Control Optimization and Sizing of Energy Storage for PV Systems Using Probabilistic Forecasts

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Abstract— **Photovoltaic systems are becoming a cost-effective solution for power systems traditionally based on diesel generators, such as islanded sites or microgrids. Indeed, PV-storage systems, which combine solar energy and energy storage systems (ESS), allow both limiting atmospheric pollution and reducing operational costs. Sizing such a system is not straightforward. It requires modeling grid code constraints as well as an adapted control strategy. In this work, we present through simulation how the integration of probabilistic PV forecasts into control strategies is an efficient way of limiting energy losses and minimizing ESS capacity. First, we present our modeling approach, based on an innovative modeling platform developed at the CEA-INES called SPIDER. The system behavior is analyzed for control strategies based on different types of forecasts and various battery sizes. The results show how the trade-off between maximizing the energy injection and limiting the ESS size can be optimized by efficiently using probabilistic forecasts.**

Keywords: Photovoltaic; forecast; ESS; control strategy; grid code; storage sizing; simulation

I. INTRODUCTION

With the deregulation of power generation and the de-carbonization targets set by countries worldwide, distributed generation with grid-connected renewable power plants is growing rapidly. Nevertheless, with an increased penetration rate of renewable sources on the grid, ensuring network reliability while satisfying the energy demand becomes more challenging. Regarding photovoltaic energy, one approach is to combine storage systems with PV plants, and define in advance an energy injection plan. In this approach, the producer first plans its injection/withdrawal, called production plan, for the day after, taking in account the solar irradiation forecasts. Then, the producer must ensure in real-time that the actual production meets the engagement to avoid being disconnected from the grid. Storage devices, like lithium-ion battery banks, are needed to compensate for forecast errors as well as PV unavailability periods to smooth the production. Some flexibility can be added, like the possibility of updating the plan during the day. In this work, we model this approach for a PV-ESS system. We present through simulations how to efficiently size energy storage systems thanks to probabilistic forecasts. First, we focus on the methodology used, by detailing grid code constraints, study case, forecasts and control strategies. Then, we analyze simulation results, through indicators such as energy losses, energy delivered to the grid and battery charging/discharging profile.

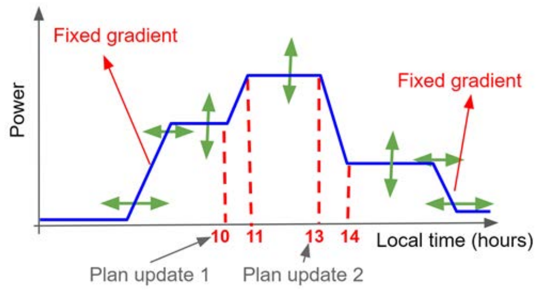

Figure 1 : Schematic of the grid code constraints

II. METHODOLOGY

A. Simulation platform

The CEA developed an advanced simulation platform, which addresses various PV applications such as self-consumption systems, microgrids or utility scale PV systems [1]. The software is called SPIDER as Simulation Platform for the Integration of Distribution Energy Resources. SPIDER is a standardized platform based on a generic open-source modeling environment (Papyrus) [2]. SPIDER relies on the model-based approach where models representing the physical system are associated to models representing the system control. Regarding the control concept, a generic multi-level architecture for Energy Management System (EMS) has been developed. Such architecture defines the EMS as a combination between several planning controls and one operation control. The planning control aims at computing system set points for a given horizon. It is based on generation or consumption power forecasts. It includes optimization methods and associated models.

B. Grid code

French Polynesia is currently redefining its grid code in order to integrate more PV systems, while maintaining grid stability [3]. For PV storage systems, an energy injection scheme with three plateau was defined, and has to be followed by the energy producer. There are a multitude of parameters to define in order to obtain such a production plan (schedules, re-announcements, etc.). In our study, the following constraints were used (Figure 1):

- The gradients at the start of the day and at the end of the day are fixed: 150 kW/min.

- The energy injection must start between 6:30 a.m. and 7:30 a.m. and end between 5 and 6 p.m.
- The start time for the 1st plateau is flexible. The end time of the 1st plateau is 10 a.m., and the start time of the 2nd plateau is 11 a.m.
- The end time of the 2nd plateau is 1 p.m. and the start time of the 3rd plateau is 2 p.m.
- The end time of the 3rd plateau is flexible.
- The maximum power of each plateau cannot exceed 75% of the installed PV capacity.

Announcements are made according to the following schedule: 1st announcement at 5 a.m., for the whole day; 2nd announcement at 10 a.m., allowing the plan to be readjusted from 10 a.m. to 6 p.m.; and 3rd announcement at 1 p.m. allowing the plan to be updated from 1 p.m. to 6 p.m.

In order to calculate this plan using forecasts, a mathematical model of the defined constraints is built in MATLAB. Once the mathematical model with its unknowns is established, we define a variable, called objective, to minimize. This variable corresponds, in our case, to the sum of several factors:

- The sum of the power differences between the production plan and the forecasts
- The difference between the initial state of charge of the battery and the final state of charge
- Finally, the difference between the maximum state of charge and the minimum state of charge over the day.

To optimize the production plan, it is necessary to minimize this objective/variable. The result is an optimized production plan, limiting the power at battery level, the charge imbalance between the start and the end of the day and excessive charge/discharge amplitudes during the day.

C. Study case and production data

The study focuses on a PV power plant of 18 MW, coupled to a lithium-ion energy storage. To analyze the operation of the PV storage system over one year of operation, we need to estimate the production of the PV plant over this same period. To do so, several methods are possible here: satellite data, meteorological data, or extrapolation of data from a known power plant. These different possibilities differ by their temporal resolution. While we have hourly data for the meteorological models, the data from known power plants are in minute time steps. The variability of production (with power drops of a few minutes) is therefore much more visible on the latter, and corresponds more to the needs of the simulation: the demand on the battery and the demand for power will thus be more realistic. It will be easier to estimate more accurately the energy exchanges during the day. Production data are therefore extrapolated from a nearby power plant that has been working for a few years.

D. Forecasting system and data

The forecasts used for this study correspond to day-ahead forecasts, called SteadyMet at Steadysun. The SteadyMet forecasts rely on multiple numerical weather models: the GFS model (25 km resolution) from NOAA, its ensemblist version GEFS (50 km), this IFS-HRES model from the ECMWF (10 km), AROME model from Météo-France (2.5 km) and the WRF model (1 km), which is calibrated and run at Steadysun. These input data are combined to generate probabilistic local weather forecasts, which are then converted into a power production using a physical solar model. Several machine learning algorithms

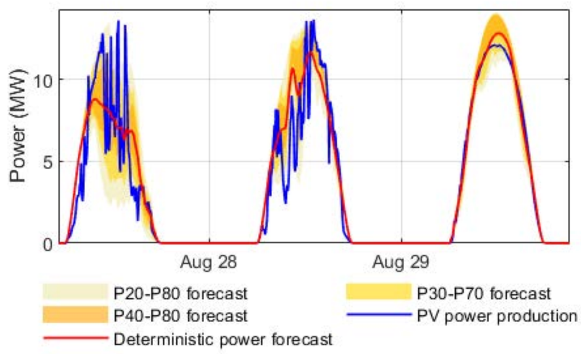

Figure 2 : Example of 3 days of PV plant power production and its corresponding probabilistic forecasts for the horizon 24h.

come into play to combine at best the meteorological information from the different models and to post-treat the power production forecasts using previous days measurements. For this study, one year of historical forecasts from SteadyMet are used.

The delivered forecasted values rely on a probabilistic approach, where confidence intervals are calculated instead of deterministic values. Indeed, for the deterministic approach, point forecasts do not give a full picture of the whole potential future outcomes, and therefore are not adapted to situations where uncertainties or risks are involved. Therefore, probabilistic predictions are more adapted to control strategies of systems, where decisions can be taken under a chosen level of risks. Calculation of percentiles relies on a combined approach of statistical data analysis and appropriate parametrization of weather models. An example of day-ahead forecast at horizon 24h for three consecutive days is shown on figure 2, where different levels of confidence are represented. For our study, in addition to the deterministic forecast, the percentile 'P30' is used, which corresponds to 70% chances that real power exceeds this value.

Given the constraints related to system control, we have recourse to several forecasts: the forecast available at 5 a.m., to carry out the production plan for the day, and the forecast available at 10 a.m. and 1 p.m. to update the production plan. The control algorithm therefore automatically chooses the forecast to use according to the planning phase.

E. Control strategies

The control scheme for the PV storage systems integrates an advanced control with two levels: one planning stage, where the production plan is calculated according to forecasts, and one operational stage where the control tries following the predefined plan. When the plan cannot be followed, the control takes an adapted decision according to the situation (curtailment, disconnection, etc.).

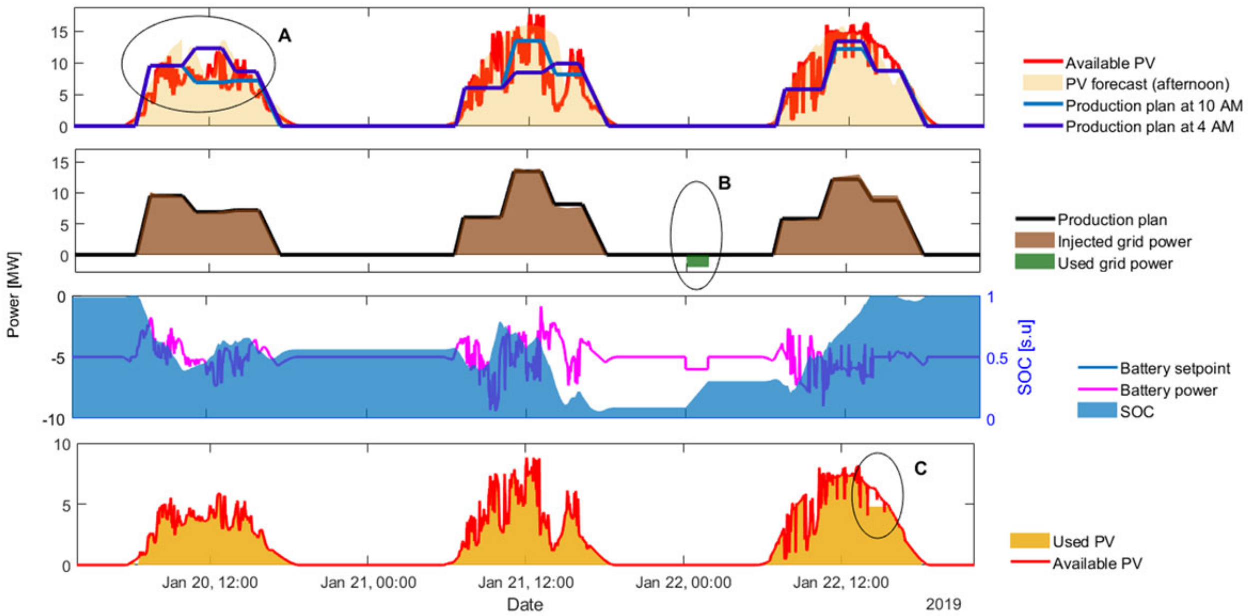

Figure 3 : Example of results for 3 days of simulation with a 16 MWh ESS and the 'Steadysun forecast' strategy. From top to bottom: 1) PV production curves, forecast and associated production plans; 2) Grid balance: Production plan, energy actually injected and energy taken from the network; 3) ESS balance: Power at ESS level and state of charge of the battery; 4) PV balance: Energy available and energy actually used.

The operational phase takes into account the following behaviors:

- Attempt to respect the power production plan.
- Disconnection from the network for the rest of the day if the injected power deviates from a tolerance threshold (+/- 10% over 15 minutes).
- Charging of the battery up to a SOC of 70% if the system is disconnected from the network.
- Night charging between 12 p.m. and 4 a.m. if the state of charge of the battery is less than a predefined threshold. In order to start the following day with a certain amount of energy reserve, while limiting grid energy consumption, a SOC threshold of 30% was defined.
- Curtailment of the PV plant power if the battery is fully charged and the production plan is less than the actual PV power.

The planning stage corresponds to the definition of production plan, respecting grid codes constraints, as explained in II.B. Several factors impact the optimization process:

- The size of the battery: this is the parameter of primary interest, as sizing the ESS is one of our objectives.
- The forecast used: it is possible to choose a more or less conservative forecast (choice of quantile) for the control. The forecast used could also vary depending on the state of charge of the battery. If the battery SOC is low, a conservative forecast is used whereas a more optimistic one can be used when the SOC is high.
- The battery state of charge is considered as a target: the production plan calculation algorithm will target a certain state of charge at the end of the day in order to perform these calculations. In our study, a target state of charge of 50% is applied.

In order to study the sizing of the storage system, the simulations are performed on batteries ranging from 12 MWh to 22 MWh with a 2 MWh energy step. No upper and lower limits for the SOC have been set in the simulations, and therefore the mentioned battery capacities correspond to the useful energy capacity of the ESS. The maximum charge and discharge AC power of the battery is set to 18 MW, meaning that power will not be limited in the simulations as PV power does not exceed 18 MW for the considered PV plant. The efficiency of the storage system is considered constant for charge and discharge, and the value 0.95 is set.

For the forecasts, we used different scenarios: 1) Perfect forecast: the PV production is known; 2) Persistence: the daily PV production profile is considered equal to the one of the previous day; 3) Probabilistic forecast: the forecast P30 and the deterministic forecast are used to estimate the

PV production. The weight applied on each forecast depends on the SOC of the ESS. Simulations are run for 1 year at 1 minute time step.

III. RESULTS

A. Simulation results example

In order to show the simulated system behavior, three days of simulation are represented on Figure 3, where the ESS capacity is 16 MWh and the forecast used for the control is the Steadysun forecast. This figure is divided into 4 parts. From the top to the bottom, we have: 1) the production curves, the 5 a.m. and the 1 p.m. production plans, and the forecast used for the 1.p.m. production plan; 2) a network balance, showing the injection plan, the energy actually injected and the energy consumed at night; 3) a battery balance, where the state of charge of the battery and the charge/discharge powers are shown; 4) a PV plant balance, where we observe the energy theoretically available and the energy actually used. The 3 selected days illustrate several aspects of the control, marked by letters A, B and C.

The event represented in A corresponds to a relevant modification of the initial production plan. Indeed, the update of the 5 a.m. production plan (dark blue) results in a more conservative plan (light blue). The corresponding SOC of the battery shows that this decision was relevant as the SOC at the end of the corresponding day is around 50%. The event B shows a night charge of the ESS as the SOC of the battery was around 10% at the end of the previous day. This low SOC is induced by an optimistic forecast. Hence, it is a production plan. Finally, the letter C shows a curtailment event, where the ESS is fully charged and PV energy exceeds production plan.

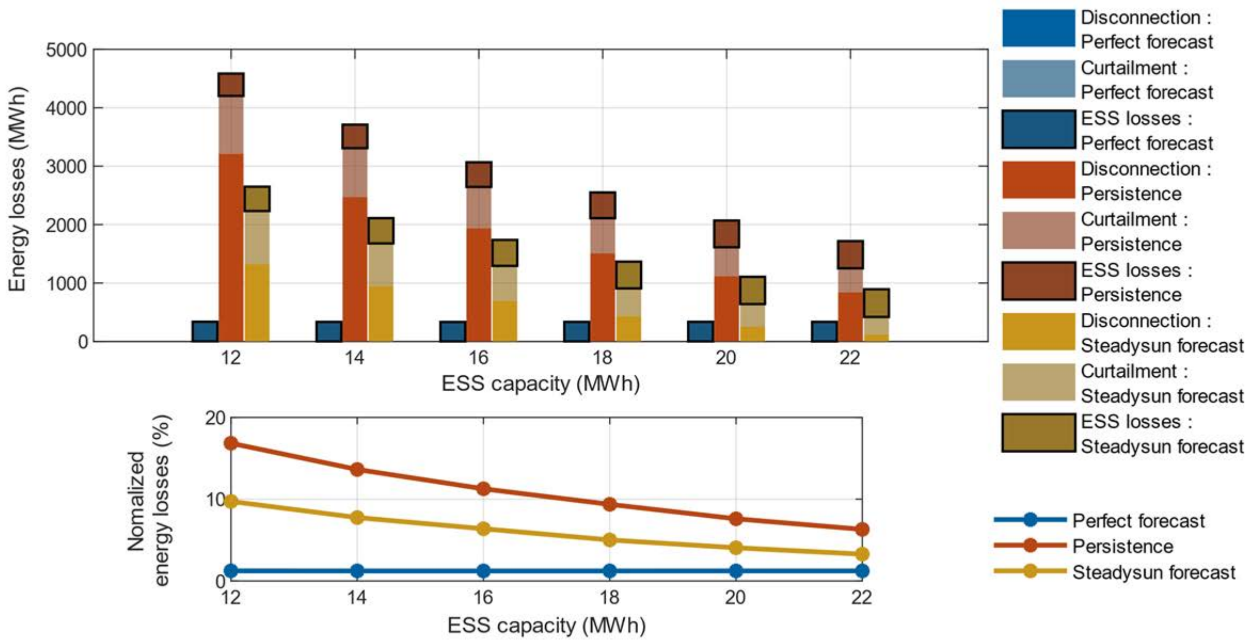

Figure 4 : Comparison of energy losses for 1 year. 3 Strategies are compared and losses are expressed in terms of absolute value (top), and values normalized by available PV energy (bottom)

B. Control strategies comparison

In order to study the impact of forecasts on the system behavior, we decide to focus on energy losses. Those losses correspond to theoretically available PV energy that is not injected into the grid for three reasons: curtailment, disconnection of the system from the grid (failure to respect production plan), and losses linked to ESS charge and discharge. They are represented for 1 year of simulation for the 3 control strategies on Figure 4. We observe that losses associated with the strategy using the perfect forecast are only due to the ESS behavior. Indeed, as forecasts are perfect, the associated production plan is always respected and no curtailment is observed. The lost energy is around 330 MWh, corresponding to 1.2% of the available PV energy regardless of battery size. This value can be considered as the lower limit of losses, but cannot be

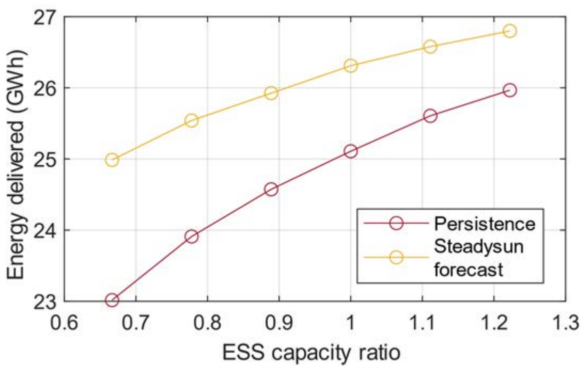

Figure 5 : Comparison of energy injected to the grid between persistence forecast and Steadysun forecast, for different ESS capacity to PV installed size ratio

achieved in reality as forecasts are associated with uncertainties.

If we now compare the losses for the persistence forecast with the Steadysun forecast, we observe that using persistence leads to higher losses. For an ESS capacity of 16 MWh, those losses reach 3067 MWh for persistence (11.3%), and 1736 MWh (6.4%) for Steadysun forecast. This is mainly induced by more important disconnections from the grid for persistence, as production plan is not respected. Therefore, using Steadysun forecast leads to a 43% decrease of losses in this case. This relative decrease can be observed with same order of magnitude regardless of the battery capacity. For Steadysun forecast, the predominant factor of losses evolves with battery capacity: for a battery capacity smaller than 16 MW, curtailment prevails, whereas ESS behavior is the main factor when capacity is higher than 20 MW. Disconnections from the grid also decrease with battery sizing, but cannot be completely avoided as there are few days with high errors of forecasts.

To quantify the impact of using Steadysun forecast versus persistence, in terms of battery capacity, the absolute energy injected into the grid was plotted for different battery capacities (Figure 5). The latter was expressed as battery capacity to PV installed power ratio. As expected, a higher amount of energies is injected when using Steadysun forecast. In order to inject the same energy with persistence, the ESS capacity ratio must be increased by 0.3. For our study case, this corresponds roughly to a 6 MWh capacity.

C. Energy storage sizing

The sizing of the ESS has to be expressed in terms of energy and AC conversion power. For the battery capacity, we have already discussed the benefit of using Steadysun forecast when compared with persistence. The performed simulations allow obtaining a detailed battery usage profile at 1 minute time step, leading to a precise evaluation of the state of charge (SOC) over time. A histogram of such SOC profile is represented on Figure 6 (left graph). This information is crucial for a detailed estimation of battery lifetime. Indeed, the number of cycles could be extracted from such profiles, hence the resulting useful percentage of initial capacity. When studying economically this kind of system for a period of several years (typically 20), one can better estimate when ESS should be replaced, or what initial oversizing battery would be ideal in order to not replace the ESS during its lifetime.

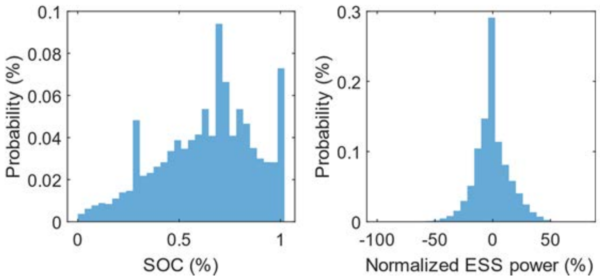

Figure 6 : Histogram of SOC and ESS power normalized by PV installed capacity for 1 year of simulation. The case 18 MWh and per Steadysun forecast is represented.

The inverter used for the ESS can also be sized by using simulation results. The power profile, expressed in power normalized by PV plant capacity, is represented on Figure 6 (right axis). Negative power corresponds to discharge of the battery, whereas positive values are used for charging periods. We observe that the required power, regardless of charge or discharge, does not exceed 60% of the PV plant capacity. Therefore, for our study case, a 10 MW inverter would be sufficient.

IV. CONCLUSION

In this work, the energy balance of PV storage systems is studied through simulations. The control strategy has been adapted to respond to specific grid code constraints, and different types of forecasts can be integrated for managing the system operation. Control strategy based on probabilistic forecasts, when compared to strategy using persistence, show benefits in terms of energy injection into the grid. This advantage has been quantified, and a decrease of roughly 45% of losses is observed between a strategy with persistence and a control using probabilistic forecasts, regardless of battery size. In terms of battery capacity, for our study case, this corresponds to a gain of 6 MWh for a 18 MW PV power plant. The simulation platform allows obtaining detailed profiles of battery demand at one minute time step. This information is of great importance for sizing the inverter used for the ESS and for a more accurate estimation of battery lifetime.

REFERENCES

[1] [1] F. Bourry, “Advanced simulation platform for the integration of photovoltaics into power systems: Spider,” in 32nd PVSEC Conference, 2016.

[2] [2] “Papyrus: an industrial-grade open-source model-based engineering tool.” [Online]. Available: https://www.eclipse.org/papyrus/index.php

[3] http://lexpol.cloud.pf/LexpolAfficheTexte.php?texte=562983