differences in outcome found in the likes of Kies et al. [33] could propagate in further studies involving P2X based storage.

2. Data & sources

2.1. Solar park static data

For each solar park, capacity data along with the tilt angle of the panels were researched manually through planning applications and industry articles or documents as available. Blanket assumptions of due south and due north azimuth angles are applied to solar parks in the northern and southern hemispheres, respectively. Data was collected for three Australian solar parks; Whiterock, Nyngan and Royalla and three Northern Irish solar parks; Rasharkin, Maghaberry and Lisburn.

2.2. ERA-5

The ERA-5 reanalysis dataset was accessed from the Copernicus Climate Data Store via the CDS API. It was downloaded in its native hourly 0.25° x 0.25° resolution in NetCDF format for the relevant locations using simple nearest point interpolation for the years 2019 and 2020. The following variables were downloaded and processed:

surface_solar_radiation_downwards – converted from J to average value in W/m^2 over each period to represent the global horizontal irradiance (GHI).

surface_solar_radiation_downward_clear_sky – converted from J to average value in W/m^2 over each period to represent the global horizontal irradiance (GHI) under a cloudless sky.
10m_u_component_of_wind & 10m_v_component_of_wind – the 10 m above ground u and v vector components of wind. The magnitude of the wind vector is calculated to give the windspeed.
2m_temperature – the 2 m above ground air temperature, converted from K to °C.

2.3. MERRA-2

The MERRA-2 dataset was accessed via NASA's Goddard Earth Sciences Data and Information Services Centre. It was downloaded in its native hourly 0.5° x 0.625° resolution in NetCDF format for the relevant locations using simple nearest point interpolation for the years 2019 and 2020. The following variables were downloaded and processed:

SWGDN – the surface incoming shortwave flux (GHI).
SWGDNCLR, – the surface incoming shortwave flux assuming a clear sky (GHI).
U10M, V10M – the 10 m above ground u and v vector components of wind. The magnitude of the wind vector is calculated to give the windspeed.
T2m – the 2 m above ground air temperature, converted from K to °C.

2.4. SCADA

Metered power output data for the Australian solar parks was obtained from the Australian Electricity Market Operator (AEMO) [37] for the full years of 2019 and 2020 in the form of supervisory control and data acquisition (SCADA) data and was not adjusted or processed further.

Metered SCADA data for the Northern Irish solar parks was obtained from the Single Electricity Market Operator (SEMO) [38] for the full years of 2019 and 2020 and was not further processed or adjusted.

3. Methodology

3.1. PV model

The open-source PVLIB Python [39,40] forms the backbone of the Solar PV modelling work in this study. Using the PVLIB Python package, one can quickly apply some of the best-established irradiance decomposition & transposition models with various PV performance models. Conveniently PVLIB Python includes data from the Sandia module parameter database for application to the Sandia Array Performance Model (SAPM) [41]. The SAPM is widely validated and has been shown to correspond well to actual PV power output measurements [42–44]. As neither the MERRA-2 dataset nor the ERA-5 explicitly provide both the DNI and DHI variables a decomposition model is used to calculate them. The same methodology is applied to both datasets for direct comparison; however, it should be noted that it is possible to calculate the DHI directly from the variables provided by the ERA-5 dataset. The DNI could then be subsequently calculated. Based on the conclusions of Lave et al. [45], the DIRINT decomposition model [46] is chosen for this work, as it was found to be the least biased of the decomposition models examined at all locations studied. This provides an estimation of the DNI and allows for the subsequent calculation of the DHI via equation (1), where φ is the solar zenith angle:

$$DHI = GHI - (DNI \times \cos(\varphi)) \quad (1)$$

Having decomposed the GHI into its modelled direct and diffuse components, a transposition model can be applied to estimate the irradiances incident on the plane of the array (POA). [45] found, when coupled with a decomposition model, mean bias differences were typically smaller with the Hay/Davies model [47] than with other transposition models. On this basis, the Hay/Davies transposition model is applied. Finally, between the modelled POA irradiances along with wind and temperature variables from the reanalysis datasets, we have all meteorological input variables required to model solar PV generation as per the Sandia Array Performance Model (SAPM) [41]. The SAPM is a well-validated empirical model [41–44] which is conveniently integrated in PVLIB Python. In this work, the relevant parameters of the latest module in the Sandia Module database included with PVLIB python, a 2014 monocrystalline/amorphous silicon hybrid module, are taken as the SAPM module parameters. The temperature parameters for a glass/polymer open rack module as per King et al. [41] are used in the SAPM cell temperature model. Next, rather than assuming a string or central inverter design, we model only the DC power availability of the chosen module and normalize the resulting timeseries by the nominal Wp capacity of the module. This normalized timeseries is then applied to the solar park in question by scaling it by the MWp capacity of the said solar park. To account for clipping, any potential DC generation greater than the solar park's MWac capacity (inverter capacity) is set equal to the AC capacity. Here it is important to highlight that, while clipping has been accounted for, DC/AC conversion losses are not accounted for and assumed to be zero. Consequently, we can already expect to see a 2–4 % positive bias in our model on this account. Finally, it should be highlighted that this approach does not consider the possible shading of module rows by other modules in a solar park. Row shading in solar parks is usually most prominent very briefly in the morning and evening when the sun is low in the sky. During these times, solar power output tends to be low. Furthermore, efforts are typically made to minimise the effects of shading when designing solar parks. As a result, the omission of a shading model is not expected to significantly distort the resulting modelled solar profiles.

3.2. Power system & LDES model

To examine the possible implications of biased reanalysis-derived PV generation profiles on power system pathways involving long-duration storage and high solar build-out, a power system dispatch model is developed in the software PLEXOS. The model is highly simplified so as to neatly distil dynamics at the generation and storage interface. Consequently, it is important to preface that this model is not intended to represent a robust and comprehensive power-system pathway, but rather, a means to examine or demonstrate a potential mechanism of error propagation in certain pathways and models. For the purposes of demonstration, the simulation is based on the Northern Irish units as they exhibit greater bias errors. No simulation is performed based on the Australian sites as it is not intended to give the impression that it is attempted to quantify the degree of error propagation for a given reanalysis dataset in each location. Naturally, the degree of propagation will vary with different energy system models. Rather, it is simply sought to demonstrate a potentially problematic dynamic that may need to be given some degree of consideration when it comes to energy system modelling. The model is built in PLEXOS to consist of 2 generators, one wind generator and one solar generator. The solar profiles were created by taking the average load factor of the Lisburn and Maghaberry Northern Irish sites as according to either the metered generation, the ERA-5 based model, or the MERRA-2 based model depending on the scenario. Rasharkin solar park was excluded on the basis that it is known to be connected to a particularly congested grid node with a maximum export capacity well below its actual inverter capacity (this was accounted for in the original model). The wind and demand profiles are taken from Ireland's Commission for Regulation of Utilities' (CRU) PLEXOS model [48] which is publicly available. The simulation is run (arbitrarily) for the year 2024, in which the CRU project an average demand of approximately 5400 MW and a peak demand of approximately 8000 MW. The simulated and metered solar profiles are based off the data for 2020, another leap year, so as the timeseries can overlap. The wind and solar generators were sized to loosely reflect the finding of

[13] that a portfolio of 70 % solar and 30 % wind capacity would minimise variability in renewable power generation. In addition to the renewable generators, a short-duration energy storage (SDES) battery unit and the H2 long-duration energy storage (LDES) unit are modelled using the PLEXOS battery object. The SDES is included given its greater round-trip efficiency for intra-day balancing of generation and demand reduces the total energy demand. As a result, it has been found that a hybrid combination of short and long duration storage can yield more cost-effective systems relative to reliance solely on less efficient long-duration storage [49,50]. The short duration energy storage is sized to yield 2 h of storage at the nominal capacity which is set equal to peak demand. The long duration energy storage is sized for 200 h of storage at the nominal capacity. The modelled system is an isolated electricity island in that no interconnection is modelled. The system is summarised in the table below.

The model is effectively an economic dispatch model with zero marginal cost generators with all units assumed available/committed. However, to ensure the battery and hydrogen-based storage units are utilized as intended, a per-MWh use of system charge is applied to the long-duration energy storage so as to implement a merit order among the storage technologies and ensure the short-duration storage is dispatched preferentially. No constraints are placed on the flexibility of either energy storage unit; however, the long-duration storage is constrained so as its state of charge at the end of the simulation is equal to its initial state of charge of 50 %. The model is solved in a single step using the Gurobi solver. Three model scenarios are run; The'MET', 'ERA' and 'MERRA' scenarios whereby the solar profiles are derived from metered generation, the ERA-5 based PV model, and the MERRA-2 based PV model respectively.

4. Results & discussion

4.1. PV model performance

Figs. 2 and 3 show density scatter plots of the modelled PV outputs from both MERRA-2 and ERA-5 sources against the measured SCADA data for the Australian and Northern-Irish sites respectively. A dense cluster of datapoints is observed around the red guideline along across all three Australian sites for both the MERRA-2 and ERA-5 based models indicating good agreement. However, White Rock exhibits a large number of outlier datapoints where the modelled outputs are significantly overestimating by higher load-factors for both datasets. Given the more symmetrical spread of errors at the Nyngan and Royalla sites, this possibly indicates more significant dispatch down or partial outage of the White Rock solar park. Here, dispatch down refers to the reduction in power output from the maximum available due to a network constraint or system level curtailment.

The Northern-Irish sites do not exhibit the same dense cluster of datapoints around the guidelines, but instead show a persistent, wide spread of errors as per Fig. 3. Notably, the MERRA-2 derived model exhibits a slightly denser line of outliers at the top of the y-axis where the model is expecting clipping due to the DC power availability exceeding the inverter capacity, but the actual metered generation realised is lower. This indicates that the MERRA-2 based model may be overestimating high generation periods more frequently than ERA-5. This is in line with [24] wherein the authors' findings demonstrate a stronger overestimation bias on the shortwave irradiance for MERRA-2 than ERA-5 at meteorological measurement stations in Ireland. In any case, it is clear that both the MERRA-2 and ERA-5 based model suffer in performance in the cloudier Northern Irish climate relative to the clearer Australian climate.

Before further commenting on any overall bias, it is important to discuss data quality and highlight some assumptions. As the SCADA data measures the net metered output injected to the grid, thought must be

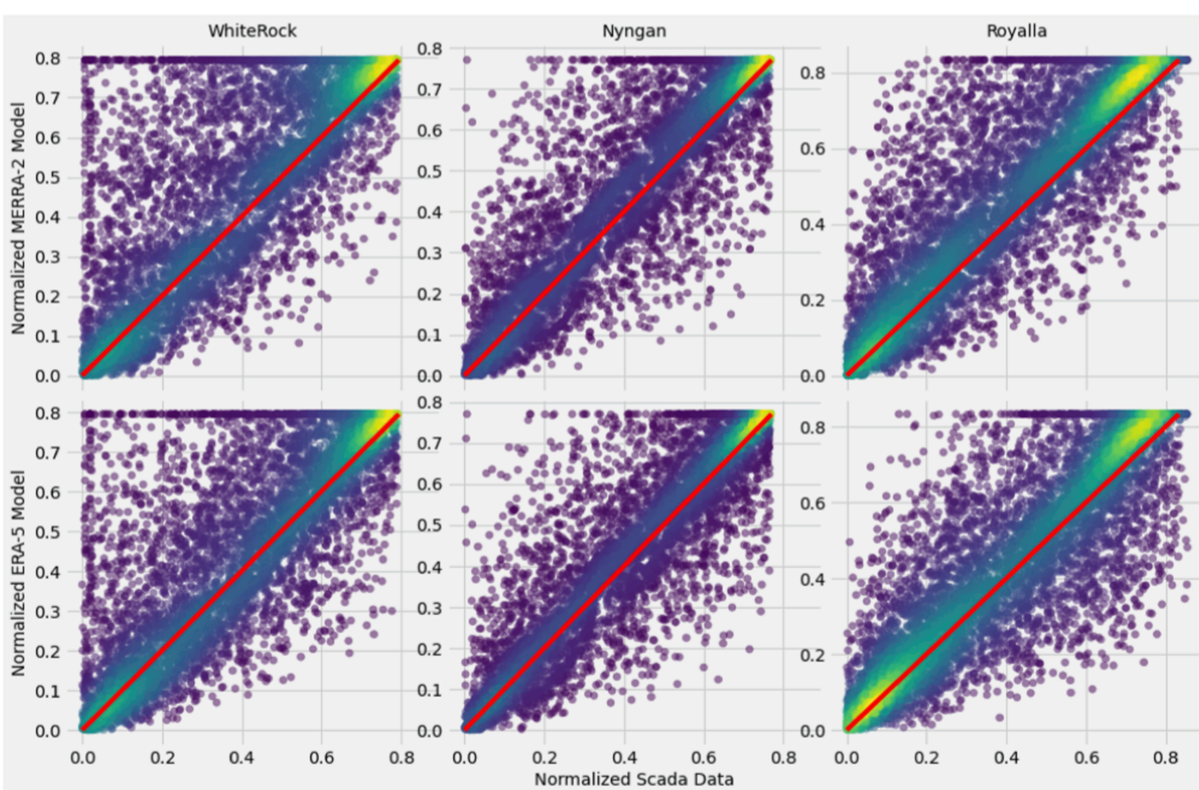

Fig. 2. Australian Sites PV Model Correlation, 2019–2020.

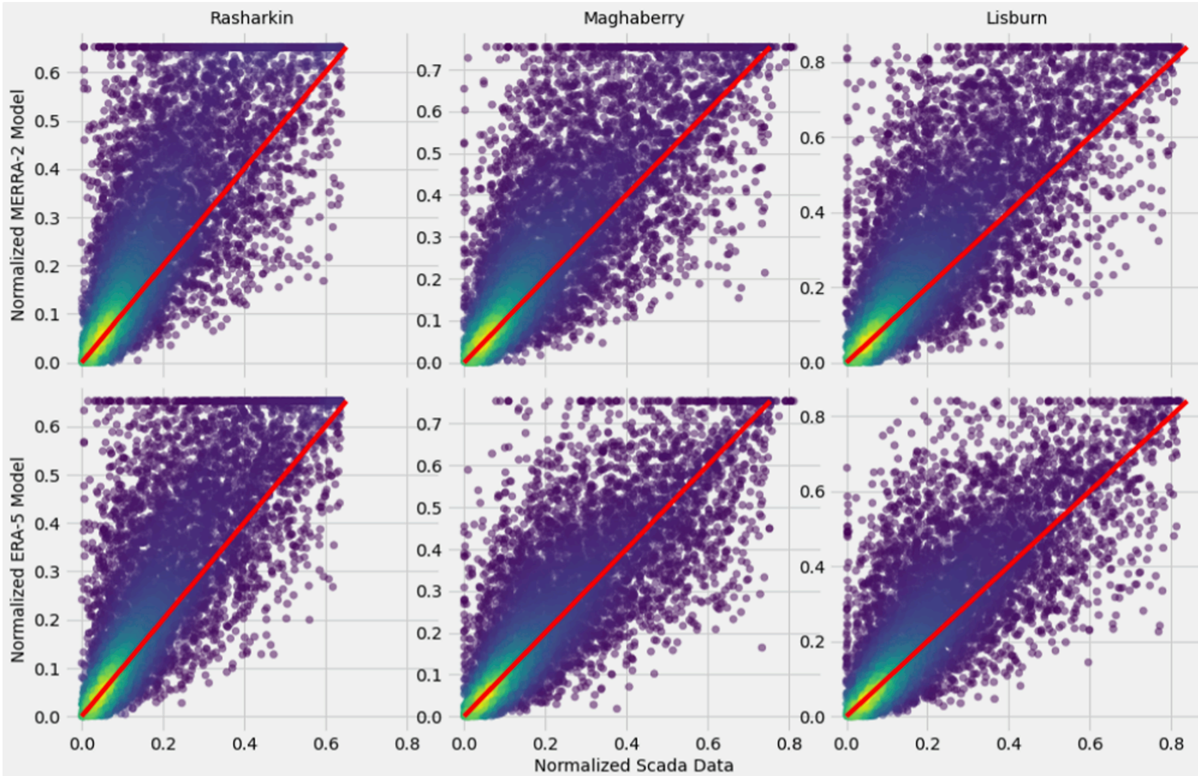

Fig. 3. Northern Irish Sites PV Model Correlation, 2019–2020.

given to the effects of dispatch down events due to constraints and curtailment. A precise discrepancy between the SCADA data inclusive of dispatch down and the potential generation in the absence of such dispatch is typically difficult to quantify for any individual power plant over a given data point. Indeed, attempting to adjust for such discrepancies without exact dispatch down data is likely to introduce bias error in any case. As such, we expect to see a degree of positive bias, where the model overestimates relative to corresponding SCADA data points when the plant has been dispatched down. This will also affect the correlations observed in Figs. 2 and 3.

In the case of the Australian Solar Parks, each of the sites are in New South Wales, the Australian state with the lowest percentage levels of curtailment of variable renewable power over 2019 & 2020 as per reporting by the Australian TSO [51]. According to AEMO's report, we would expect to see the bias introduced by curtailment amounting to less than 4 %, though this is likely to vary from site to site. The system operator in Northern Ireland, SONI publishes similar reports [52,53] indicating dispatch down equivalent to 4.2 % and 6.3 % of the available solar energy in 2019 and 2020 respectively. Consequently, we expect dispatch down to have introduced a bias of 5 %. This is, of course, expected to vary by site.

Table 1 lists the mean bias errors (MBEs) of both models as a percentage of the actual metered generation. When considering unmodelled inverter losses, module soiling and dispatch down events, the ERA-5 based simulations of the Australian sites do not appear to exhibit any large bias. In the case of the MERRA-2 data however, there is evidence of moderate overestimation bias. Nyngan solar park exhibits a weaker MBE than the other two sites for both reanalysis datasets. It is possible that this arises in part because the Nyngan park is made up of cadmium telluride (CdTe) modules, which perform better in high temperatures than crystalline silicon modules, which are the assumed module technology in our PV model. For the Northern-Irish sites the large positive bias errors suggest a general overestimation bias when modelling solar PV with both reanalysis datasets. This is in line with the underestimation of cloud events by numerical weather models that is well documented across the literature and evident in Figs. 4 and 5. Figs. 4 and 5 plot the (DC) capacity-normalised mean bias error for both models at each site against percentiles of the clearness index 'k_t' according to the reanalysis data. The clearness index is calculated as per equation (2) by taking the ratio of the surface incoming radiation to the surface incoming radiation assuming a clear sky. A dynamic bias trend with a reasonably consistent general outline is revealed across all sites. Due to this difficulty experienced by the numerical models in resolving cloud events, it follows that the models' overestimation biases deteriorate further when the actual climate is typically cloudier. This is apparent through the comparison of the Australian and Irish sites. This trend is also potentially evident amongst the three Australian solar sites whereby Nyngan solar park seems to exhibit a weaker dynamic bias trend with the modelled clearness index than the other two sites. Nyngan is located inland in a drier area of New South Wales relative to the other two sites. In nearly every case examined, ERA-5 outperforms MERRA-2 under the current modelling framework with both the overall bias and dynamic bias trend reduced with ERA-5 relative to MERRA-2 (see Table 2).

$$k_t = \frac{GHI}{GHI_{clr}}$$

Given the dynamic bias trends exhibited in Figs. 4 and 5, it follows that, where a strong seasonal trend exists in the clearness index (or cloud patterns), it is possible that a strong seasonal bias is introduced to the

Table 1
Simulation Capacities & Storage Efficiencies.

Generator	Capacity (MW)	Storage Capacity (MWh)	Charge Efficiency (%)	Discharge Efficiency (%)
Wind	15,000	–	–	–
Solar PV	30,000	–	–	–
SDES (Battery)	8000	16,000	90	90
LDES (H2)	7000	200,000	70	50

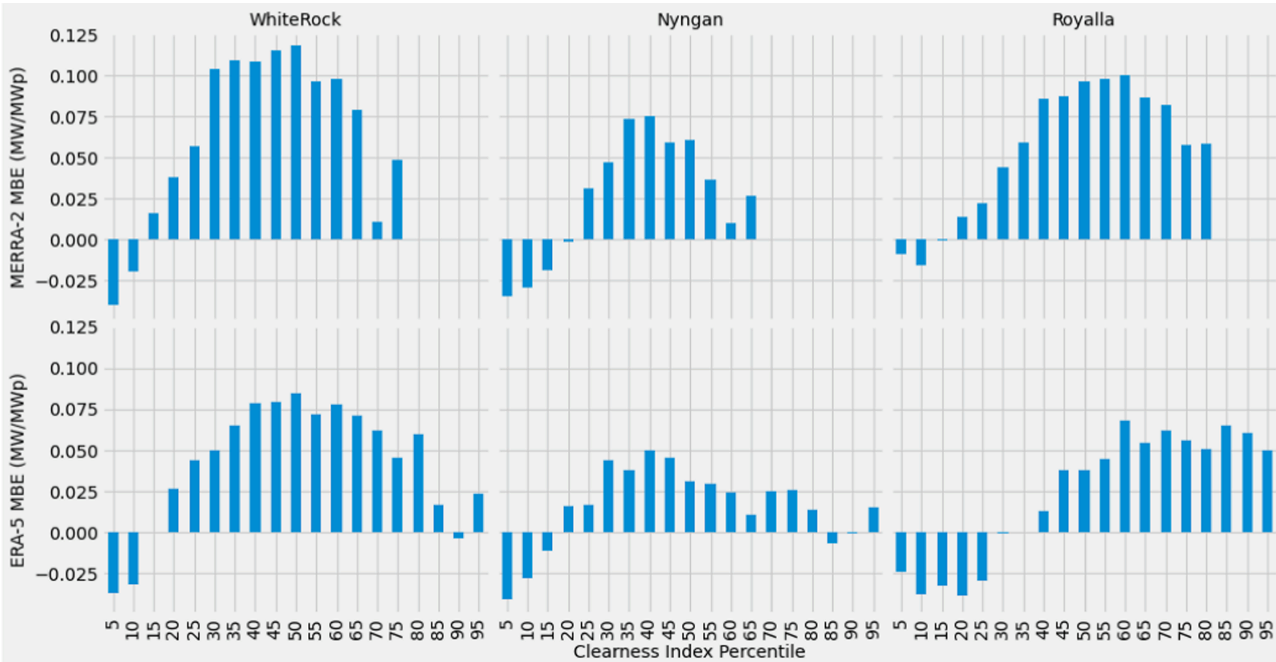

Fig. 4. Model Mean Bias Error vs. Clearness Index, Australian Sites.

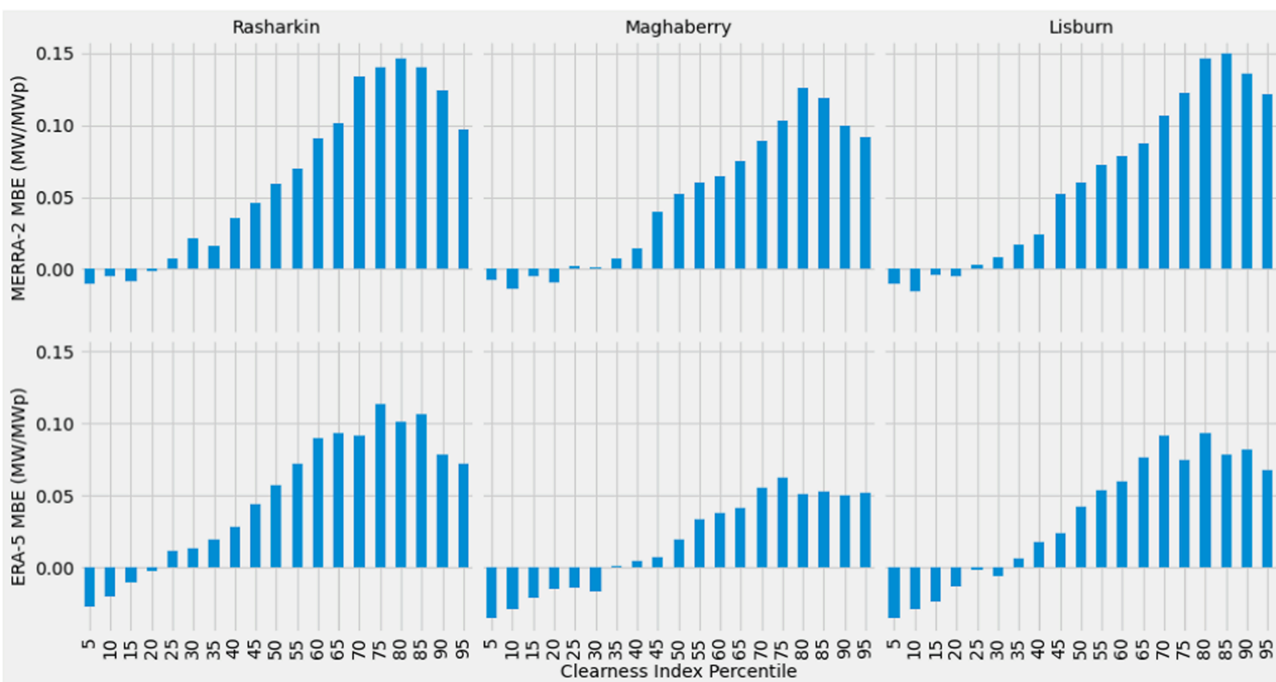

Fig. 5. Model Mean Bias Error vs. Clearness Index, Northern Irish Sites.

Table 2
PV Model Mean Bias Errors MBE %.

Site	WhiteRock	Nyngan	Royalla	Rasharkin	Maghaberry	Lisburn
ERA-5	13.1	1.6	7.6	33.1	11.8	22
MERRA-2	19.1	4.8	17.2	43.1	29	37.3

overall solar profile. This could introduce error when studying the seasonal complementarity of wind and solar power as in [13] or hybrid wind-solar power systems with long-duration storage. Take for example, the Northern Irish sites studied. Fig. 6 demonstrates a significant monthly trend in the average clearness index according to the MERRA-2 data with a profile that generally suggests clearer less cloudy summers

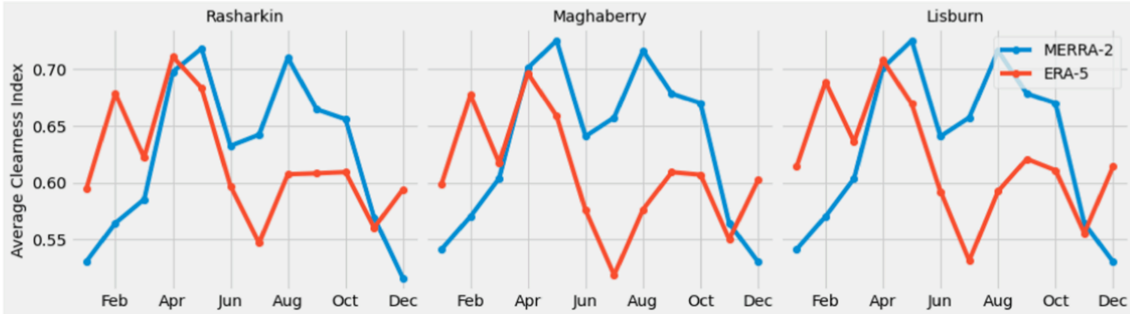

Fig. 6. 2019–2020 Monthly Average Clearness Index, Northern Irish Sites.

and cloudier winters. The ERA-5 data appears to disagree with that of MERRA-2 and suggests clearer less cloudy weather in the spring and a flatter cloudier trend from midsummer onwards. In line with the dynamic bias trend with clearness index and the apparent seasonality of the MERRA-2 clearness index, the MERRA-2 derived model exhibits a monthly trend in the overall bias error as seen in Fig. 7. Similarly, the ERA-5 derived model also exhibits greater bias in the months that the clearness index is thought to be higher as per the original ERA-5 data. Notably, it follows that, if one were to examine the role that Solar PV might play in balancing the lower wind power production on the Irish grid during the summer months, the MERRA-2 dataset could overstate the contribution of solar PV or indeed underestimate the need for seasonal storage in low-wind summer months in particular.

Locational biases are a common feature of reanalysis datasets and it would therefore be pertinent to point out the limited sample size of solar farms in the current work before drawing inference. However, when considering both the literature and the recurring trend of bias and clearness index, the overall picture is indicative of consistent systematic overestimation bias. To better contextualise this on a global level, the MERRA-2 derived renewables.ninja solar profiles for the large bank of solar farms in the PLEXOS World model of [11] are compared to a simulation of the same, over the same full year (2015) using the current work's PV model with ERA-5 as input data. The resulting capacity factors are displayed in Fig. 8. The red line marks where the x and y axes are equal in value for easier visualization. If the consistently better performance of ERA-5 under the current work's modelling framework is extrapolated onto Fig. 8, a marked global overestimation bias by MERRA-2 is suggested. The two models can be seen to be in better agreement for sites with higher capacity factors which supports the thesis of a generally smaller degree of bias in less cloudy regions with higher solar potential. In addition to the site-specific analyses presented, this trend raises a warning in terms of extrapolation of studies or validations from countries with high solar potential and lower cloud incidence to cloudier climates with lower solar potential.

4.2. LDES modelling

Having run the simple PLEXOS model for each solar input data scenario the operational pattern of the LDES (Hydrogen storage) infrastructure and its total energy requirement can be examined with consideration of the influence of the biases exhibited in section 4.1. Fig. 9 shows the 'state-of-charge' of the long duration storage for each simulation scenario, referred to here as the normalized hydrogen reserve. To some extent, agreement amongst the scenarios at the start and end of the simulation is forced due to the constraint on the initial and final state of charge. Outside of this, the metered generation based

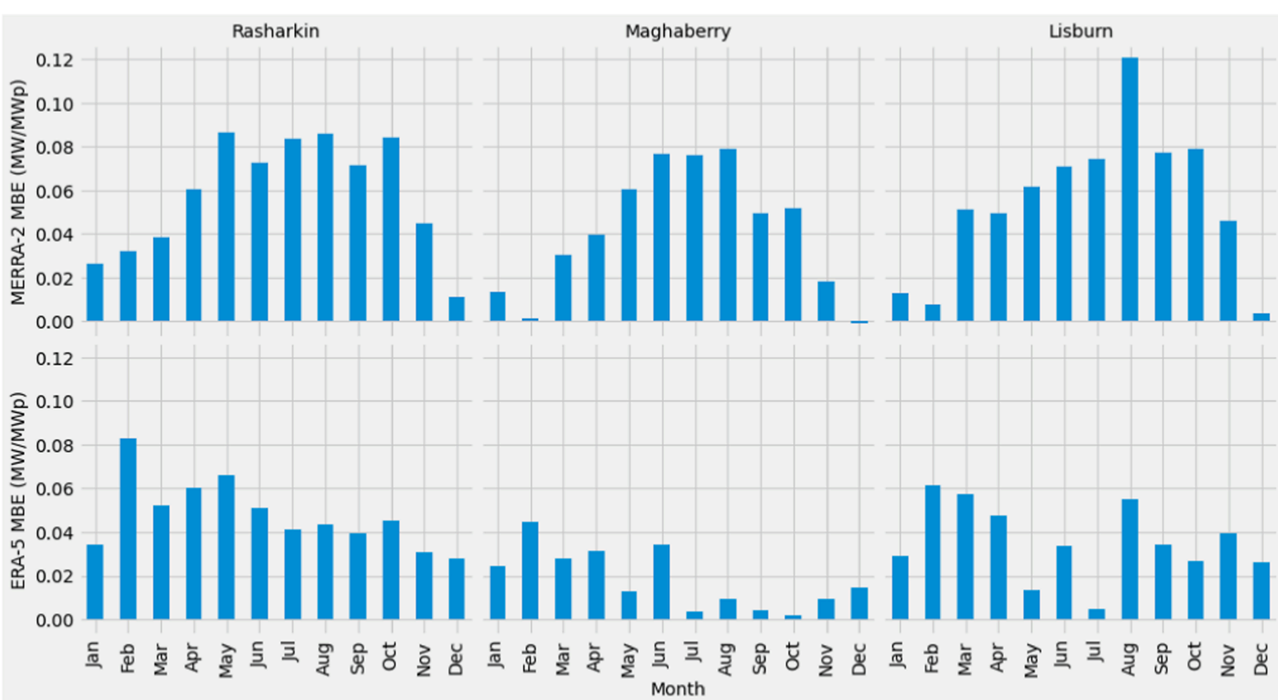

Fig. 7. 2019–2020 Monthly Average Model MBE, Northern Irish Sites.

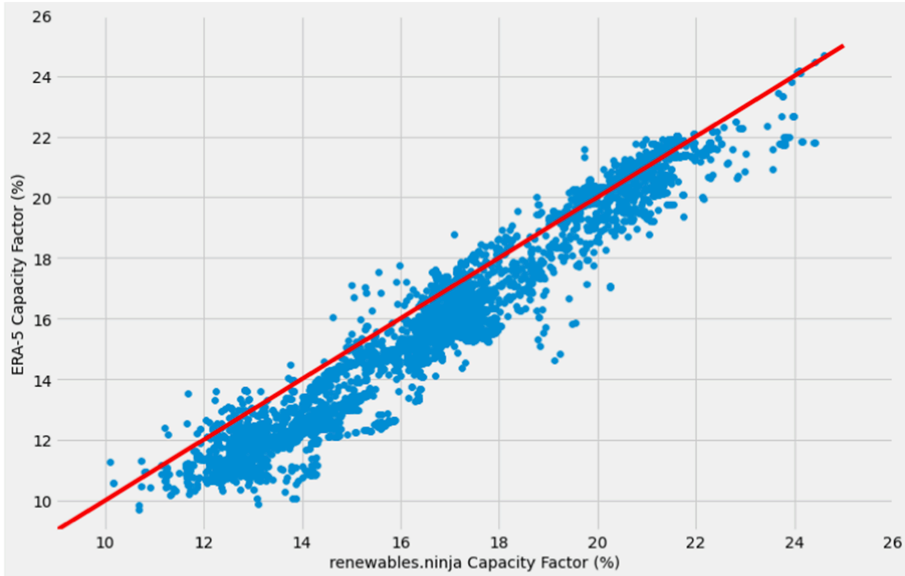

Fig. 8. ERA-5 Derived Capacity Factors vs. PLEXOS World PV Capacity Factors.

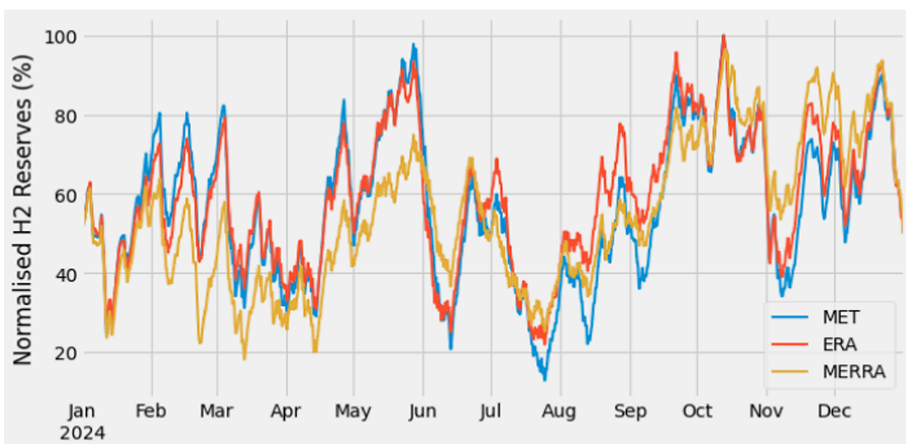

Fig. 9. Simulated Hydrogen Storage Charge State.

solar profile scenario and the ERA-5 based solar profile scenario are generally in close agreement with the exception of August & September. However, the MERRA-2 based solar profile scenario, whilst roughly agreeing on the timing of peaks and troughs in hydrogen reserves, differs quite significantly on their magnitudes and is distinctly distorted relative to the 'MET' scenario. This is interesting given that the MERRA scenario solar profile is more biased than the ERA scenario profile. Most notably, the MERRA scenario does not see the H2 reserve charged to the

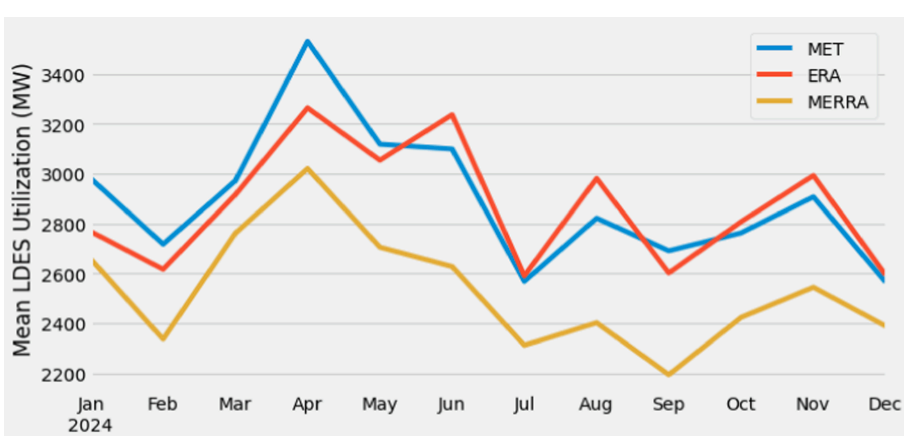

Fig. 10. Simulated Hydrogen Storage Utilization.

high peak in May/June that both the ERA and MET scenario agree closely on. It is hypothesized that this is likely due to the utilization charge associated with the LDES and greater estimated solar generation in the summer according to the MERRA-2 derived profile, as this would allow the simulation to simply cycle the short-duration battery energy storage more frequently for less cost than charging and discharging the LDES. As a result, the MERRA scenario appears to underestimate the need for seasonal storage during the low-wind summer months for the given solar power generation capacity. This follows logically from the dynamic bias-profile previously observed and the strong intra-annual trend in clearness index suggested by the MERRA-2 data.

Fig. 10 plots the average monthly utilization, calculated as the absolute value of the net generation of the LDES, in each scenario. Again, the MET and ERA scenarios agree reasonably closely whereas the MERRA scenario significantly underestimates the utilization of the LDES unit. It would follow that, per the given capacity in this scenario, the levelized cost of storage (LCOS) of the P2X-based storage is distorted. In this case, the levelized cost of storage would be inflated in the MERRA scenario given a lower volume of stored electricity delivered to the system over which to spread the capital cost of the installation.

Fig. 11 shows the cumulative difference in the de-rated margin and the cumulative difference in the electrolyser load between the MERRA and the MET scenarios. In this case, the de-rated margin is defined as the sum of the renewable generation less the underlying system demand (or simply the net generation once the charging and discharging of storage is excluded). Clearly, the moderate bias error on the generation profile which yields the difference in net generation between scenarios proliferates into a much more significant error on the total electrical load requirement of the electrolyser. This is demonstrated through the total cumulative error just shy of a gigajoule on the de-rated margin culminating in close to 2.5 GJ in cumulative error on the electrolyser load over the simulated period. In other words, an error on the available energy supply has yielded an error on the total energy requirement of the simulation that is magnified by a factor of approximately 2.5. This demonstrates the mechanism by which low-round trip efficiencies can lead to the propagation of initial bias error on power profiles resulting in larger errors on the total energy requirement of a simulation as originally hypothesized. Evidently, this could skew resource adequacy assessments of certain power system pathways to a concerning extent, particularly over long simulation periods.

5. Conclusions

In this work we have consolidated the existing literature with respect to biased model-derived irradiance data and further examined ERA-5 and MERRA-2, two reanalysis datasets that are frequently applied to model renewable power profiles in energy modelling studies. While some studies suggest local variance in the direction of bias on these irradiance datasets, we have presented evidence that suggests the MERRA-2 reanalysis dataset exhibits a generally global overestimation bias. It is further suggested that in cloudier local climates with poorer solar resources, the overestimation bias by MERRA-2 is larger. The ERA-5 dataset, whilst exhibiting a better performance relative to MERRA-2 when modelling Solar PV output, also presents a deterioration in cloudy climates that leads to overestimation bias.

In many instances, such as in clearer climates, the bias errors yielded in modelling solar PV with reanalysis data could be relatively small if fully accounting for losses in the PV model chain. However, this work has demonstrated that studies involving storage technologies with low round-trip efficiency, such as long-duration Hydrogen based storage, could see large propagation in these initial input errors. It has been shown that particular care should be taken when such studies include large solar PV build-out in cloudy climates. Whilst the ERA-5 dataset managed to commendably reproduce simulated outputs close to those yielded when profiles leveraging metered generation data were input, the MERRA-2 based model led to significantly distorted charging & discharging patterns and underestimated the utilization of the long-duration storage asset. Based on this work, we recommend energy system-modellers employing MERRA-2 to simulate solar PV output should now migrate to ERA-5 to avoid significant errors in estimating total energy requirement, levelized cost of storage, or capacity requirements for low-round trip efficiency energy storage technologies.

Data Availability

The simulated PV outputs of this work, the corresponding SCADA data, the PLEXOS model and the required inputs are openly available via data repository at: https://doi.org/10.17632/jf27d9wy3z.1.

CRediT authorship contribution statement

Duncan Mathews: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft. **Brian Ó. Gallachóir:** Writing – review & editing, Supervision. **Paul Deane:** Software, Writing – review & editing, Supervision.

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.

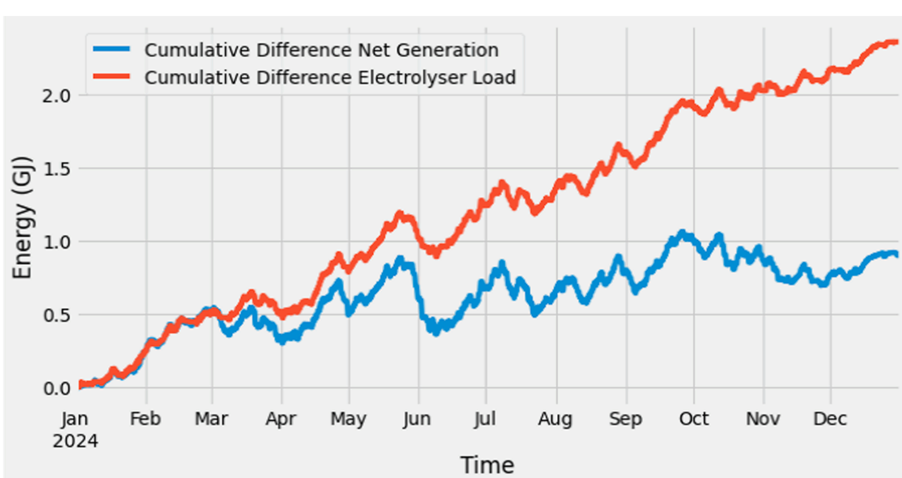

Fig. 11. Bias Error Propagation.

Data availability

Data will be made available on request.

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