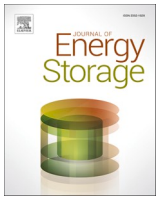
Journal of Energy Storage 48 (2022) 104093



Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est





Assessing the influence of solar forecast accuracy on the revenue optimization of photovoltaic + battery power plants in day-ahead energy markets

Rafael Antunes Campos [a,*], Giuliano L. Martins [a,b], Ricardo Rüther [a]

[a] Universidade Federal de Santa Catarina/UFSC, Caixa Postal 476, Florianopolis, SC 88040-900, Brazil
[b] Anhalt University of Applied Sciences, Köthen, Germany

ARTICLE INFO

Keywords:
Photovoltaic plant
Photovoltaics
Energy storage
Renewable energy
Battery systems

ABSTRACT

Energy storage has become a subject of great interest in the last years due to the increasing penetration of non-dispatchable renewable energy power plants, especially solar photovoltaics (PV) and wind. Energy storage systems can add value to the grid in many ways: energy schedule optimization, ancillary services, renewable energy integration at high penetration levels, and so on. However, from the perspective of the asset's owner, it is important that the system regulator provides a regulatory framework and energy prices that stimulate the private plant operator to dispatch its energy storage system to assist the grid and get rewarded by these operations. An optimization problem is presented from the perspective of an asset owner with a PV plant and battery energy storage system. From this perspective, the agent must know the day-ahead spot-market energy prices and predict the day-ahead PV generation to decide on how to dispatch the battery system. We have evaluated 11 forecast accuracies to assess how the forecast accuracy can impact on the agent's total revenue.

The findings showed that, if the agent's objective is to use the battery system only to guarantee the contracted energy, the battery system does not add as much value as it could; and higher forecast uncertainties lead to higher revenues, because the battery will then operate closer to the tariff arbitrage strategy, which is the optimal strategy for battery dispatch, independent of PV generation, relying only on the spot-market energy prices.

1. Introduction

Battery energy storage systems (BESS) have become a subject of great interest in recent years due to the their rapidly declining prices, and the increasing penetration of non-dispatchable renewable energy power plants such as solar photovoltaics (PV) and wind. BESS have already been proved to be a valuable asset in many situations [1], by mitigating curtailment losses in non-dispatchable RE sources [2–4], operating in spot market using tariff arbitrage strategies [5–7], participating in reserve markets [8] and ancillary services [9]. However, from the perspective of the asset's owner, it is important that the current regulation provides a regulatory framework and energy prices that stimulate the private plant operator to dispatch an energy storage system to assist the grid and get rewarded by these operations. McPherson et al. [10] presented a review on electricity market rules and show that spot market prices and the market design can significantly change the dispatch strategy.

The optimal dispatch of energy storage systems has been studied in a variety of situations, with special emphasis on integrated renewable energy applications. Sahoo and Hota [11] developed a bidding strategy for a microgrid with renewable energy and energy storage using Improved Whale Optimization Algorithm (IWOA) for maximizing the profit, and taking the uncertainties with the renewable sources and load into account. Yang et al. [12] proposed a rolling optimization planning

List of abbreviations including units and nomenclature: ε_{PV}, random component of PV real generation; $\varepsilon_{forecast\#n}$, random component of PV forecast accuracy #n; ANN, artificial neural network; BESS, battery energy storage system; E_0, nitial energy stored into the battery; E^{bat}_{min}, minimum stored energy allowed; E^{bat}_{max}, maximum stored energy allowed; O&M, operation and Management; PLD, Hourly spot-market energy price (US$/MWh); PV_{real}, photovoltaic real generation (kWh); PV_{contr}, photovoltaic contracted generation (kWh); $PV_{forecast\#n}$, predicted photovoltaic generation with forecast accuracy #n (kWh); P_{bat}, energy dispatched from battery (kWh); P_{min}, battery minimal power output (kW); P_{min}, battery maximal power output (kW); R, revenue (US$).

* Corresponding author.
E-mail address: rafaelcampos.ufsc@gmail.com (R.A. Campos).

https://doi.org/10.1016/j.est.2022.104093
Received 27 October 2021; Received in revised form 19 January 2022; Accepted 22 January 2022
Available online 25 January 2022
2352-152X/© 2022 Elsevier Ltd. All rights reserved.

framework of an integrated energy system considering compressed air energy storage. For day-ahead markets, Li et al. [13] proposed a new Stochastic p-Robust Optimization (SPRO) method to deal with the financial risks of the day-ahead price uncertainty. Most of the dispatch strategies have PV generation forecast as an input and, for simplification, it is usual to consider a perfect forecast to validate the optimization strategies [6,8,14].

The International Energy Agency (IEA) PVPS Task 16 has published important work related to solar forecasting, such as best practices guidelines [15]. Beside, there is an effort within research community of standardize and gather the existent solar forecasting literature [16], recently showing that Root Mean Square Error (RMSE) is one of the main metrics for forecasting intercomparison [17].

Recent improvements in solar forecasting will not lie only in the models themselves, spectral and angular considerations were observed to affect PV power modeling [18]. Overirradiance events have shown impact in PV generation [19], and recent literature shows that might occur more frequently in high insolation seasons [20]. Beside, availability and component failure can impact forecasting; thus enhanced granularity in time-varying failure rate has been seen to diverge from annual considerations [21]. Therefore, future state-of-art solar forecasting models shall consider such aspects, in order to improve overall accuracy and dispatchability of PV power plants.

Deterministic, or point-forecast, provide a future expected value, and tend to be more commonly issue in industry to base decision-making [17]; on the other hand, probabilistic ones provide an interval of confidence, considering an uncertainty, causing difficulties in intercomparing models, although recent literature addressed this concerns [22,23].

Forecasting accuracy improved significantly throughout the decades. Following the growth of the solar energy industry, PV power plants Operation & Management (O&M) fomented the increase, variety, and accuracy of forecasting models. For instance, Skycam based models demonstrated important improvement for short-term accuracy, Rodríguez-Benitez et al. [24] showed that all-sky-image methods can provide reliable solar forecasting up-to 90 min; Paletta et al. [25] analyzed deep learning models in relation to sky-camera imagery, showing significant improvement from traditional sky image based very short-term solar forecasting, reaching 20.4% forecasting skill, beside, with similar strategy, Feng and Zhang [26] achieved 25.14% of forecasting skill.

Artificial Neural Network (ANN) models have appeared with different approaches and input variables, for example Pereira et al. [27] used ANN as a means of a corrective algorithm to a well stablish numerical weather prediction (NWP) model; on the other hand Marquez et al. [28] proposed ann ANN model itself, using satellite and ground telemetry as inputs.

In the case of day-ahead forecasting errors, which are relevant to plan energy dispatch strategies, Dewangan et al. [29] evaluate several models, achieving a Mean Absolute Percentual Error (MAPE) of 11.08% for persistence, and an interesting 4.03% for combined Support Vector Regression with Gaussian Kernel (SVRGC) model. Beside, Yagli et al. [30] showed accuracy for sequential reconciliation methods, with nMBEs varying among 7.48%, 0.03%, -0.43% and -0.68%.

Even though several theoretical models are present in the literature, they do not always comply with recommendations and needs for O&M purposes, and recent literature has been aware of those constraints [31]. For example, Yang et al. [32] proposed and evaluated a pattern-matching algorithm complying with real-time market conditions, showing nMBEs from -0.35% up to -0.02%, depending on the period and region evaluated. In addition, concepts such as Perez's *Perfect Forecast* were presented [33], mitigating errors and energy losses with the use of energy storage systems.

2. Motivation

In Brazil, since January 1st, 2021, hourly energy prices took effect, which used to be weekly [34]. This change is the main driver to increase the application of energy storage systems together with non-dispatchable renewable energy plants. Currently, BESS are not allowed to supply ancillary services and reserve power markets in Brazil; due to that, the spot market is the only revenue source option for these sistems, and it is well known that only stacking BESS potential benefits can make them cost competitive. The current Brazilian regulation is based on an hourly based contracted energy, in which the generator undertakes to generate 8760 bins of energy, one for each hour of the year. If the power plant does not supply the contracted energy for each hour, its owner must pay or get paid the difference between the generated and the contracted energy valued by the spot market energy price at that time.This work presents a dispatch strategy for PV + battery power plants and assesses how the dispatch strategy is affected by the day-ahead PV forecast accuracy, in the context of the current energy market model in Brazil. The aim of the dispatch strategy is to avoid the differences between the generated and the contracted energy, not using the energy storage for tariff arbitrage.

Table 1
Probability distributions used to simulate different values for forecasts skills.

Forecast #	Type of distribution	Mean (μ)	Standard deviation (σ)
1 (perfect forecast)	Normal	0	0
2	Normal	-0.1	0
3	Normal	-0.1	0.05
4	Normal	-0.1	0.1
5	Normal	-0.1	0.5
6	Normal	0	0.05
7	Normal	0	0.1
8	Normal	0	0.5
9	Normal	0.1	0
10	Normal	0.1	0.05
11	Normal	0.1	0.1
12	Normal	0.1	0.5

3. Methodology

The methodology applied is composed of three main steps: (i) real PV (PV_{real}) generation simulation by adding a random component to the contracted energy; (ii) forecasting the day-ahead hourly generation profile by adding a random component to PV_{real}; (iii) optimizing of the battery dispatch strategy based on the forecasted and contracted generations. The complete process is detailed below.

The real PV generation is calculated through Eq. (1).

$$PV_{real} = PV_{contr} \cdot (1 + \varepsilon_{PV}) \quad (1)$$

Where PV_{contr} is the contracted hourly generation in kWh, and ε_{PV} is the random component to add a random difference between PV_{Real} and $PV_{contr.}$. The hourly ε_{PV} values are samples from a normal distribution with a mean of zero and a standard deviation of 10%.

An analogous formula is applied to calculate the hourly values for the different forecasted accuracies, as stated by Eq. (2).

$$PV_{forecast\#n} = PV_{real} \cdot \left(1 + \varepsilon_{forecast\#n}\right) \quad (2)$$

Where $PV_{forecast\#n}$ stands for the forecasted generation for the nth forecast accuracy. The difference between the different forecasted accuracies comes from different distributions of $\varepsilon_{forecast\#n}$, which is sampled from distributions presented in Table 1. Therefore, each row presented in Table 1 emulates a forecasting accuracy, with prediction skills summarized by the corresponding distribution.

Then, for each forecasting accuracy, the dispatch optimization takes place. It results in the hourly battery dispatch which maximizes the revenue from the battery operation. The revenue of the PV + battery system arrangement is calculated using Eq. (3), where P_{bat} is the power dispatched from the battery, and PLD stands for the spot-market price (*PLD – Preço de Liquidação de Diferenças*, in Portuguese), which is

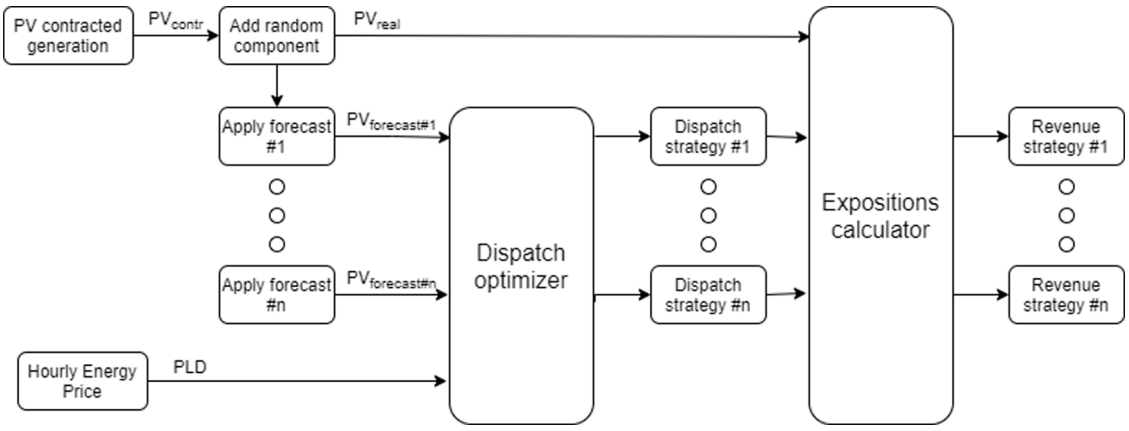


Fig. 1. Flowchart for the complete revenue assessment for each forecast accuracy.

Table 2
PV plant and BESS technical characteristics.

PV Plant	
Nominal Power	1.6 MWp
Mount type	Single-axis tracker
Battery Storage System	
Capacity	1 MW–1 MWh
Initial stored energy (E_0)	500 kWh
Minimum energy stored (E_{min})	100 kWh

available at every 21:00 for the day ahead. It is worth noting that the first term of Eq. (3) is constant and is based on a contract, so it does not depend on the real PV generation and, if $PV_{real} = PV_{contr}$, the revenue is equal to this term.

$$R = (PV_{real} + P_{bat} - PV_{contr}) \cdot PLD \tag{3}$$

For a given period, the total revenue is the sum of each hourly revenue, as stated by Eq. (4).

$$R = \sum (PV_{real} + P_{bat} - PV_{contr}) \cdot PLD \tag{4}$$

The dispatch optimization tries to optimize the revenue by finding the P_{bat} values that maximize R; thus, Eq. (5) presents the maximization problem.

$$max\ R = max \sum (PV_{real} + P_{bat} - PV_{contr}) \cdot PLD \tag{5}$$

However, PV_{real} and PV_{contr} are constants; therefore, the optimization problem can be simplified to Eq. (6).

$$max\ R = (PV_{real} - PV_{contr}) + \ max \sum PLD \cdot P_{bat} \tag{6}$$

The energy stored in the battery must be between its minimum and maximum states of charge. This constraint is summarized by Eq. (7).

$$E_{min}^{bat} \leq E_0^{bat} + \sum P_{bat} \leq E_{max}^{bat} \tag{7}$$

Beside, the battery has limitations regarding its maximum power output, as stated by Eq. (8).

$$P_{min} \leq P_{bat} \leq P_{max} \tag{8}$$

Once the battery operation is cyclical, the operator has to choose how much energy stored is required by the end of the day.

Finally, the maximization problem presented in Eq. (6) is solved by linear programming with the constraints presented in Eqs. (7) and (8). Fig. 1 illustrates the flowchart of each step described.

The technical characteristics of the PV plant and the battery system are presented in Table 2.

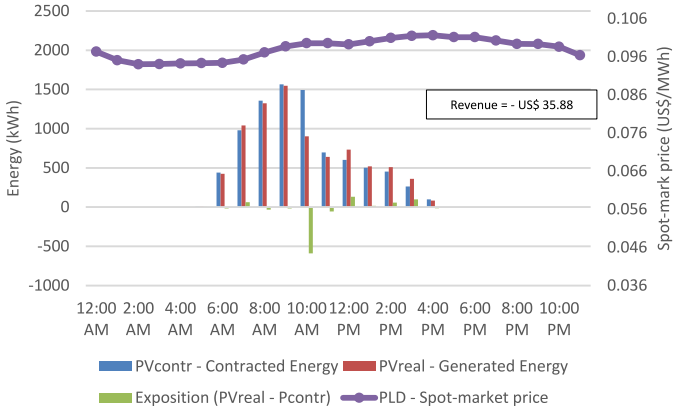


Fig. 2. Hourly contracted energy (P_{contr}), real generated energy (P_{real}), exposition ($P_{real} - P_{contr}$) and spot-market price (PLD) for the analyzed day.

4. Results and discussion

A Monte Carlo simulation approach was used, and the process described in Fig. 1 was simulated 1000 times for each forecasting accuracy presented in Table 1.

The real PV generation, the contracted PV generation, and the expositions are presented in Fig. 2, as well as the spot-market energy price (PLD). For this scenario, the total revenue was US$[1] -35.88, which is a result of the expositions valued at the hourly price. Thus, for a scenario without energy storage, this would be the PV plant's revenue. It is worth noting that the optimization strategy aims to use surplus energy to attenuate deficits, and it is not allowed to charge the battery directly from the grid.

The results from the Monte Carlo simulation are summarized in the boxplots presented in Fig. 3. The average revenue obtained are presented in Table 3.

4.1. Perfect forecast

The first box summarizes the perfect forecast, with mean zero and standard deviation also zero. The perfect forecast results in knowing exactly the exposition for each hour of the day. The hourly dispatch is presented in Fig. 4. The total revenue for the scenario with the perfect

[1] Values converted from Brazilian Reais (R$) to United States Dollars (US$). Exchange rate from 06th October of 2021. R$ 1.00 : US$ 0.18 .

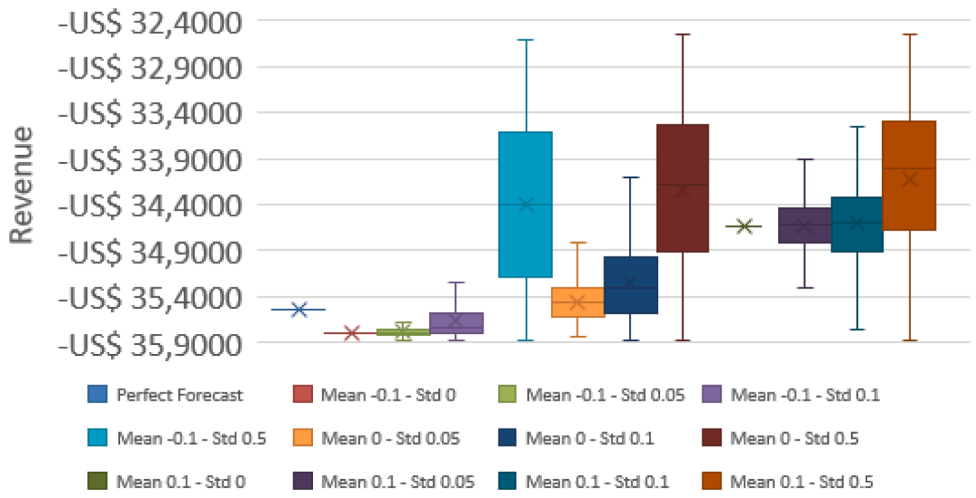


Fig. 3. Boxplot of the Monte Carlo simulation results for each forecasting accuracy.

Table 3
Probability distributions used to simulate different revenue values for forecasts skills.

Forecast #	Mean (μ)	Standard deviation (σ)	Average revenue (US $)
0 (without BESS)	–	–	-35.88
1 (perfect forecast)	0	0	-35.54
2	-0.1	0	-35.80
3	-0.1	0.05	-35.77
4	-0.1	0.1	-35.65
5	-0.1	0.5	-34.41
6	0	0.05	-35.31
7	0	0.1	-35.24
8	0	0.5	-34.24
9	0.1	0	-34.63
10	0.1	0.05	-34.63
11	0.1	0.1	-34.60
12	0.1	0.5	-33.59

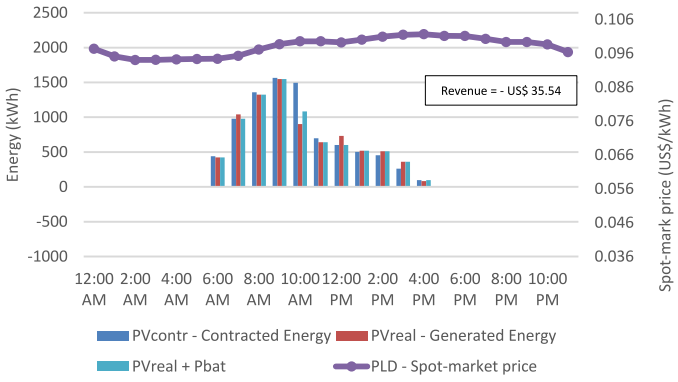


Fig. 4. Hourly contracted energy (PV_{contr}), real generated energy (PV_{real}), total energy injected into the grid ($PV_{real} + P_{bat}$), and spot-market price (PLD) for the analyzed day.

forecast is US$ -35.54, US$ 0.34 higher than the scenario without energy storage. The PVreal + Pbat bar presented in Fig. 4 is the total energy dispatched from the PV + battery plant. It can be seen that at 10:00 there is an energy deficit (negative exposition) and the battery acts in order to reduce this deficit, although not nullifying the deficit. It does not nullify the deficit due to an important condition: the energy stored by the end of the day must be equal to the initial energy store.

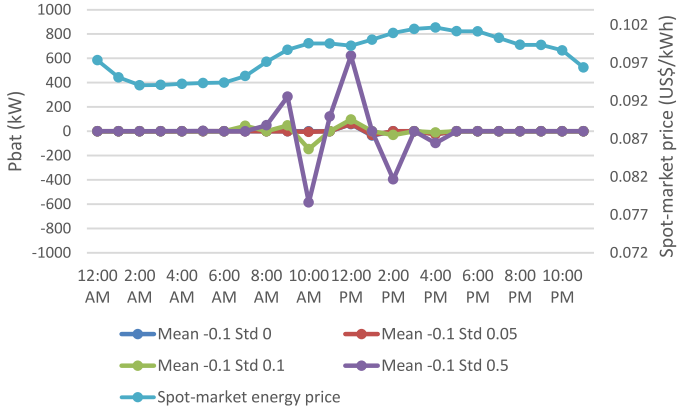


Fig. 5. Hourly battery dispatch and spot-market price (PLD) for the forecast accuracies with mean of -0.1.

4.2. Non-perfect forecasts

From the second to the fifth, the boxes in Fig. 3. represent the scenarios with forecast accuracies with mean -0.10 and standard deviations of 0, 0.05, 0.10, and 0.50, respectively. From the sixth to the eighth, the boxes represent the scenarios with forecast accuracies with mean 0 and standard deviations of 0.05, 0.10, and 0.50. The last four boxes represent the scenarios with a mean of 0.1 and standard deviations of 0, 0.05, 0.10, and 0.50.

It can be noted that the higher the mean of the forecast error, the higher the revenue obtained. Also, the higher its standard deviation, the higher the revenue as well.

In the problem described by Eq. (6), it is clear that the maximum revenue does not depend on the PV real generation, or the PV contracted generation, but depends only on the spot-market energy price and the battery dispatch. The maximum revenue is the result of a strategy that is also independent of the PV generation values. This strategy is the tariff arbitrage operation. Therefore, from the asset owner's perspective, it is more advantageous to operate a battery system as an independent asset than operating it together with a PV plant.

4.2.1. Standard deviation effect

Fig. 5 presents the optimal dispatch obtained for the forecast accuracies 2 to 5. It shows that the forecasts with higher standard deviation lead to deeper charges and discharges of the battery, resulting therefore in higher revenues. Also, the higher the standard deviation, the closer

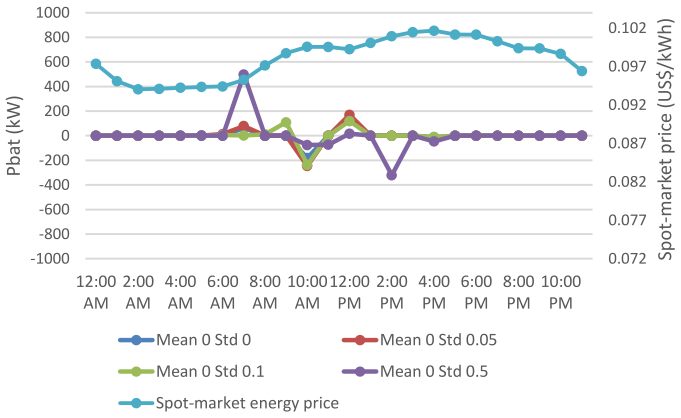


Fig. 6. Hourly battery dispatch and spot-market price (PLD) for the forecast accuracies with mean of 0.

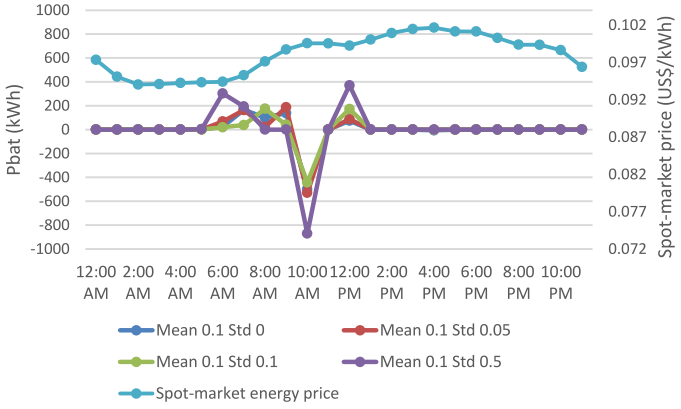


Fig. 7. Hourly battery dispatch and spot-market price (PLD) for the forecast accuracies with mean of 0.1.

the battery operation is from the tariff arbitrage strategy. The same behavior is found for the scenarios with mean 0 and 0.1, presented in Figs. 6 and 7.

4.2.2. Mean effect

The mean proposed in Table 1 represents the average error of a forecast in the long term. This means that the forecast accuracies with a mean of -0.1 tend to underestimate the real values, and the forecast accuracies with a mean of 0.1 tend to overestimate these values. Therefore, if the strategy does not allow the battery to charge from the grid directly, and the forecast accuracy tends to predict generations that are below the contracted values, the battery can not be charged. This behavior leads the battery to not dispatch in many cases in which it should, leading to smaller revenues as well.

On the other hand, the forecast accuracies with a mean higher than zero predict more energy production than the contracted values. This leads the battery to be charged whenever necessary, since the forecast expects surplus energy for almost all hourly bins. Then, the battery charges and discharges almost freely, since again it tends to dispatch closest to the tariff arbitrage strategy.

5. Conclusion

An optimization problem was presented from the perspective of an asset owner with a PV plant and battery energy storage system. From this perspective, the power plant operator must know the day-ahead spot-market energy prices and predict the day-ahead PV generation to decide how to dispatch the battery system. We evaluated 11 forecast accuracies to assess how the forecast accuracy can change the agent's total revenue. The main findings of this study were that, from the perspective of a BESS + PV asset operating from day-0:

- The optimal strategy for battery dispatch is independent of PV generation and relies only on the spot-market energy prices.

And, If the agent's objective is to use the battery system only to guarantee the contracted energy:

- The battery system does not add as much value as it could;
- The forecast accuracy can lead to a higher revenue, leading the battery operate closer to the tariff arbitrage strategy.

Therefore, under the conditions described here, integrating energy storage with renewable non-dispatchable plants to guarantee the contracted energy is not optimal from the agent's perspective. Instead, operating the battery system for tariff arbitrage is more profitable. In this context, an accurate PV forecast does not seem to be critical. Similar studies using the methodology proposed here can be carried out for ancillary services and reserve markets and for more complex market rules to assess how critical is the forecast accuracy for other regulatory backgrounds.

CRediT authorship contribution statement

Rafael Antunes Campos: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Giuliano L. Martins:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ricardo Rüther:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

We confirm that we have authority for publication and that the manuscript is not under consideration for publication elsewhere, nor has it been published previously.

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

Acknowledgments

The authors acknowledge with thanks the Brazilian Electrical Energy Regulatory Agency ANEEL, ENGIE Brasil Energia, and Guascor/Siemens for financing the R&D project in battery energy storage system integrated with utility-scale photovoltaic plants.

References

[1] O. Palizban, K. Kauhaniemi, Energy storage systems in modern grids—matrix of technologies and applications, J. Energy Storage 6 (2016) 248–259, https://doi.org/10.1016/j.est.2016.02.001.

[2] F.R. Segundo Sevilla, D. Parra, N. Wyrsch, M.K. Patel, F. Kienzle, P. Korba, Techno-economic analysis of battery storage and curtailment in a distribution grid with high PV penetration, J. Energy Storage 17 (2018) 73–83, https://doi.org/10.1016/j.est.2018.02.001.

[3] R. Antunes Campos, L. Rafael do Nascimento, R. Rüther, The complementary nature between wind and photovoltaic generation in Brazil and the role of energy storage in utility-scale hybrid power plants, Energy Convers. Manag. 221 (2020), 113160, https://doi.org/10.1016/j.enconman.2020.113160.

[4] F. Mohamad, J. Teh, C.M. Lai, Optimum allocation of battery energy storage systems for power grid enhanced with solar energy, Energy 223 (2021), 120105, https://doi.org/10.1016/j.energy.2021.120105.

[5] D. Metz, J.T. Saraiva, Use of battery storage systems for price arbitrage operations in the 15- and 60-min German intraday markets, Electr. Power Syst. Res. 160 (2018) 27–36, https://doi.org/10.1016/j.epsr.2018.01.020.
[6] P.E. Campana, L. Cioccolanti, B. François, J. Jurasz, Y. Zhang, M. Varini, et al., Li-ion batteries for peak shaving, price arbitrage, and photovoltaic self-consumption in commercial buildings: a Monte Carlo Analysis, Energy Convers. Manag. 234 (2021), 113889, https://doi.org/10.1016/j.enconman.2021.113889.
[7] M. Legrand, R. Labajo-Hurtado, L.M. Rodríguez-Antón, Y. Doce, Price arbitrage optimization of a photovoltaic power plant with liquid air energy storage. Implementation to the Spanish case, Energy 239 (2021), 121957, https://doi.org/10.1016/j.energy.2021.121957.
[8] I. Staffell, M. Rustomji, Maximising the value of electricity storage, J. Energy Storage 8 (2016) 212–225, https://doi.org/10.1016/j.est.2016.08.010.
[9] J. Cho, A.N. Kleit, Energy storage systems in energy and ancillary markets: a backwards induction approach, Appl. Energy 147 (2015) 176–183, https://doi.org/10.1016/j.apenergy.2015.01.114.
[10] M. McPherson, B. McBennett, D. Sigler, P. Denholm, Impacts of storage dispatch on revenue in electricity markets, J. Energy Storage 31 (2020), 101573, https://doi.org/10.1016/j.est.2020.101573.
[11] A. Sahoo, P.K. Hota, Impact of energy storage system and distributed energy resources on bidding strategy of micro-grid in deregulated environment, J. Energy Storage 43 (September) (2021) 103230, https://doi.org/10.1016/j.est.2021.103230.
[12] D. Yang, M. Wang, R. Yang, Y. Zheng, H. Pandzic, Optimal dispatching of an energy system with integrated compressed air energy storage and demand response, Energy 234 (2021), 121232, https://doi.org/10.1016/j.energy.2021.121232.
[13] Z. Li, Q. Zhang, Q. Guo, S. Nojavan, Pumped hydro energy storage arbitrage in the day-ahead market in smart grid using stochastic p-robust optimization method, Sustain. Cities Soc. 75 (2021), 103274, https://doi.org/10.1016/j.scs.2021.103274.
[14] S. Liu, S. Silwal, J. Kleissl, Power and energy constrained battery operating regimes: effect of temporal resolution on peak shaving by battery energy storage systems, J. Renew. Sustain. Energy (2021), https://doi.org/10.1063/5.0061813 (in Press.
[15] M. Sengupta, A. Habte, S. Wilbert, C. Gueymard, J. Remund. Solar resource for high penetration and large scale applications. 2021.
[16] D. Yang, J. Kleissl, C.A. Gueymard, H.T.C. Pedro, C.F.M. Coimbra, History and trends in solar irradiance and PV power forecasting: a preliminary assessment and review using text mining, Sol. Energy 168 (2018) 60–101, https://doi.org/10.1016/j.solener.2017.11.023.
[17] D. Yang, S. Alessandrini, J. Antonanzas, F. Antonanzas-Torres, V. Badescu, H. G. Beyer, et al., Verification of deterministic solar forecasts, Sol. Energy (2020) 1–18, https://doi.org/10.1016/j.solener.2020.04.019.
[18] N. Lindsay, Q. Libois, J. Badosa, A. Migan-Dubois, V. Bourdin, Errors in PV power modelling due to the lack of spectral and angular details of solar irradiance inputs, Sol. Energy 197 (2020) 266–278, https://doi.org/10.1016/j.solener.2019.12.042.
[19] L.R. do Nascimento, T. de Souza Viana, R.A. Campos, R. Rüther, Extreme solar overirradiance events: occurrence and impacts on utility-scale photovoltaic power plants in Brazil, Sol. Energy 186 (2019) 370–381, https://doi.org/10.1016/j.solener.2019.05.008.
[20] G.L. Martins, S.L. Mantelli, R. Rüther, Evaluating the performance of radiometers for solar overirradiance events, Sol. Energy 231 (2022) 47–56, https://doi.org/10.1016/j.solener.2021.11.050.
[21] H. Abunima, J. Teh, Reliability modeling of PV systems based on time-varying failure rates, IEEE Access 8 (2020) 14367–14376, https://doi.org/10.1109/aCCESS.2020.2966922.
[22] K. Doubleday, V. Van Scyoc Hernandez, B.M. Hodge, Benchmark probabilistic solar forecasts: characteristics and recommendations, Sol. Energy 206 (2020) 52–67, https://doi.org/10.1016/j.solener.2020.05.051.
[23] D. Yang, A universal benchmarking method for probabilistic solar irradiance forecasting, Sol. Energy 184 (2019) 410–416, https://doi.org/10.1016/j.solener.2019.04.018.
[24] F.J. Rodríguez-Benítez, M. López-Cuesta, C. Arbizu-Barrena, M.M. Fernández-León, M. Pamos-Ureña, J. Tovar-Pescador, et al., Assessment of new solar radiation nowcasting methods based on sky-camera and satellite imagery, Appl. Energy 292 (2021), 116838, https://doi.org/10.1016/j.apenergy.2021.116838.
[25] Q. Paletta, G. Arbod, J. Lasenby, Benchmarking of deep learning irradiance forecasting models from sky images – an in-depth analysis, Sol. Energy 224 (2021) 855–867, https://doi.org/10.1016/j.solener.2021.05.056.
[26] C. Feng, J. Zhang, SolarNet: a sky image-based deep convolutional neural network for intra-hour solar forecasting, Sol. Energy 204 (2020) 71–78, https://doi.org/10.1016/j.solener.2020.03.083.
[27] S. Pereira, P. Canhoto, R. Salgado, M.J. Costa, Development of an ANN based corrective algorithm of the operational ECMWF global horizontal irradiation forecasts, Sol. Energy 185 (2019) 387–405, https://doi.org/10.1016/j.solener.2019.04.070.
[28] R. Marquez, H.T.C. Pedro, C.F.M. Coimbra, Hybrid solar forecasting method uses satellite imaging and ground telemetry as inputs to ANNs, Sol. Energy 92 (2013) 176–188, https://doi.org/10.1016/j.solener.2013.02.023.
[29] C.L. Dewangan, S.N. Singh, S. Chakrabarti, Combining forecasts of day-ahead solar power, Energy 202 (2020), 117743, https://doi.org/10.1016/j.energy.2020.117743.
[30] G.M. Yagli, D. Yang, D. Srinivasan, Reconciling solar forecasts: sequential reconciliation, Sol. Energy 179 (2019) 391–397, https://doi.org/10.1016/j.solener.2018.12.075.
[31] D. Yang, W. Li, G.M. Yagli, D. Srinivasan, Operational solar forecasting for grid integration: standards, challenges, and outlook, Sol. Energy 224 (2021) 930–937, https://doi.org/10.1016/j.solener.2021.04.002.
[32] D. Yang, E. Wu, J. Kleissl, Operational solar forecasting for the real-time market, Int. J. Forecast. 35 (2019) 1499–1519, https://doi.org/10.1016/j.ijforecast.2019.03.009.
[33] R. Perez, M. Perez, M. Pierro, J. Schlemmer, S. Kivalov, J. Dise, et al., Perfect operational solar forecasts: a scalable strategy toward firm power generation, in: Proceedings of the ISES Solar World Congress 2019, 2020, pp. 2237–2247, https://doi.org/10.18086/swc.2019.45.07. IEA SHC Int Conf Sol Heat Cool Build Ind 2019.
[34] ANEEL. Resolução normativa 910 de 2020 2021:20–1.