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Value of deterministic day-ahead forecasts of PV generation in PV+Storage operation for the Australian electricity market

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Abstract

During the last decade, numerous solar forecasting tools have been developed to predict the energy generation of photovoltaic (PV) farms. The quality of solar forecasts is assessed by comparing predictions with measured solar data. However, this methodology does not consider the added value of the forecasts for their applications. As a consequence, what value could be given to the improvement of forecasts considering this evaluation framework?

To answer this question, this work compares the value of different operational solar forecasts for a specific application. The aim is to look for relationships between the economic value and the error metrics defined to evaluate the forecast quality.

A new generation of large-scale PV plants integrates ESS. The aim is to add flexibility to the injection of the production into the grid and thus to maximize the profit by taking advantage of the possibilities offered by the electricity market, such as energy arbitrage. To optimize the operation of these specific ESS, forecasting of the solar production is of paramount importance. The study case considered in this work is a large-scale PV farm of several megawatts associated with Li-ion batteries in the Australian energy market context.

For this specific case study, the results show that the metrics used to evaluate the forecast quality based on the mean absolute error (MAE) have an almost linear relationship with the economic gain brought by applying the forecast. More precisely, an improvement of 1% point in MAE results approximately in an increase of 2% points in economical gain.

Keywords: large-scale PV, energy storage, solar forecasting assessment, operation scheduling, optimization, electricity market, forecast value

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1. Introduction

Solar forecasts for horizons ranging from several minutes to several days ahead are available and well documented in the literature. Numerous state of the art studies on the topic have already been published during the past 10 years (Diagne et al., 2013; Antonanzas et al., 2016; Sobri et al., 2018). Currently, the performances of the forecasts are estimated by comparing the forecasts with measurements of solar irradiation or energy production of an associated system (PV, CSP, etc.) (Perez et al., 2013; Blaga et al., 2019; Yang et al., 2020). A common framework based on this testing approach is widely used by the academic community in the realm of solar forecasting. The main error metrics are the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the forecast skill based on the RMSE (Coimbra et al., 2013). Solar forecasts are produced to anticipate the future production of solar renewables, to improve grid operation and to decrease the cost of energy production. Indeed, they are important inputs to optimize the scheduling of unit commitments for grid management or to achieve the optimal control of Energy Storage System (ESS) needed to add flexibility to solar renewables. As a consequence, the value of solar forecasts must also be evaluated with reference to their use.

A gap currently exists between the developers of solar forecasts and the community that develops algorithms to integrate them into energy and power management systems (EMS and PMS) such as an optimal controller of ESS. On one hand, solar forecasts are evaluated without considering their added value for the users (Perez et al., 2013; Blaga et al., 2019; Yang et al., 2020). As a consequence, the improvement of solar forecasts are mainly driven by the reduction of the square error between the predictions and the observations. On the other hand, even if several works propose operational solar forecast as input of optimization methods used to manage energy systems (Ramahatana and David, 2019; Faraji et al., 2020; Pousinho et al., 2014; Iliadis, Petros et al., 2019), only few of them consider their added value or assess the gain of an enhancement of the forecasts (Wittmann et al., 2008; Kraas et al., 2011). In the domain of microgrids, where the literature about optimal control of ESS is abundant, real forecasts are even seldom used. Most of the works use historical records as “perfect forecasts” (Riffonneau et al., 2011; Nguyen et al., 2009; Luu et al., 2015; Morais et al., 2010; Wouters et al., 2015) or perturbed measured data (Abdulla et al., 2018; Bridier et al., 2016; Choi and Min, 2018). As a consequence, results are missing an accurate idea of the value of actual solar forecasts.

As mentioned above, forecasts for solar PV farms are typically assessed on the accuracy of the prediction to actual performance, rather than in the effectiveness of the generation system in delivering a desirable financial objective. Currently, the RMSE and the forecast skill also based on the RMSE initially proposed by Coimbra et al. (2013) tend to be the most predominant error metrics used in the academic literature to rank solar deterministic forecasts (Blaga et al., 2019; Yang et al., 2020). The estimation of the market value requires one to model and to simulate the selected application. Such a process is expensive in both time and calculation means. Some propositions exist to assess the economic value of weather forecasts without simulating the system. They are based on the cost caused by an error of forecasts such as the cost-loss function approach proposed by Richardson (2000). For

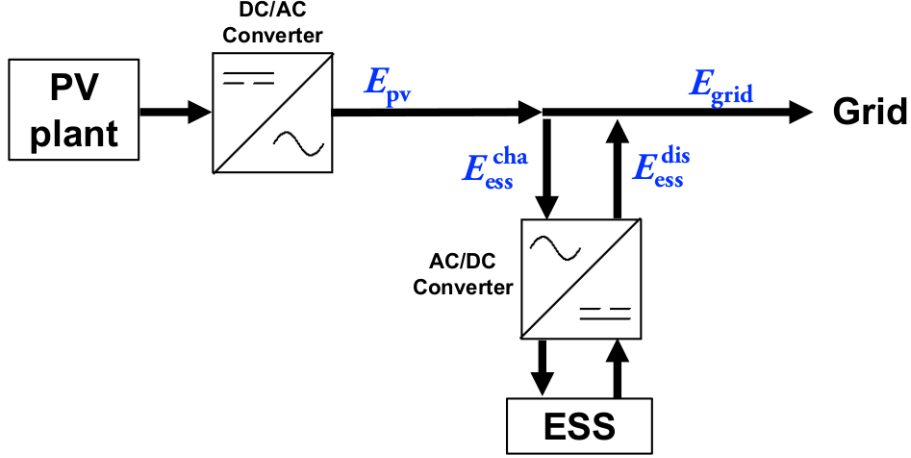


Figure 1: Schematic of the system model. The exchanged energy used to model the balance of the system (see Eq. 1) are given in blue font. The arrows indicate the direction for positive valued energy flows.

43 instance, this method is relevant to assess the economic performance of renewable production
 44 forecasts in the case of energy trading when the cost of an error of forecasts is perfectly
 45 known. However, when an ESS is introduced in the system, adding the possibility to shift
 46 the energy production, the problem becomes more complex and this simple approach is not
 47 suitable.

48 The aim of the present work is to evaluate the quality and the value of different state
 49 of the art solar forecasts. First, the assessment of quality will be done with the framework
 50 commonly used by the solar community. Then, we will evaluate the value of the forecasts
 51 for a specific application: the day-ahead scheduling of an ESS associated with a large-scale
 52 PV plant in the Australian electricity market context. Finally, we will highlight the link
 53 between the error metrics commonly used to assess the quality of forecasts and their impact
 54 on the economic of the selected application.

55 The remainder of this article is organized as follows. The next section details the system
 56 that is studied and its associated models. Section 3 presents the optimization problem and
 57 how the forecasts are implemented. Then Section 4 describes the measured and forecast
 58 data used to simulate the case study. Section 5 gives the evaluation framework. And finally,
 59 Section 6 presents the results and the associated discussion.

60 2. System model

61 The ESS integration selected for this work aims at increasing the revenue of a large-
 62 scale PV farm using the bulk energy price arbitrage of the Australian National Electricity
 63 Market (NEM). The goal of an energy arbitrage strategy is to benefit from the variations

64 of the electricity prices, i.e. to buy energy when the price is low and to sell it when it
65 is more profitable. The Hornsdale Power Reserve (HPR), built by Tesla and located at
66 the Hornsdale Wind Farm in Jamestown, South Australia, well illustrates this type of ESS
67 usage. Indeed the main source of revenue of the HPR comes from energy arbitrage. It is
68 also worth noting that non negligible additional revenue of the HPR comes from contingency
69 frequency control ancillary services (FCAS) (Aurecon Group, 2020). An extensive literature
70 focused on the use of storage for energy arbitrage in the context of increasing penetration of
71 intermittent renewable exists. For instance, Zhao et al. (2015) give an overview on the topic
72 but restricted to wind farms and Berrada and Loudiyi (2016) extend the review to take into
73 account the PV plants.

74 In this work, the storage is added to a PV farm to firm and to shift in time the PV
75 generation in order to benefit from better selling prices. A classical type of PV and storage
76 coupling is assumed. The ESS is connected to the AC bus between the PV farm and the
77 grid connection point (see Fig. 1). With this configuration, the total power of the system
78 is not limited by the maximum power of the inverter of the PV plant. However, to benefit
79 from possible investment tax credit (ITC) (IRENA, 2020), the ESS will charge exclusively
80 with the energy generated by the PV plant. The EMS controls the system and aims at
81 maximizing the revenue provided by the electricity generation. The energy balance of the
82 system is given by the following equation:

$$E_{\text{grid}} = E_{\text{pv}} - E_{\text{ess}}^{\text{cha}} + E_{\text{ess}}^{\text{dis}}, \quad (1)$$

83 where E_{pv} and E_{grid} are respectively the energy produced by the PV field and the energy
84 supplied to the grid. And $E_{\text{ess}}^{\text{cha}}$ and $E_{\text{ess}}^{\text{dis}}$ correspond to the charge and discharge of the
85 storage system. In the following subsection details are given of the different models used to
86 compute these energies.

87 *2.1. PV system model*

88 Detailed models of PV systems, such as the ones proposed in the pvlib package (Holmgren
89 et al., 2018), could produce very accurate results in comparison with real systems but they
90 also require a detailed description of the system components (i.e. PV modules and inverters).
91 As highlighted by Mayer and Gróf (2021), the choice of the PV system model has a little
92 impact on the accuracy of the whole chain of conversion ranging from the available solar
93 resource to the PV system generation. Furthermore, as the case study is an imaginary
94 case, the PV system model will be used to compute both the real PV production and the
95 forecasted PV production. Thus, we propose here to use simple but efficient models for the
96 PV system as they offer the best trade-off between complexity of implementation of the PV
97 model and accuracy of the results of the study.

98 The direct current (DC) PV production $E_{\text{pv}}^{\text{DC}}$ is computed with a simple model proposed
99 by Luque and Hegedus (2011). This model takes into account the solar energy received on
100 the tilted plane of the solar modules, so called global tilted irradiation (GTI in Wh/m²),
101 and the temperature of the modules T_{pv} . Eq. (2) and (3) give the computation details.
102 The temperature of the modules (Eq. (2)) depends on the ambient temperature T_{air} , the

Parameter	Value
Area (A)	1.64 m ²
Efficiency at STC ($\eta_{\text{pv}}^{\text{STC}}$)	0.195
Temperature coefficient ($\text{TC}_{\text{pv}}^{\text{STC}}$)	-0.0038 °C ⁻¹
Temperature NOCT ($T_{\text{pv}}^{\text{NOCT}}$)	46 °C
Total installed costs (C_{pv})	2175 AUD/kW

Table 1: Characteristics of the modules LG NEON2 320 Wp and utility-scale PV costs in Australia (IRENA, 2019)

103 temperature of the module observed under the nominal operating cell temperature $T_{\text{pv}}^{\text{NOCT}}$
104 and the received irradiance GTI. Then Eq. (3) computes the PV production, with A the area
105 of the PV plant, $\eta_{\text{pv}}^{\text{STC}}$ the efficiency and $\text{TC}_{\text{pv}}^{\text{STC}}$ the temperature coefficient of the selected
106 modules under the standard test conditions (STC). For our case study, we chose modules
107 LG NEON2 with a peak power of 320 W because this model is currently very popular in
108 Australia. Table 1 presents the main characteristics of this module, which are used in Eqs.
109 (2) and (3):

$$T_{\text{pv}} = T_{\text{air}} + (T_{\text{pv}}^{\text{NOCT}} - 20) \times \text{GTI}/800, \quad (2)$$

$$E_{\text{pv}}^{\text{DC}} = \text{GTI} \times A \times \eta_{\text{pv}}^{\text{STC}} \times (1 - \text{TC}_{\text{pv}}^{\text{STC}} \times (T_{\text{pv}} - 25)). \quad (3)$$

111 Even if we assume a large-scale PV plant with a peak power of at least several megawatts,
112 the production will be derived from a PV system of 1 MW_p, i.e. 3125 modules for a total
113 area of approximately 5000 m². This specific installed power will allow normalizing all the
114 results.

115 To compute the AC output of the PV plant ($E_{\text{pv}} = \eta_{\text{inv}} E_{\text{pv}}^{\text{DC}}$), the simple inverter model
116 proposed by Riffonneau et al. (2011) has been used. A second order polynomial of the DC
117 power ratio r estimates the global efficiency of the inverter η_{inv} as follow:

$$\eta_{\text{inv}} = 1 - (0.0094 + 0.043r + 0.04r^2)/r, \quad (4)$$

$$r = \frac{E_{\text{pv}}^{\text{DC}}}{\Delta t P_{\text{inv}}}. \quad (5)$$

119 In Riffonneau et al. (2011), the DC power ratio of the inverter r is the ratio between the
120 DC PV power and the nominal power of the inverter P_{inv} . Here, we assume that the DC
121 output power of the PV farm is constant during a time step Δt and can be easily derived
122 from the produced DC energy as indicated in Eq. (5). To take into account the working
123 limits of the inverter, we also set its start-up at 10% and its clipping at 110% of the nominal
124 power P_{inv} as observed by King et al. (2007). Hence, when the ratio r is below 0.1 the
125 inverter does not work and when r is above 1.1 the inverter caps the production. Finally,
126 we define a rated power of the inverter equal to the installed capacity of PV (i.e. an inverter
127 of 1 MW for 1 MW_p of PV). For grid connected systems, it is common to have the inverter
128 rating match or be slightly smaller than the peak installed PV capacity (Luque and Hegedus,
129 2011).

130 *2.2. ESS model*

131 Numerous technologies of ESS are currently available. They are commonly classified
 132 regarding their capacity, power and response time. With few hours of production per day
 133 and fast variations of their output, PV systems require ESS with very short response time
 134 and with a power in the same order of magnitude of the installed power. Electrochemical
 135 batteries and more specifically Li-ion ones are currently the most affordable ESS that possess
 136 these properties. Thus, as many PV operators, we naturally choose to use Li-ion batteries.
 137 The power units associated to the batteries are AC/DC converters. In this work, we assume
 138 a constant efficiency for these converters. The current and expected future characteristics
 139 of the selected ESS model were derived from a recent report published by the International
 140 Renewable Energy Agency (IRENA, 2017) and they are given in Table 2¹. The self-discharge
 141 of the Li-ion batteries, around 0.1% per day, is neglected because we assume that the ESS
 142 will realize almost a full-cycle every day.

143 To compute the energy transfers corresponding to a variation of the state of charge
 144 ΔSOC of the ESS, we applied the round trip efficiency to the charging phase while the
 145 discharge is only subject to the efficiency of the AC/DC converter. Eqs. (6) and (7) below
 146 detail how the charging and discharging energies are obtained:

$$E_{\text{ess}}^{\text{cha}} = \frac{\Delta SOC_{\{\Delta SOC > 0\}}}{\eta_{\text{ess}}^{\text{cha}} \times \eta_{\text{ess}}} \times ESS_{\text{capa}}, \quad (6)$$

$$E_{\text{ess}}^{\text{dis}} = -\Delta SOC_{\{\Delta SOC < 0\}} \times \eta_{\text{ess}}^{\text{dis}} \times ESS_{\text{capa}}, \quad (7)$$

148 where ESS_{capa} is the rated capacity of the ESS and $\eta_{\text{ess}}^{\text{cha}}$, $\eta_{\text{ess}}^{\text{dis}}$ and η_{ess} are respectively the
 149 charging, discharging and round-trip efficiency of the ESS. Their values are given in Table
 150 2. As a discharge corresponds to a negative variation of the SOC (i.e. $\Delta SOC < 0$), one can
 151 notice that a minus is added to Eq. (7) to obtain a positive energy of discharge $E_{\text{ess}}^{\text{dis}}$ and
 152 thus to be coherent with the Eq. (1) about the energy balance of the overall system.

153 The ageing model proposed by Riffonneau et al. (2011) is used to evaluate the level of
 154 degradation of the batteries. This model is simple and appealing. Indeed, it assumes a
 155 linear degradation of the capacity of the batteries that can be applied to a large number
 156 of technologies. Let's consider a discharge of the ESS corresponding to the decrease of the
 157 state of charge $\Delta SOC_{\{\Delta SOC < 0\}}$. The associated reduction of the state of health ΔSOH is

$$\Delta SOH = z \times \Delta SOC_{\{\Delta SOC < 0\}}. \quad (8)$$

158 In the Eq. (8) above z is the ageing coefficient that can be derived from the ESS life
 159 time CLF expressed in number of full cycles and from the corresponding reduction of the
 160 state of health of the ESS as follows

$$z = \frac{SOH_0 - SOH_{\text{min}}}{CLF \times ESS_{\text{capa}}}, \quad (9)$$

¹An exchange rate of 1.4 USD/AUD has been used to convert the capital expenditures (CAPEX) and operating expenses (OPEX) proposed in (IRENA, 2017).

Parameter	Value		
	2020	2025	2030
Round trip efficiency (η_{ess})	0.955	0.961	0.968
State of charge (SOC_{max} and SOC_{min})	1 - 0.1	1 - 0.1	1 - 0.1
Charging ($\eta_{\text{ess}}^{\text{cha}}$) / Discharging efficiency ($\eta_{\text{ess}}^{\text{dis}}$)	0.98	0.98	0.98
Power unit limit ($P_{\text{max}}^{\text{cha}} / P_{\text{max}}^{\text{dis}}$)	3.5 W/Wh	3.5 W/Wh	4 W/Wh
Life time in equivalent full-cycles (CLF)	2406	3032	3820
State of health (SOH_0 and SOH_{min})	1 - 0.8	1 - 0.8	1 - 0.8
ESS cost ($C_{\text{ess}}^{\text{capa}}$)	452 AUD/kWh	325 AUD/kWh	234 AUD/kWh
Conversion units cost ($C_{\text{ess}}^{\text{power}}$)	119 AUD/kW	92 AUD/kW	70 AUD/kW
Annual O&M costs ($C_{\text{ess}}^{\text{om}}$)	1.5% of investment cost		

Table 2: Current and future characteristics of Li-ion NMC (cathode combination Nickel-Manganese-Cobalt) batteries and of the associated AC/DC power units (IRENA, 2017).

161 where SOH_0 and SOH_{min} are respectively the initial and critical state of health of the
162 ESS. Their values are given in Table 2. This model will be used during the simulations to
163 decrease the actual ESS capacity after every discharge. Furthermore, the ESS should be
164 changed when the SOH reaches SOH_{min} and the corresponding cost should be added to the
165 operation costs. But, in our study case we will consider a 10 years period for the economical
166 analysis (see Subsection 5.2) and SOH_{min} will not be reached.

167 2.3. Grid model

168 The electricity produced by the production system is sold to the grid at the spot price
169 (C_{grid}). We assume that the grid operator will buy the whole supplied energy. Furthermore,
170 the size of the considered power plant is not significant enough to influence the spot prices of
171 the electricity market. The Australian Energy Market Operator (AEMO) defines the spot
172 price as the selling price of electricity for the energy producers. It corresponds to an average
173 price computed every half-hour. The details of the computation of the spot price are given
174 in AEMO Markets (2018).

175 3. Data

176 3.1. Ground measurements

177 The ground measurements correspond to two consecutive years (2016 and 2017) of air
178 temperature (T_{air}), Global Horizontal Irradiation (GHI), Beam Normal Irradiation (BNI)
179 and Diffuse Horizontal Irradiation (DHI) measured at Adelaide Airport (34.95° N, 138.51° S).
180 The site experiences a Mediterranean climate with a significant annual GHI of approximately
181 1760 kWh/m²/year. The initial sample rate of the records is 1 minute and an averaging was
182 applied to the data to obtain 30 minute means. Considering only the daylight hours, the
183 raw measurements present less than 1% of missing data. The shorter gaps, corresponding to
184 a maximum of 30 minutes, were filled by linear interpolation. The longer gaps, (e.g. there
185 is a gap of 3 consecutive days between January and February 2017) were filled with GHI
186 estimations corresponding to the same period from the MERRA-2 reanalysis available for

187 free via the SoDa portal (MINES ParisTech, 2020). The comparison between the MERRA-2
188 estimations and the 2 years of data used in this work gives a mean bias error (see Eq. 18)
189 of +7%. This result is consistent with assessments done for other regions (Zhang et al.,
190 2020). Considering the very small rate of missing data and this slight overestimation of
191 the MERRA-2 data, we assume that the gap filling will not affect the overall results of the
192 study.

193 No PV generation was recorded on-site as the study case is an imaginary power plant of
194 1MWp with storage. We assume PV panels facing North and inclined at 35° , which is
195 the tilt that maximizes the annual solar energy received on the plane of the PV modules.
196 The solar energy received on the PV modules (GTI), is derived from the measured GHI,
197 DHI and BNI by using a transposition model. Here we use the anisotropic transposition
198 model proposed by Hay and Davies (1980) with an albedo of 0.2. Then, from the GTI
199 and the measured air temperature (T_{air}), the PV output is computed with the PV model
200 depicted in Section 2.1. According to Hofmann and Seckmeyer (2017), the estimation of the
201 PV production by the combination of selected models results in a very low mean error (less
202 than 2% in average).

203 3.2. Forecasts

204 The goal of this work is to analyse the effect of the error of solar forecasts on the
205 revenues of the selected system. The scheduling optimization studied here requires day-
206 ahead forecasts of the PV generation profile with a 30-min time step. Regarding this horizon
207 of forecast, Numerical Weather Predictions (NWP) are the most suitable (Diagne et al.,
208 2013; Antonanzas et al., 2016). Indeed, they commonly exhibit the best accuracy for forecast
209 horizons ranging from 6 hours to several days ahead. NWP are commonly associated with
210 post-processing methods that permit decreasing their error when compared with GHI ground
211 measurements. To generate the PV production forecasts from the GHI ones, the following
212 combination of models is required:

- 213 1. A decomposition model that divides the GHI in the beam (BNI) and diffuse (DHI)
214 components of the solar irradiance;
- 215 2. A transposition model that computes the solar energy received on the plane of the PV
216 modules (GTI) from the GHI, BNI and DHI;
- 217 3. And a PV production model that converts the received solar energy in electricity
218 generation.

219 3.2.1. GHI Forecasts

220 The short-term NWP of the GHI used in this work are provided by the European Centre
221 of Medium-range Weather Forecasts (ECMWF) (Leutbecher and Palmer, 2008) and National
222 Centers for Environmental Prediction (NCEP) (NCEP, 2015). The ECMWF maintains and
223 runs the Integrated Forecast System (IFS). IFS is a global high resolution NWP model that
224 generates weather forecasts for the entire earth with a spatial resolution of 0.125° in both
225 latitude and longitude and temporal resolution of 1 hour for the 4 first days of forecast.
226 The NCEP also runs a global NWP model called GFS (Global Forecast System). However,

227 GFS exhibits a coarser resolution than the IFS model with a spatial resolution of 0.250° and
228 temporal resolution of 3 hours for the 4 first days of forecasts. The GHI forecasts with a
229 lead-time of up to 4 days were retrieved from the nearest pixel to the Adelaide airport. To be
230 consistent with the Australian market rules, i.e. a 30-min time granularity (see Section 2.3),
231 the raw forecasts need to be downscaled. For instance, the forecasts of the NCEP, which
232 have a time step of 3 hours, must be converted into a 30-min time series. Several methods of
233 oversampling exist such as the linear, cubic or spline interpolations or the nearest neighbors
234 approach proposed by Mueen et al. (2017) and used by Yang et al. (2019a) to downscale
235 NWP. If these techniques are suitable to downscale most of the meteorological parameters,
236 they are not appropriate to solar irradiation time series as mentioned by Blanc and Wald
237 (2010). Indeed, the energy of the oversampled time series is not equal to the original time
238 series. In this work, we used the method proposed by the ENDORSE project (Espinar et al.,
239 2011). Based on iterative linear interpolations, this method has been designed specifically
240 to downscale time series of solar data. The method respects an energy consistency property
241 and therefore, in terms of energy, the oversampled time series is equal to the original time
242 series. Thus, the downscaling does not add additional bias to the new time series.

243 As proposed by the literature about solar forecast evaluation, a reference model, the
244 persistence, is also used (Sengupta et al., 2017). Several versions of the persistence are
245 available (Yang, 2019). In this work, we use the day ahead persistence of the clear sky index
246 (*kt*Persistence*): the daily profile of the clear sky index of the current day is repeated for
247 the next days. Compared to the GHI persistence, the *kt*Persistence* takes into account
248 the seasonal evolution of the solar path and it provides slightly better results. The clear
249 sky irradiances needed to compute the clear sky index were provided by the McClear model
250 (Lefèvre et al., 2013) available for free on the SoDa website (Atmosphere Monitoring Service,
251 2020). This model uses the Aerosol Optical Depth (AOD), water vapor and ozone data from
252 the MACC project.

253 3.2.2. PV Forecasts

254 The forecasts of the direct current PV generation are derived from the GHI forecasts
255 via the combination of a decomposition model, a transposition model and a PV model. We
256 explained previously that the PV production of reference was computed using the transpo-
257 sition model proposed by Hay and Davies (1980) and the PV model developed by Luque
258 and Hegedus (2011). The same models will be used to obtain the PV forecasts. Regarding
259 the decomposition of the GHI, we propose to test two state-of-the-art models. Indeed, the
260 decomposition of the GHI is one of the main source of error to derive the GTI and as con-
261 sequence to compute the PV generation (Gueymard, 2009; Hofmann and Seckmeyer, 2017;
262 Mayer and Gróf, 2021). The first model is the well-known Erbs model (Erbs et al., 1982).
263 This model, developed forty years ago and based only on the clearness index, combines sim-
264 plicity and accuracy. Furthermore, it is widely used by the community and thus appears to
265 be a very good competitor for comparison studies, (Hofmann and Seckmeyer, 2017; Mayer
266 and Gróf, 2021). Second, we used the decomposition model developed by Boland, Ridley
267 and Lauret, so called BRL, initially developed in Adelaide (Ridley et al., 2010). This more
268 recent and more complex model considers multiple predictors as inputs. It is also widely

Raw NWP		Post-processed NWP		
ECMWF	before PV conversion	ECMWF-WBb	ECMWF-NNb	ECMWF-PARb
	after PV conversion	ECMWF-WBa	ECMWF-NNa	ECMWF-PARa
NCEP	before PV conversion	NCEP-WBb	NCEP-NNb	NCEP-PARb
	after PV conversion	NCEP-WBa	NCEP-NNa	NCEP-PARa

Table 3: List of the forecasts derived from the two NWP models considered in this work.

used because it is one of the best models in terms of accuracy (Hofmann and Seckmeyer, 2017; Bertrand et al., 2015) and it is suitable to generate reliable solar forecasts (Mayer and Gróf, 2021).

Using the combination of models described in the previous paragraph, we derived PV predictions from the GHI forecasts of the two considered NWP (i.e. NCEP and ECMWF) and also from the clear sky index persistence (i.e. kt^* Persistence). In addition, we also propose to use the simple day-ahead persistence of the PV output.

3.2.3. Post-processing

Raw NWP are commonly post-processed to reduce their error. It is worth noting that the aim of the post-treatment is to increase the agreement between the forecasts and the measurements. This does not mean that the post-processed NWP should produce better PV forecasts for different indicators at the same time (e.g. quality and value). To evaluate this assumption, we propose to test three different post-processing methods. The first technique produces a forecast without bias (noted WB) by simply subtracting the mean bias error (see Eq. 18) from the raw NWP. Second, the bias correction is done by an Artificial Neural Network (noted NN) as proposed by Lauret et al. (2014, 2016). The third method uses a rolling horizon approach based on a periodic autoregressive stochastic process (noted PAR) (Franses and Paap, 1994; Voyant et al., 2018). A systematic description of the NN and PAR methods is given in the appendix. The post-processing techniques presented above will be applied to the NWP of the GHI but also to the PV forecast derived from the raw NWP. Indeed, even if the literature in the domain provides mainly results concerning post-processing of the GHI, the energy operators likely prefer to post-process the PV forecasts.

3.2.4. Overview of the forecasts used

We evaluate 31 different forecast models in this work. For reference three persistence models are used: the day-ahead persistence of the PV output (Persistence) and two day-ahead clear-sky persistence (kt^* Persistence) models, one associated the Erbs decomposition and the other with the BRL decomposition. The remaining 28 models are based on 7 forecasts for the PV output, formed from a combination of each of the two NWP models, ECMWF and NCEP, three post processing methods and each of the two decomposition methods, Erbs and BRL. Table 3 presents the 14 combinations of NWP and post-processing options before and after converting to PV output; note that evaluating the raw NWP models “before PV conversion” are not the subject of this work.

4. Formulation of the optimization problem using Linear Programming (LP)

The LP formulation of the optimization problem only requires consideration of linear relationships for the cost function and the constraints. As we assume a constant efficiency of the converter associated to the ESS and also a linear behavior of the batteries, the proposed optimization problem is linear. Five decision variables are considered: the charge ($E_{\text{ess}}^{\text{cha}}$) and discharge ($E_{\text{ess}}^{\text{dis}}$) energy of the batteries, the energy purchased or injected to the grid (E_{grid}), the energy generated by the PV plant (E_{pv}) and the state of charge of the ESS (SOC). The objective to maximize is the revenue generated by the energy supplied to the grid and it is stated as

$$R(E_{\text{pv}}, E_{\text{ess}}^{\text{dis}}, E_{\text{ess}}^{\text{cha}}, E_{\text{grid}}, SOC) = \sum_{t=1}^T C_{\text{grid}}(t) E_{\text{grid}}(t), \quad (10)$$

where C_{grid} is the spot price of electricity and T is the number of considered time steps. In our case study, we run the optimization for the next three days with a time granularity (Δt) of 30 minutes. So we have $T = 144$ time steps. The objective is subject to the following constraints:

- The boundaries of the decision variables, which are given by the technical specifications of the different component of the system (see Section 2 and Table 2):

$$0 \leq E_{\text{pv}} \leq E_{\text{pv}}^{\text{max}}, \quad (11)$$

$$0 \leq E_{\text{ess}}^{\text{dis}} \leq P_{\text{max}}^{\text{dis}} \times \Delta t, \quad (12)$$

$$0 \leq E_{\text{ess}}^{\text{cha}} \leq P_{\text{max}}^{\text{cha}} \times \Delta t, \quad (13)$$

$$-\infty \leq E_{\text{grid}} \leq +\infty, \quad (14)$$

$$SOC_{\text{min}} \leq SOC \leq SOC_{\text{max}}. \quad (15)$$

It is worth noting that the energy generated by the PV plant is here considered as a decision variable. Indeed, the operator could choose to curtail the PV production if this action avoids additional cost, for instance when the spot price is negative. Thereby, the energy generated by the PV plant is bounded by the maximum available production (Eq. (11)).

- The energy balance of the system derived from Eq. (1):

$$E_{\text{pv}} + E_{\text{ess}}^{\text{dis}} - E_{\text{ess}}^{\text{cha}} + E_{\text{grid}} = 0. \quad (16)$$

- And the variation of state of charge between two time steps corresponding to the energy that flows in and out of the ESS:

$$(SOC(t) - SOC(t-1)) \times ESS_{\text{capa}} = \eta_{\text{ess}} \eta_{\text{ess}}^{\text{cha}} E_{\text{ess}}^{\text{cha}} - \frac{E_{\text{ess}}^{\text{dis}}}{\eta_{\text{ess}}^{\text{dis}}}, \quad (17)$$

with $SOC(0)$ the initial state of charge.

329 4.1. Implementation of the forecasts

330 Considering the current Australian regulation, large-scale PV plants with storage of a
331 power of 5 MW or more correspond to scheduled generators which sell their electricity
332 through the spot market (AEMO Markets, 2018). As a consequence, the managers of large-
333 scale PV farms integrated with an energy storage must schedule the output profile of their
334 systems and bid for their prices. Two delivery times are in use. The pre-dispatch, which can
335 be seen as a day-ahead market, requires the submission of the initial production schedule and
336 price bands at 12:30pm of the current day until 12:30pm of the next day with a half-hourly
337 time step corresponding to the period used to compute the settlement price, also called spot
338 price (AEMO System Capability, 2016). As the interval used for the real time dispatch is
339 5 minutes, generators may submit rebids of their production and prices 5 minutes before
340 the start of the next five-minute dispatch interval (AEMC, 2015). Only the 5 minute rebids
341 are mandatory. The day ahead submission of the production profile is optional but highly
342 recommended for the main energy suppliers. This work focuses on day-ahead forecasts. So,
343 only the pre-dispatch stage will be considered. Furthermore, this study is in agreement with
344 the recent recommendation of the Australian Department of the Environment and Energy
345 to assess the suitability of a day-ahead market (Finkel et al., 2017).

346 The day-ahead PV production forecasts are implemented in the optimization with a
347 receding horizon approach. Three days of forecasts are used to optimize the schedule of the
348 ESS operation but only the first day of the resulting optimal schedule is used to run the
349 system. Receding horizon is a widely used approach in energy planning (Yang et al., 2019b).
350 Indeed, it permits updating efficiently the operation schedule of the production units when
351 a new forecast is available.

352 As the forecast is inherently uncertain, the execution of schedule generated by the opti-
353 mization will obviously generate deviations with the expected energy balance. During the
354 running of the system, these deviations will be compensated by the storage and by curtailing
355 the PV production. In case the storage is empty and the system is not able to ensure the
356 production plan, we assume that the operator will submit a rebid of their production on the
357 5 minutes market. So, we will not consider penalties in this work.

358 5. Evaluation framework

359 Two attributes of the forecasts will be tested in this work. Firstly, we evaluate the
360 agreement between forecasts and observations. Secondly, we establish the value of the
361 forecasts in giving a benefit for the user. Additionally in this section, we will investigate
362 hybrid metrics that straddle the space between quality and value.

363 5.1. Forecast quality

364 A framework dedicated to the evaluation of the quality of solar deterministic forecasts is
365 now widely used by the academic community and also by forecast providers. This framework
366 is detailed in numerous works (Perez et al., 2013; Coimbra et al., 2013; Sengupta et al.,
367 2017; Blaga et al., 2019). All the metrics defined in this framework are directly derived
368 from the difference between observations X_{obs} and forecasts $\widehat{X}_{\text{fcst}}$ (Eq. (21)). In this work

369 we will assess the quality through the Mean Bias Error (MBE, Eq. (18)), the Root Mean
 370 Square Error (RMSE, Eq. (19)), the Mean Absolute Error (MAE, Eq. (20)) for a set of N
 371 observation/forecast pairs. These metrics are given as:

$$\text{MBE} = \frac{1}{N} \sum_{i=1}^N \text{err}(i), \quad (18)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \text{err}(i)^2}, \quad (19)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N | \text{err}(i) |, \quad (20)$$

374 where

$$\text{err}(i) = \widehat{X}_{\text{fcst}}(i) - X_{\text{obs}}(i) \text{ for } i = 1, 2, \dots, N. \quad (21)$$

375 In order to get intelligible results expressed as percentages, these three metrics will be
 376 normalized by the mean of observed irradiation and by the installed PV power when they
 377 correspond respectively to irradiation forecasts and PV generation forecasts.

378 The Forecasting Skill (FS) will be also provided in this work. The FS refers to the
 379 relative RMSE improvement of a specific method compared to a benchmark forecast (Eq.
 380 (22)). The day-ahead persistence of the clear sky index (see Section 3) will be the reference
 381 forecast in this work. Even if the FS will give exactly the same information as the RMSE
 382 for our case study. The FS, given by

$$\text{FS} = 1 - \frac{\text{RMSE}(\text{method})}{\text{RMSE}(\text{kt*Persistence})}, \quad (22)$$

383 could be used in comparison studies. Fig. 2 to 4 give a graphical overview of the MBE,
 384 RMSE and MAE for the 31 considered PV forecasts. Table 4, which gives the error metrics
 385 that quantify the forecast quality, is given at the end of the paper. One can see that the
 386 persistence based forecasts experience the worst RMSE and MAE. Most of the forecasts
 387 based on the ECMWF model outperform the ones derived from the NCEP model. It is also
 388 worth noting that the PAR and NN post-processing methods, which set up a minimization of
 389 the square error between observations and forecasts, decrease the RMSE of the raw NWPs.
 390 However, they also tend to increase the MAE. As a consequence, a ranking based on the
 391 MAE will result in a totally different classification than a ranking based on the RMSE as is
 392 commonly done with the FS.

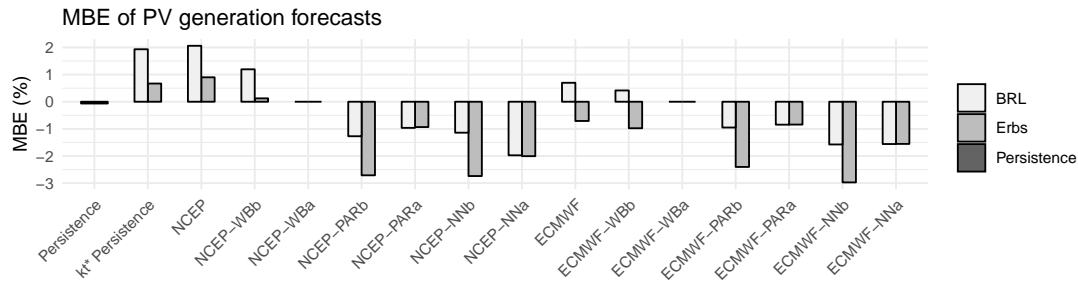


Figure 2: Mean Bias Error (MBE) of the PV production forecasts.

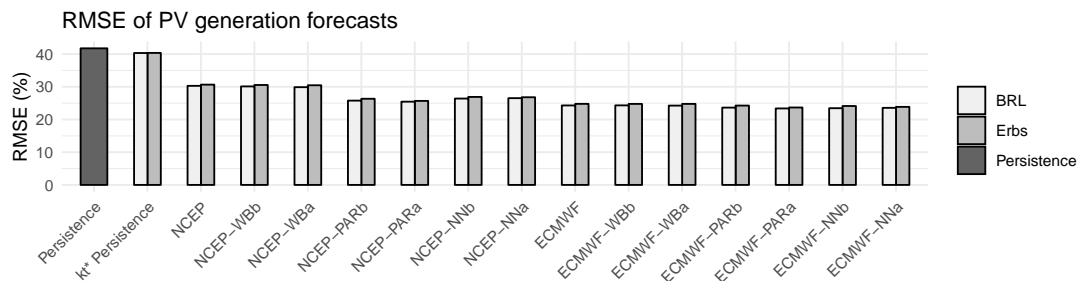


Figure 3: Root Mean Square Error (RMSE) of the PV production forecasts.

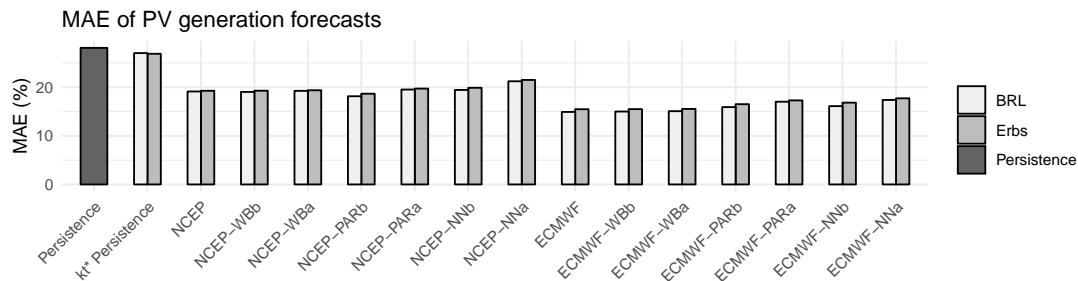


Figure 4: Mean Absolute Error (MAE) of the PV production forecasts.

393 *5.2. Forecast Value*

394 The IRENA recently released a report that defines an Electricity Storage Valuation
 395 Framework (ESVF) (IRENA, 2020). This global approach is designed for a large set of
 396 end-users such as policy makers, project developers, energy operators, etc. Indeed, both
 397 monetisable and non-monetisable benefits are included in the ESVF. This work will only
 398 focus on the fourth step of the ESVF dedicated to the simulation of storage operation and
 399 to the evaluation of the revenues (i.e. monetisable benefits).

400 The objective here is to determine the benefits on revenues of the addition to the PV
 401 plant of an ESS operated with improved forecasts. Several approaches are proposed in the
 402 literature. For instance, the Levelized Cost of Storage (LCOS) evaluates the cost of the
 403 energy supply by an ESS to a grid (Pawel, 2014). However, the LCOS does not give a direct
 404 quantification of the economic gain provided by the forecast to the owner. In this work, the
 405 added value will rely on the difference of revenues of the system with and without ESS as
 406 proposed by Fathima and Palanisamy (2015) or Bridier et al. (2016). For our case study,
 407 the revenue of reference R_0 , is the cash flow generated by the PV farm without storage and
 408 consequently without need of forecast. In the Australian context, such a PV farm is a semi-
 409 scheduled plant that sells its production at the spot price. We will assume a very optimistic
 410 revenue of reference R_0 considering that the whole energy produced by the PV plant will be
 411 sold. Considering a simulation of the PV farm without storage using the solar irradiation
 412 measurements and the spot prices of 2017, R_0 is 201,629 AUD/year for an installed power
 413 of 1 MW. As the scale of the revenue is difficult to interpret, we propose to assess the value
 414 of the forecasts with the economic gain. This rate, expressed in percent (Eq. 23) is the
 415 relative difference between the revenue of reference R_0 and the revenue of the system with
 416 the ESS R , which is the objective function of the optimization problem detailed in Eq. 10
 417 (see Section 4). The economic gain is proportional to the revenue and has the advantage to
 418 be easier to interpret and reads as

$$gain = \frac{R - R_0}{R_0} \times 100. \quad (23)$$

419 In addition to the economic gain, we will compute the Net Present Value (NPV) of the
 420 ESS. The NPV is a useful figure to decide whether or not it is of value to invest in the
 421 ESS. A negative NPV highlights a bad investment. Whereas, a high value for the NPV
 422 is indicative of an important pay back on investment. The NPV computation is based on
 423 the methodology defined in the famous report initially published by the NREL in 1995 and
 424 released as a book ten years after (Short et al., 2005). Similar to the economic gain, the
 425 NPV considered in this work relies only on the additional cash flow generated by the ESS
 426 (i.e. $R - R_0$). Fig. 5 shows the evolution of the NPV for an ESS capacity ranging from
 427 0 MWh/MW_{pv} to 3 MWh/MW_{pv} and considering the year of investment in the storage.
 428 Perfect forecasts have been used to schedule the ESS operations and to obtain these results.
 429 Considering the IRENA prices for the ESS (see Table 2) and the current financial situation
 430 (Grant Thornton and Clean Energy Pipeline, 2019), the investment in the ESS should be
 431 suitable from 2025. These results must be handled with care because we consider the energy
 432 arbitrage as the only source of revenue and the spot price of 2017. However, this point is
 433 not the aim of this work and here the NPV will be used to evaluate the optimal size of the
 434 ESS, which is around 1.8 MWh/MW_{pv}.

435 5.3. Intermediate metrics

436 We can define the intermediate metrics used in this work as a combination of quality
 437 and value without the need of simulating the studied energy system. Thus, they could be

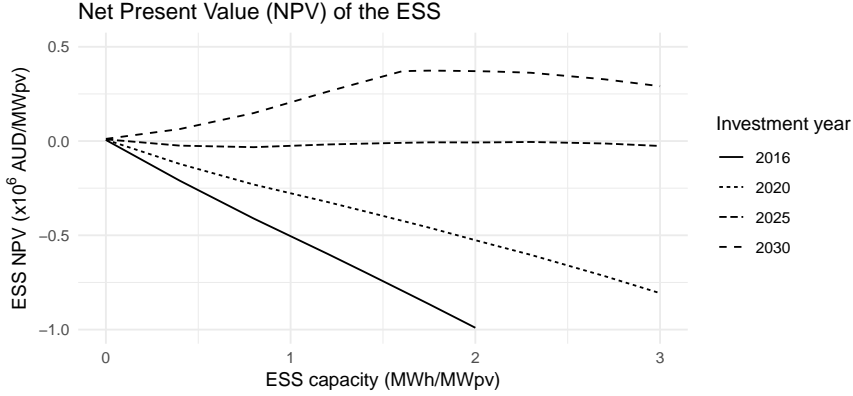


Figure 5: Net Present Value (NPV) of the ESS considering the size of the storage, the year of investment and the current financial situations (5.75% discount rate, inflation rate 2%, 10 years analysis period (Grant Thornton and Clean Energy Pipeline, 2019)).

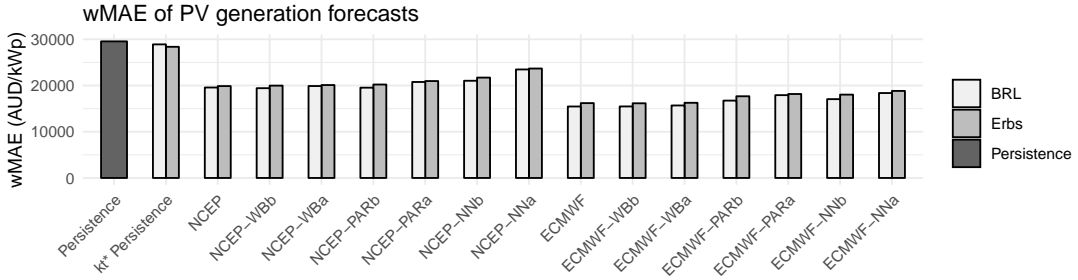


Figure 6: Weighted Mean Absolute Error (wMAE) of the PV production forecasts.

438 considered as hybrid indices able to link the quality of the forecast with the added value for
 439 the user through a simple approach.

440 The first intermediate metric proposed in this work is derived from the weighted mean
 441 absolute error (wMAE) defined by Antonanzas et al. (2020), which was designed to choose
 442 the best solar forecast for market operators. They proposed to weight the absolute error
 443 observed at each time step with the downward and upward prices corresponding to the prices
 444 at which the system respectively buys and sells electricity to compensate the deviations from
 445 the production schedule. In our case, these prices correspond to the spot price (C_{grid}), which
 446 fluctuates at each time step and the wMAE is defined in Eq. 24. Errors of forecast weigh
 447 heavier when the electricity price is high. Fig. 6 provides an overview of wMAE of the
 448 considered PV forecasts. Even if slight differences appear, the wMAE tends to behave like
 449 the MAE for our case study. The wMAE is defined by

$$\text{wMAE} = \frac{1}{N} \sum_{i=1}^N | [\hat{X}_{\text{fcst}}(i) - X_{\text{obs}}(i)] \times C_{\text{grid}}(i) |. \quad (24)$$

450 Another metric based on the recent work of Perez et al. (2019) will also be studied in this

451 work. This metric is derived from the concept of "Firm kWh premium" that refers to the
452 Levelized Cost of Energy (LCOE) required to firm the power forecasts through storage and
453 overbuilding of the PV generation capacity. The lower the LCOE, the better the quality
454 of the forecasts. This new metric differs considerably from the previous ones because it
455 does not only consider the instantaneous difference between forecasts and observations.
456 Indeed, the storage size required to firm the PV generation and consequently the capital
457 expense (CAPEX) are highly affected by a succession of large positive or negative errors.
458 Furthermore, assumptions on PV costs, storage costs, maintenance and life time have to
459 be made. For this work, the case study has already fixed most of these parameters (see
460 Tables 2 and 1). In our opinion, a metric based on this approach is worthy of investigation
461 because it straddles the space between quality and value of the forecasts. We propose here
462 a simplified version the "Firm kWh premium" that only takes into account the CAPEX
463 required to firm the forecasts and no loss of energy through the ESS. Indeed, the LCOE is
464 highly dependent on the CAPEX and we want to propose a metric easy to compute that
465 requires a few assumptions. The formulation of the proposed Firm Power Forecasts (FPF)
466 metric, expressed in dollars per installed kilowatts of PV (PV_{power}), is given by the following
467 equation:

$$\text{FPF} = \min_{\{osf\}} \left[\frac{(ESS_{\text{capa}} \times C_{\text{ess}}^{\text{capa}} + ESS_{\text{power}} \times C_{\text{ess}}^{\text{power}} + (osf - 1) \times PV_{\text{power}} \times C_{\text{pv}})}{PV_{\text{power}}} \right], \quad (25)$$

468 where osf is the oversizing factor applied to the actual installed PV power. It is important
469 to note that in this work, the oversizing factor is not applied to a PV capacity required to
470 produce the yearly energy of the forecasts, like in (Perez et al., 2019), but directly to the
471 actual installed PV power. The FPF value results from an easy to solve one-dimensional
472 optimization because the objective function is convex and osf is the unique decision param-
473 eter (i.e. the unique parameter to vary). For our case study, the optimal value of osf ranges
474 from 1.1 to 2.2. These two values correspond respectively to the models *kt*Persistence* and
475 *ECMWF-WBa*. For a fixed osf there is a single value of the ESS capacity and power that
476 minimizes the FPF. The following equations give a simple way to compute them:

$$ESS_{\text{capa}} = \max(pcse(1), \dots, pcse(N)), \quad (26)$$

$$pcse(i) = \begin{cases} \sum_{k=1}^i pcse(k-1) + err(k) & \text{if } \sum_{k=1}^i pcse(k-1) + err(k) > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (27)$$

$$ESS_{\text{power}} = \max(|pcse(2) - pcse(1)|, \dots, |pcse(N) - pcse(N-1)|), \quad (28)$$

$$err(i) = \widehat{X}_{\text{fcst}}(i) - osf \times X_{\text{obs}}(i) \text{ for } i = 1, 2, \dots, N. \quad (29)$$

477 $pcse$ can be interpreted as the positive values of the cumulative sum of the forecasting
478 errors and, in a sense, it refers to the accumulated energy in the ESS. A negative value of

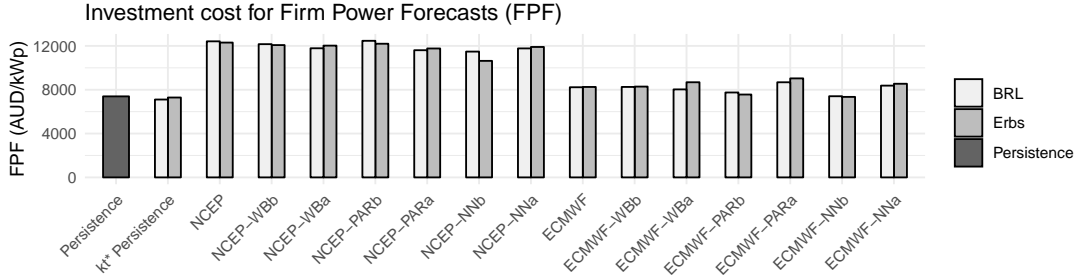


Figure 7: Firm Power Forecast (FPF) of the PV production forecasts.

479 *pcse* indicates that we can curtail the production. The error of forecast *err* is exactly the
 480 same as in Eq. 21, but in the case of the FPF computation the observed amount of energy
 481 is multiplied by the oversizing factor *osf*.

482 Fig. 7 gives the FPF for the considered PV forecasts. As it is highly sensitive to
 483 successions of positive or negative errors, this intermediate metrics gives a totally different
 484 ranking than the other metrics used in this work. Indeed, the persistence based forecasts
 485 experience the lowest FPF.

486 6. Results

487 First of all, it is important to reiterate that the aim of this work is not to rank the
 488 forecasts between them. Such a goal requires consideration of numerous sites and maybe
 489 a large variety of applications. The objective here is to show that correlations could exist
 490 between metrics defined to assess the quality of point forecasts and the added value brought
 491 by an ESS managed with improved forecasts. This is why we generated many different PV
 492 forecasts in order to support our results with a significant number of metric/value pairs.
 493 In this section are presented graphical views of the results (i.e. scatter plots). Interested
 494 readers can refer to Table 4 in the appendix to get the all the corresponding numerical
 495 results.

496 Fig. 8 plots the gain as a function of the MBE (a), the MAE (b) and the RMSE (c),
 497 which are currently the three main metrics used to assess the quality of a solar forecast.
 498 First, compared to the PV farm alone, the gain provided by the storage managed with day-
 499 ahead forecasts ranges from around 25% to more than 55% for the perfect forecast. Thus, an
 500 improvement of the forecast can significantly improve the revenue of such a system. Second,
 501 we arbitrarily grouped the forecasts by family (i.e. same color and shape for persistence,
 502 ECMWF and NCEP based forecasts). Thus, one can easily observe that the relationships
 503 between the selected metrics and the economical gain strongly depend on the type of model
 504 used to derive the solar forecasts. Finally, the persistence based forecasts, commonly used as
 505 a benchmark, give an identical and even slightly better gain than the worst forecasts derived
 506 from the NCEP model. However, the forecast skill based on the RMSE (see Table 4) shows
 507 a clear improvement of the quality of these forecasts when compared to the persistence.

508 If we focus on Fig. 8(a), we can observe that a positive bias leads globally to a better
 509 revenue in the same family of forecasts. If we look in detail at the rules of the optimization
 510 and at the structure of the costs associated to an error of forecast, this result is obvious.
 511 Indeed, if an outcome higher than the forecast occurs when the storage is full, the algorithm
 512 curtails the PV production. On the contrary, when the ESS is empty, an outcome lower
 513 than the forecast is balanced by a purchase from the grid without penalties. Thus a forecast
 514 that generates a positive bias (i.e. overestimation) leads to less curtailments and results in
 515 selling more energy. The application of dissuasive penalties would maybe lead to a totally
 516 different result. The same type of relationship between the MBE and the economic value of
 517 forecasts has already been observed by Ramahatana and David (2019) for the minimization
 518 of the costs of a microgrid. Furthermore, very low biases, ranging between -3% and +2%,
 519 are observed in this study. This relationship would have not been observed for higher biases
 520 because the possible benefits of a strong overestimation will be compensated by its costs.
 521 Indeed, an important overestimation of the forecasts results in the impossibility to time-shift
 522 the energy because the ESS will always be empty. However, for our case study, if the MBE
 523 seems suitable to rank the improvement in terms of gain inside a family, it is not able to give
 524 relevant information to compare forecasts originated by different types of model. In Fig.
 525 8(b), a linear relationship between the MAE and the gain seems to appear for the forecasts
 526 derived from the ECMWF and NCEP. For these two families of forecasts, an improvement
 527 of 1 percentage point in MAE results approximately in an increase of 2 percentage points in
 528 gain. Though, the forecasts based on the persistence are not aligned with this relationship.
 529 Even if they have clearly worst values of MAE (i.e. at least 5 percentage points more), they
 530 do not result in strongly lower gains than the NWP based forecasts. The economic gain
 531 defined in this work is proportional to the expected revenue for the user. As a consequence,
 532 the linear relationship observed between the MAE and the gain is also valid for the revenue,
 533 which is the key indicator for the users. Finally, Fig. 8(c), which plots the gain versus the
 534 RMSE, shows that the predominant error metric used in the academic literature to assess
 535 the quality of a forecast is unable to provide any relevant information about the added value
 536 of forecasts in the considered case study. The results observed in Fig. 8 are in tune with
 537 industry requirements. Indeed, users of solar forecasts commonly ask for provision of the
 538 MAE. The predominance in the academic literature of the RMSE (Blaga et al., 2019) and
 539 by consequence of the the forecast skill based on the RMSE to compare and to rank solar
 540 forecasts should be questioned. Given the results of this case study, we assume that a better
 541 value is likely reached when all the quality metrics of a forecast (i.e. MBE, MAE and RMSE)
 542 are improved simultaneously.

543 In order to go further, Fig. 9 gives the gain as a function of the two intermediate
 544 metrics proposed in this work. The wMAE shows a similar behavior as the MAE. Except
 545 for the persistence based forecasts, the gain is almost proportional to the wMAE. With a
 546 lower slope and a best alignment of the points, the wMAE is even better to discriminate
 547 two forecasts that present close values of wMAE. This result agrees with the approach
 548 proposed by Richardson (Richardson, 2000) that defines a cost-loss function based on the
 549 cost associated to the consequences of a forecast error. Indeed, the linearity observed between
 550 the gain and the MAE and also with the wMAE highlights the underlying structure of the

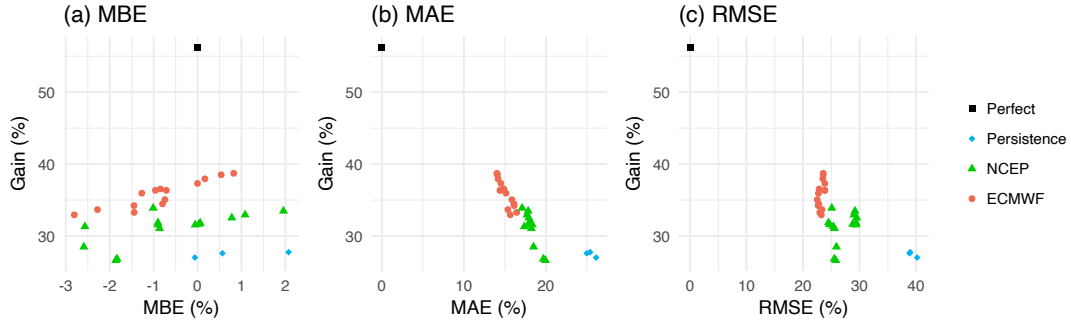


Figure 8: Relationship between economical gain of the ESS managed with day-ahead PV forecasts and error metrics defined into the classical evaluation framework used to assess the quality of the forecasts.

551 costs associated to an error of forecast. In this specific case study, the cost of a forecast error
 552 is almost proportional to the level of this error. And more exactly, weighting the error of
 553 forecasts with the spot price offers an interesting approximation of the cost caused by these
 554 errors. Finally, the FPF metric, that rewards forecasts with a low level of serial correlation
 555 of their errors, does not show any clear relationships with the economical gain. This measure
 556 of the forecasting error, initially designed to minimize the LCOE of a firm power generation,
 557 seems to not be suitable to study the possibilities offered by the energy arbitrage market.

558 Looking in detail at the numerical results summarized in Table 4, we can see that forecasts
 559 without post-processing give the best economical gains for both ECMWF and NCEP. Indeed,
 560 the selected post-treatment methods minimize the RMSE (PAR and NN) or the MBE (WB).
 561 But in return, they deteriorate the MAE. For the specific case study of this work, a good
 562 post-processing should have reduced the MAE. A last point is also worth noting. The post-
 563 processing of the PV forecasts leads in almost all the cases to slightly better results for
 564 both quality metrics (i.e. MBE, RMSE and MAE) and value (i.e. economic gain) than the
 565 post-processing of the raw GHI provided by the two considered NWP.

566 Regarding the influence of the decomposition model, one can easily note that the BRL
 567 model has better results than the Erbs model for all the metrics used to assess the quality
 568 of the forecasts. Consequently, the use of the BRL model also leads to better a economical
 569 gain. The accuracy of the decomposition model is an important factor to take into account.
 570 However, for the case study of this work, compared to the choice of the NWP and of the
 571 post-processing method, the influence of the decomposition model is of lower-ranking.

572 7. Conclusion

573 This work proposes to highlight relationships between metrics used to assess the quality
 574 of deterministic forecasts and the added value of these forecasts for the users. A specific
 575 case study based on an imaginary PV farm coupled with an ESS aiming to maximise the
 576 revenues using the energy arbitrage opportunities has been used. The deterministic solar
 577 forecast feeds an optimisation model that generates the charge/discharge profile of the ESS
 578 one day-ahead. Even if this case study is inspired by real systems, all the results are obtained
 579 by simulating an imaginary system.

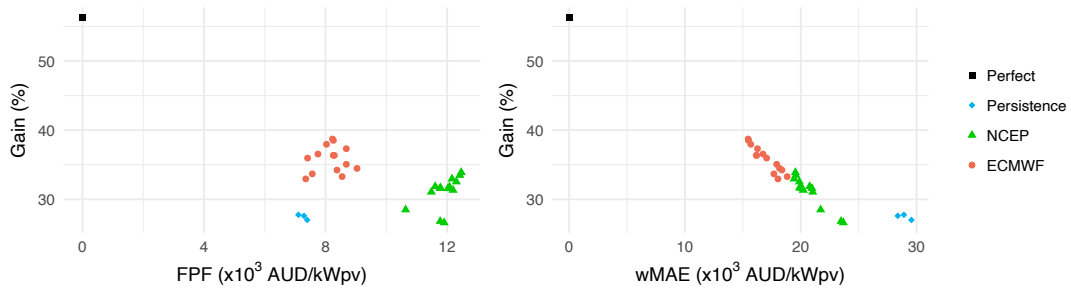


Figure 9: Relationship between economical gain of the ESS managed with day-ahead PV forecasts and the intermediate metrics.

580 The evaluation framework currently in use by most of the academic researchers of the
 581 domain has been used to assess the quality of the forecasts. Here, we used the main ones
 582 (i.e. MBE, MAE, RMSE and the forecast skill based on the RMSE) to evaluate quality of
 583 our solar forecasts. In addition, we propose to study two intermediate metrics, the weighted
 584 MAE (wMAE) and the Firm Power Forecasts (FPF), which are easy to compute, which
 585 require few assumptions about the system and which do not need simulation of the system.
 586 These intermediate metrics are initially designed to evaluate the value of forecasts under
 587 specific conditions.

588 The results of this work highlight that the metrics based on the Mean Absolute Error
 589 (MAE and wMAE) exhibit an almost linear relationship with the economical gain of the
 590 forecasts provided by the two tested NWP models. It is shown that an improvement in
 591 quality measured by the MAE and wMAE metrics results in an increase of the economical
 592 gain. Conversely, the persistence based forecasts do not show the same tendency and lead to
 593 poor gain. Furthermore, for the specific case studied in this work, the metrics based on the
 594 Root Mean Square Error (RMSE), such as the forecast skill widely used by the academic
 595 community, are less efficient to assess the gain provided by an improvement of the forecast
 596 quality. This results stress that is it important to consider more than one metric to relevantly
 597 assess the quality of a forecast.

598 In order to validate and to expand the study of the relationships between the metrics
 599 designed to assess the quality of solar forecasts and the associated gain for the user, this kind
 600 of study should be done on cases based on real systems and also on other types of systems and
 601 usages of the forecasts. For instance, ancillary services markets are an important additional
 602 source of revenue for solar plants equipped with ESS.

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607 **9. Appendices**

608 **Appendix A PAR Post-processing**

609 In the development of MOS equations based on RPR (rolling periodic regression), past
 610 measurements (GHI or PV power) and archived NWP model forecast (NCEP or ECMWF)
 611 are used with a multivariate regression model to determine the best output minimizing
 612 the sum of squared residuals. The regression coefficients (Φ_h) are estimated by the most
 613 common estimator using both experimental and observed data. A classical formalism using
 614 the Moore–Penrose pseudo-inverse matrix (Penrose, 1956) is used and generates Φ_h for
 615 particular predictand according to the time horizon (h). This estimator is theoretically
 616 unbiased and consistent if the errors have finite variance and are uncorrelated with the
 617 regressors. Considering the time step (30min) and the 72h max forecast horizon, the RPR
 618 model is equivalent to 144 AR models (equivalent to the periodic autoregressive model PAR
 619 in (Franses and Paap, 1994; Voyant et al., 2018): one model for each h . In the case of
 620 GHI predictions (the approach is equivalent for the PV power) and considering the (1×4) -
 621 dimensional vector of explanatory variables X (GHI_{NWP} for the NWP output concerning the
 622 GHI, GHI_{CS} for the clear sky model, θ_z for the solar zenith angle and \hat{N} for the nebulosity
 623 predicted by the NWP):

$$X = [\widehat{\text{GHI}}_{\text{NWP}}(t+h), \text{GHI}_{\text{CS}}(t+h), \sin(\theta_z(t+h)), \hat{N}(t+h)]. \quad (\text{A.1})$$

624 And the (1×5) -dimensional column vector Φ_h :

$$\Phi_h = [\phi_{1h}, \phi_{2h}, \phi_{3h}\phi_{4h}, \phi_{5h}]^T. \quad (\text{A.2})$$

625 The RPR model is equivalent to:

$$\widehat{\text{GHI}}(t+h) = X \times \Phi_h. \text{ for } h = 1 : 144. \quad (\text{A.3})$$

626 Rather than operate the training step 1 time for the 144 parameters, a rolling analysis of
 627 a time series model is often used to assess the model’s stability over time. When analyzing
 628 meteorological time series data using a statistical model, a key assumption (which is not
 629 really proved) is that the parameters of the model are constant over time. In this study, we
 630 propose a parameter estimate over a rolling or moving window of a fixed size through the
 631 sample (1 year and operated each day) (Numan, 2016; Yuan and Vanrolleghem, 1999). If
 632 the parameters change at some point during the sample, then the rolling estimates should
 633 capture this instability and improve the predictor performance. Note that this methodology
 634 is possible due to the low resources required for the use of linear model, more than 50,000
 635 parameters estimated (365×144) in less than 5 seconds with a basic laptop.

636 To post-process the PV production, slight changes are operate in the inputs. Instead of
 637 the GHI, we used the PV production forecasts derived from the NWPs. In the same way,
 638 instead of the GHI_{CS}, we used a PV production under clear sky condition derived from the
 639 clear sky irradiances (global, diffuse and direct) provided by the McClear model (Lefèvre
 640 et al., 2013) and available for free on the SoDa website (Atmosphere Monitoring Service,

641 2020). As for the forecasts, the transposition models of Hay and Davies (1980) with an
 642 albedo of 0.2 has been used to compute the tilted irradiance.

643 Appendix B NN Post-processing

644 Artificial Neural Networks (ANNs or simply NNs) are data driven approaches capable
 645 of performing a non-linear mapping between sets of input and output variables. The most
 646 popular form of neural network is the so-called multilayer perceptron (MLP) structure (see
 647 (Bishop, 1995) for details). The MLP structure consists of an input layer, one or several
 648 hidden layers and an output layer. The input layer gathers the model’s input vector \mathbf{x} while
 649 the output layer yields the model’s output y . Fig. 10 represents a one hidden layer MLP.

650 The hidden layer is characterized by several non-linear functions (or hidden neurons).
 651 The non-linear function (also called activation function) is usually the tangent hyperbolic
 652 function $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$. Therefore, a neural network with d inputs, h hidden neurons and a
 653 single linear output unit defines a non-linear parameterized mapping from an input vector
 654 \mathbf{x} to an output y given by the following relationship:

$$y = y(\mathbf{x}, \mathbf{w}) = \sum_{j=0}^h \left(w_j f \left(\sum_{i=0}^d w_{ji} x_i \right) \right). \quad (\text{B.1})$$

655 The NN parameters, denoted by the parameter vector $\mathbf{w} = \{w_j, w_{ji}\}$, govern the non-linear
 656 mapping.

657 The NN parameters \mathbf{w} are estimated during a phase called the training or learning phase.
 658 During this phase, the NN is trained using a dataset (called training set) of N input and
 659 output examples. The second phase, called the generalization phase, consists of evaluating
 660 the ability of the NN to generalize, that is to say, to give correct outputs when it is confronted
 661 with examples that were not seen during the training phase. Notice that these examples are
 662 part of a data set called test set.

663 As mentioned above, NNs have the appealing capability to recognize patterns in data.
 664 Indeed, NNs are able to approximate any continuous function at an arbitrary accuracy,
 665 provided the number of hidden neurons is sufficient. However, it is necessary to match
 666 the complexity of the NN to the problem being solved. The complexity determines the
 667 generalization capability (measured by the test error) of the model since a NN that is too
 668 complex will give poor predictions. In the NN community, this problem is called overfitting.
 669 Several techniques like pruning or Bayesian regularization (Bishop, 1995) can be employed
 670 to control the NN complexity. In this work, we used the Bayesian Technique in order to
 671 control the NN complexity and therefore the generalization capability of the model (Bishop,
 672 1995).

673 In the present work, an NN is designed to derive the bias correction function. More
 674 precisely, the NN output (i.e. the modeled bias $BiasC$) is related to the predicted clear sky
 675 index and the solar zenith angle SZA . For instance, the MOS-corrected ECWMF forecasts
 676 denoted here $ECWMF_c$ are then obtained by subtracting the modeled bias from the original

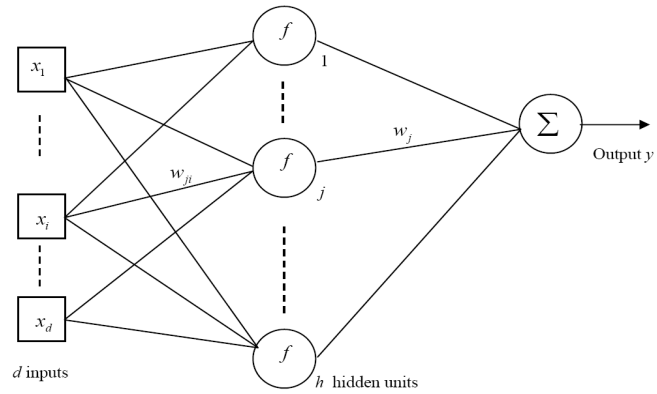


Figure 10: Sketch of a MLP with d inputs and h hidden units, in our case, $d=2$ (clear sky index and $\cos(\text{SZA})$). The output y is the modeled bias correction.

677 raw ECMWF forecasts ECMWF_o :

$$\text{ECMWF}_c = \text{ECMWF}_o - \text{Bias}C. \tag{B.2}$$

Forecasting model	Decomp. model	MBE (%)	RMSE (%)	MAE (%)	FS (%)	wMAE (AUD/kW _{pv})	FPF (AUD/kW _{pv})	Economical gain (%)			
								2016	2020	2025	2030
Perfect	-	0	0	0	100	0	0	55,6	55,8	56,0	56,3
Persistence	-	-0,06	40,2	26,1	-3,3	29,55	7,39	26,5	26,6	26,8	27,0
Persistence.kt	Erbs	0,57	38,8	25	0	28,37	7,29	26,9	27,2	27,4	27,6
Persistence.kt	BRL	2,07	39	25,4	0	28,9	7,11	27,2	27,3	27,5	27,8
NCEP	Erbs	0,78	29,5	17,9	24	19,88	12,3	32,0	32,1	32,3	32,5
NCEP	BRL	1,96	29,2	17,8	25,1	19,57	12,42	33,0	33,1	33,3	33,5
NCEP_BRb	Erbs	0,06	29,4	17,9	24,3	19,97	12,08	31,3	31,4	31,6	31,8
NCEP_BRb	BRL	1,08	29	17,7	25,6	19,42	12,16	32,5	32,6	32,8	33,0
NCEP_Bra	Erbs	-0,05	29,3	18	24,5	20,1	12,03	31,1	31,2	31,4	31,6
NCEP_Bra	BRL	0,03	28,8	17,9	26,1	19,89	11,78	31,2	31,3	31,5	31,7
NCEP_PARb	Erbs	-2,57	25,4	17,4	34,7	20,22	12,2	30,8	30,9	31,1	31,3
NCEP_PARb	BRL	-1,01	25,1	17,1	35,6	19,53	12,47	33,3	33,5	33,7	33,9
NCEP_PARa	Erbs	-0,9	24,7	18,3	36,4	20,97	11,77	31,1	31,2	31,4	31,6
NCEP_PARa	BRL	-0,9	24,5	18,2	37,1	20,77	11,61	31,3	31,5	31,6	31,9
NCEP_NNb	Erbs	-2,59	25,9	18,5	33,3	21,71	10,63	28,0	28,1	28,3	28,5
NCEP_NNb	BRL	-0,86	25,5	18,2	34,4	21,03	11,48	30,6	30,7	30,9	31,1
NCEP_Nna	Erbs	-1,86	25,8	19,9	33,6	23,67	11,9	26,1	26,2	26,4	26,6
NCEP_Nna	BRL	-1,83	25,5	19,7	34,5	23,48	11,77	26,3	26,4	26,6	26,8
ECMWF	Erbs	-0,71	23,9	14,4	38,6	16,19	8,25	35,7	35,9	36,1	36,4
ECMWF	BRL	0,82	23,6	14	39,5	15,46	8,23	38,1	38,2	38,5	38,7
ECMWF_BRb	Erbs	-0,96	23,8	14,4	38,6	16,15	8,29	35,7	35,9	36,1	36,4
ECMWF_BRb	BRL	0,54	23,6	14,1	39,5	15,47	8,26	37,9	38,0	38,3	38,5
ECMWF_Bra	Erbs	0	23,9	14,5	38,6	16,26	8,68	36,7	36,9	37,1	37,3
ECMWF_Bra	BRL	0,17	23,5	14,2	39,7	15,68	8,03	37,3	37,5	37,7	38,0
ECMWF_PARb	Erbs	-2,28	23,4	15,4	39,9	17,67	7,56	33,1	33,3	33,4	33,7
ECMWF_PARb	BRL	-0,84	22,9	14,9	41,3	16,74	7,75	35,9	36,1	36,3	36,5
ECMWF_PARa	Erbs	-0,8	22,8	16,1	41,3	18,16	9,04	33,9	34,0	34,2	34,5
ECMWF_PARa	BRL	-0,74	22,5	15,8	42,2	17,92	8,68	34,5	34,6	34,8	35,1
ECMWF_NNb	Erbs	-2,81	23,2	15,7	40,2	18,03	7,35	32,4	32,5	32,7	32,9
ECMWF_NNb	BRL	-1,27	22,7	15,1	41,7	17,05	7,41	35,3	35,5	35,7	36,0
ECMWF_Nna	Erbs	-1,44	23	16,4	40,9	18,83	8,54	32,7	32,9	33,1	33,3
ECMWF_Nna	BRL	-1,45	22,7	16,1	41,8	18,37	8,38	33,6	33,8	34,0	34,2

Table 4: Forecast quality metrics, intermediate metrics and values of the PV forecasts

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