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Stochastic dynamic programming for energy management of an overplanted offshore wind farm with dynamic thermal rating and storage

Alexandre Faye-Bédrin^{1,2}, Anne Blavette¹, Pierre Haessig², Salvy Bourguet³, Ildar Daminov³

Abstract—We study the optimal energy management of an offshore wind farm which combines “overplanting” (more production than transmission capacity), “dynamic thermal rating” (DTR, transiently exporting more than the steady-state transmission capacity thanks to the large thermal inertia of the soil surrounding the export cable) and an energy storage (to mitigate both curtailments and forecast errors). This forward-looking setting, which aims at further reducing the Levelized Cost of Energy of offshore wind power, creates an optimization problem with both temporal couplings and uncertain inputs. The difficulty of this energy management problem comes from having time constants separated by several orders of magnitude due to the thermal inertia of the cable surroundings. We propose an approximate solution based on large GPU implementation of Stochastic Dynamic Programming (SDP). In our performance comparisons, SDP outperforms simpler rule-based energy management schemes while we also explore the benefit of DTR in the context of overplanting.

Index Terms—overplanting, dynamic thermal rating, energy storage, optimal energy management, stochastic dynamic programming

I. INTRODUCTION

The installed power capacity of offshore wind energy is growing, reaching almost 60 GW worldwide at the end of 2021, and with a rhythm of capacity increase expected to accelerate in the coming years [1]. However, although already competitive in some markets before the 2022 energy crisis, the levelized cost of energy (LCOE) of this energy source is still greater than the LCOE of other energy sources in most markets [2]. Hence, cost reductions are necessary to render this energy source competitive worldwide.

Several options are envisaged in this perspective, including overplanting, combined or not with dynamic thermal rating (DTR) [3]. Overplanting consists in sizing a wind farm at a greater rated power than the steady-state rated power of its export cable. This allows a better exploitation of low and mildly energetic periods while requiring curtailment during more energetic ones. Overall, this approach enables to increase

the annual energy production of a wind farm. Under these conditions, DTR may be allowed, which consists in considering the temperature constraints of the cable (temperature being the actual limiting factor for power export), rather than considering more conservative, steady-state electrical current constraints which are less relevant in the case of a fluctuating power output.

The goal of these approaches is to maximize the use of the wind farm electrical infrastructure, that is to say operate it closer to its technical limits.

However, managing optimally a wind farm with overplanting (combined or not with DTR) is more complex as additional constraints on the power export must be considered. These constraints consist of a current constraint, and/or of a thermal constraint if DTR is considered. The farm optimal energy management therefore consists for the wind farm manager in finding the farm power profile which will maximize the revenue that can be extracted from the power production. The associated control variables consist of the curtailed power, as well as the stored power when an energy storage unit is present. In this paper, we consider the latter (and more complex) case where offshore storage is included in the farm.

As it will be detailed in the state-of-the-art in Section II, the addition of power and/or thermal constraints in the optimal energy management problem requires the development of a new methodology for their integration in existing solving techniques. This new methodology is presented in this paper, as well as a case study where the performance of the proposed method is compared with heuristics.

It is also important to mention that the optimal energy management of a wind farm has become more and more complex, and that this trend is expected to continue in the future, independently of their situation regarding overplanting. More and more requirements are indeed applied to wind farms, regarding for instance their short-term expected power production, their ability to provide ancillary grid services, etc.

In this context, new requirements have emerged in small electrical networks presenting a high penetration level of renewables. In some French non-interconnected islands for instance, renewable farm managers may be penalised if their actual power profile presents a significant mismatch compared to their day-ahead declaration [4]. Also, the European balance responsible party scheme implies that deviations from day-

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ahead/intra-day forecast production/consumption profiles may be either penalized or rewarded [5]. Hence, in the context of the optimal energy management of a wind farm, it is important to consider also the potential penalties/revenues associated with the deviations from the day-ahead power production forecast. This is performed in this paper where we consider the most stringent conditions, i.e. deviations are always penalized, as it will be detailed in Section III.

This paper presents a state-of-the-art in Section II, the modeling and proposed methodology in Section III, a description of the case study in Section IV, and finally the results in Section V, with a conclusion in Section VI.

II. STATE OF THE ART

A. Optimal energy management under uncertainty

Deciding the energy flows in an offshore wind farm is an energy management problem which is itself a *dynamic optimization* problem (also called optimal control). It is dynamic in the sense that operational decisions at each instants are coupled through time due to the presence of inertia (or “state” or “memory”) in the system which makes each decision affect future decisions. In the present context, temporal couplings from 1) the presence of an energy storage and 2) the thermal inertia of the cable considered for DTR. In this paper, we do not study the optimization of the day-ahead commitment, but otherwise it would be a third source of temporal coupling. What’s more, since we model the fact that, at each decision instant, the future wind power production is uncertain, the problem falls in the class of *stochastic dynamic optimization*. This class of problem gets naturally analyzed, at least theoretically, in the framework of Stochastic Dynamic Programming (SDP) [6]. Due to numerical complexity (see III-A), it is often the case that approximate solutions are used instead, with the two most popular being perhaps Model Predictive Control (MPC: uncertain inputs replaced by point forecast) and Reinforcement Learning (RL: use of interpolation with basis functions). A specialized variant, SDDP, is also powerful but requires convexity of the problem which is too restrictive here [7]. In this work, we use a direct numerical implementation of SDP, although being at the edge of applicability in terms of state space dimension, to benefit from its effective handling of both uncertainty and dynamics, without the need to tune basis functions like in RL.

B. Optimal energy management of wind farms with overplanting

The vast majority of works on the inclusion of dynamic thermal rating in power systems covers onshore networks composed in majority of transformers and overhead lines [8].

Considering underground cable systems is more challenging as, unlike transformers or overhead lines, the thermal behaviour of cables is usually modeled with more complex, non-linear models, which may be incompatible with the optimization methods developed for transformers and overhead lines [9]. In addition, the larger inertia presented by underground cable systems leads to a more complex multi-scale,

time-coupled problem. The decision resulting from an energy management optimisation study must indeed be made at a fine temporal resolution (e.g. 1 hour) over a relatively short horizon (typically the 24 hours of the next day) while the cable temperature may take months before reaching its steady-state temperature when the cable is applied its rated power.

Among the works considering underground cable systems, in the case of either an onshore or an offshore wind farm, most works focus on improving their sizing. In some of them, a degree of freedom for the control of the wind farm is considered in the form of curtailment. This requires solving the associated energy management problem in order to define a (sub-)optimal curtailment strategy. Most of these works consider a deterministic energy management strategy [10]-[11].

However, to the best of the authors’ knowledge, only a minority of research works consider optimizing the energy management of the wind farm under uncertainty while taking into account the cable temperature constraints. Among these research works, Hernandez Colin et al. [12] proposed probabilistic algorithms based on Markov models to determine the hours- to day-ahead power production planning of an offshore wind farm. This methodology introduces a learning-based probabilistic estimation of the risk linked to a violation of the maximum allowed temperature constraint, and estimates the curtailment strategy to be performed. Liu et al. have also developed a probabilistic framework to determine the hours-ahead power production planning of a wind farm based on an ARMA model of the wind power forecast, still in order to define the curtailment strategy [13]. Kazmi et al. [14] formulated the optimal sizing of a wind farm as a two-stage MILP problem, where the inner stage covers the optimal energy management of the farm. The cable thermal behaviour is modeled through a linearized model. In addition to the uncertainty in wind power production, the authors also considered the uncertainty on the availability of power components (i.e. related to their probability of failure).

In all these works, no offshore energy storage is considered, despite a growing interest in this type of applications [15]. Contrary to the cases where no storage is considered, optimizing the energy management strategy of a wind farm including storage is therefore based on two degrees of freedom (i.e. curtailment and storage), as opposed to a single degree of freedom in the form of curtailment only. This renders the associated problem more complex and requires the development of new methodologies. Presenting such a methodology is the first goal of the proposed paper.

In addition to the consideration of storage, the proposed paper also considers the cost/revenue which may be generated from power imbalances. In other words, the revenue of a wind farm manager is not considered in this paper as composed only of the revenue generated from its power production, but also on the cost/revenue associated with the mismatch between the electricity production declared in advance and the actual production.

The forecast of the imbalances, which are financially man-

aged by the BRP and assumed to be reflected on the revenue of energy providers, attracts more and more attention as they may be exploited to increase their revenues, despite the fact that this may be worrying for grid operators. As renewables are becoming the main cause of imbalances in many power systems, such imbalances may indeed become more and more predictable at different lead times. Research works on imbalance volume and price forecasts is therefore emerging [16], [17], [18].

C. Summary

The optimal energy management of an overplanted wind farm, including energy storage and allowing DTR is a relevant problem which has not been tackled yet in the existing literature, to the best of the authors' knowledge. In order to solve this problem, we have identified SDP as a relevant method. This method has indeed proven to be efficient for solving the problem of the optimal energy management under uncertainty of wind farms including storage, although the inclusion of cable temperature constraints had not been considered yet. The inclusion of such constraints renders the considered problem more complex and required the development of a new methodology which is described in this paper. It implies modeling the cable thermal behaviour with a small number of state variables in order to be usable with SDP.

III. MODELING AND METHODOLOGY

A. Introduction to SDP

Stochastic Dynamic Programming is a method for computing the optimal control for a system that can be described with a dynamic and an instant cost [6], as precised next.

At any given moment k , the system state x_k evolves in response to a control u_k and a perturbation w_k :

$$x_{k+1} = f_k(x_k, u_k, w_k) \quad (1)$$

In our case, x includes the storage state and some information in the thermal model, while u can be a combination of power curtailment and storage input. System dynamic f is where storage (Eq. III-B1) and thermal models operate.

The goal of SDP is to minimize the value of a stochastic cost function, in the form:

$$J = \mathbb{E}_w \left[\sum_k^{K-1} c_k(x_k, u_k, w_k) + g(x_K) \right] \quad (2)$$

There is no special assumption on the instant cost function c_k , which allows SDP to be used in complex cases, including ones with non-convex cost functions.

The cost function can be decomposed in Bellman functions, recursively defined for k diminishing from $K - 1$ to 0 with

$$J_k^*(x_k) = \min_{u_k} \mathbb{E}_w \left[\begin{array}{c} c_k(x_k, u_k, w_k) \\ + J_{k+1}^*(f_k(x_k, u_k, w_k)) \end{array} \right] \quad (3)$$

and initialized, in our case, with $J_K^*(x_K) = g_K(x_K) = 0$. The optimal control law μ (such that $u_k = \mu_k(x_k)$) is then computed for each time step in the same order.

Usually, the control law computation is performed off-line (ahead of time), as it can be computationally expensive, and so it can be used almost instantly on-line¹.

Because the control law μ has to be calculated for every possible state of the system x (in the case x is composed of continuous variables, we can use a mesh discretization of the state space –with a regular grid in our case), the number of state variables should remain low (no more than 4-5) in order to be computable: this is the *curse of dimensionality*.

B. Problem formulation

1) *System dynamics*: The controlled system includes wind turbines, a storage device, and an export cable. The problem is formalized within a discrete time framework.

At every moment k , wind turbines can produce an electrical power $P_{prod,k}$. Some of this power can be curtailed (curtailment is called $P_{cur,k} \geq 0$) or stored ($P_{sto,k}$ being the power supplied to the storage). Stored energy $E_{sto,k}$ evolves the following way:

$$E_{sto,k+1} = \begin{cases} E_{sto,k} + \Delta t \times \eta P_{sto,k} & \text{when } P_{sto,k} > 0 \\ E_{sto,k} + \Delta t \times \frac{1}{\eta} P_{sto,k} & \text{when } P_{sto,k} \leq 0 \end{cases} \quad (4)$$

with Δt the duration of one time step and η the efficiency.

Stored energy has to stay within fixed limits: $E_{sto,min} \leq E_{sto,k} \leq E_{sto,max}$

As a result of production, curtailment, and storage management, power $P_{grid,k} = P_{prod,k} - P_{sto,k} - P_{cur,k}$ is transmitted to the export cable.

Based on weather predictions, a production commitment $P_{grid,k}^*$ has been decided one day ahead. The error between realized and predicted available power $P_{mis,k} = P_{prod,k} - P_{grid,k}^*$ is a stochastic variable that exhibits persistence (a positive auto-correlation). This behaviour can be captured by a first order auto-regressive model[19]:

$$P_{mis,k+1} = \phi P_{mis,k} + w_{mis,k} \quad (5)$$

where $w_{grid,k}$ is a white noise and $0 < \phi < 1$.

2) *Objective function*: The instant cost c_k is the financial cost induced by the difference between commitment and transmitted power. We chose this cost to be quadratic, although it could be replaced with any other function:

$$c_k = (P_{grid,k} - P_{grid,k}^*)^2 = P_{dev,k}^2 \quad (6)$$

3) *Cable constraints*: Cables are rated for their nominal capacity P_{max} , that is the sustained power a cable is able to carry without overheating. The strategy that ensures that the transmitted power never exceeds the nominal capacity ($P_{grid,k} \leq P_{max} \forall k$) is called static rating (SR).

SR is actually the simplest way to achieve a cable temperature that does not cause deterioration of the insulating material. It is however not the most permissive nor cost-efficient method in the case of overplanting: by design, it will cause power

¹In our case, we perform the computation *day-ahead*, which is not exactly off-line nor on-line. This tightens the compute time requirements.

curtailment to stay below the nominal capacity of the cable, but does not consider the temperature in any other way.

In the hope of a better result, we can replace the power constraint by a thermal constraint, which is the principle of DTR: $\theta_k \leq \theta_{max}$. Temperature being a consequence of carried power (through Joule losses), one way to implement such a constraint is actually to set what we call a dynamic power constraint, that is to say a dynamically computed upper bound for the transmitted power: $P_{grid,k} \leq P_{max,k}$. If the temperature can be calculated by an invertible model F_k (such that $\theta_{k+1} = F_k(P_{grid,k})$, with k implicitly denoting the state of the cable), it is possible to use the inverse model to find the maximum power the cable is capable of carrying during one time step without damaging itself: $P_{max,k} = F_k^{-1}(\theta_{max})$.

The next step is to find a thermal model suited to this purpose, which also fits the requirements of SDP.

C. Thermal modeling

1) *Existing thermal models:* The reference model, that we used for validation, was developed for another paper [20] based on IEC standards 60287 and 6853-2. It is based on a two-cell RC equivalent circuit modeling the cable itself, coupled to the solution to the heat equation in the ground surrounding the cable.

Other models have been explored. Some are based on the physical equations, such as FEM or RC-lattice based models [21]. Some others are built on data analysis [22]: based on past behavior, they estimate the temperature evolution in a more or less close future. This last class of models includes time-series based models, machine learning, and process models.

2) *Proposed thermal model:* The idea behind SDP is to take decisions while trying to predict, with the help of a model, what the consequences will be in the near and far future. While we did not formally know what should be the properties of said model, we can infer that it should at least be good (that is to say precise) at predicting in the short term, and that it should give a plausible tendency for the long term.

One model that has given interesting results is a modification of the reference model : we replaced the heat equation with a third RC cell that aims to approximate its behavior, in order to mimic the IEC reference model in the short term and on a steady state. The result is a relatively simple 3-RC ladder model (see Fig. 1), that obeys a linear differential equation:

$$\frac{d\bar{\theta}}{dt} = A\bar{\theta} + B \times W, \bar{\theta} \in \mathbb{R}^3 \quad (7)$$

Then, assuming Joule losses $W = \frac{R}{3} \times \left(\frac{P_{grid}}{U}\right)^2$ are constant during each time step, the temperature prediction can be computed:

$$\bar{\theta}_{k+1} = F_k(P_{grid,k}) = f(\bar{\theta}_k, W_k) \quad (8)$$

This model is invertible, which allows to compute the maximum power allowed during one time step $P_{max,k}$ as explained in III-B3.

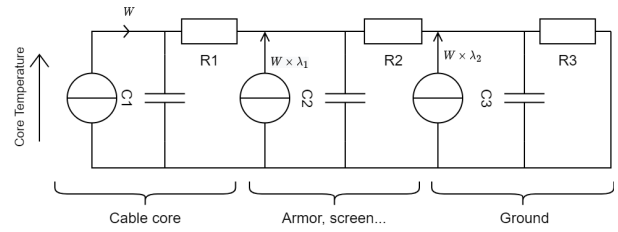


Fig. 1. Schematics of the 3-RC ladder model.

Assuming we only have access to a measure of the cable core temperature, we need to reconstruct the values of the other cells in order to be able to apply the optimal control law μ_k . For this purpose, we used a state observer, an asymptotic Kalman filter, which also allows us to correct prediction errors caused by the reduced order model.

D. Description of the compared strategies

In order to estimate the value of both SDP and dynamic thermal rating for our purpose, we defined six strategies.

The first three strategies are heuristics that minimize the instant cost function, without considering the future. In other words, they are greedy algorithms. The difference between these three heuristics lies in the set of constraints they consider regarding the power transmission capability: Heuristic H_Nolim does not consider any constraint (it would be inapplicable and only serves as a point of reference), Heuristic H_Plim considers static power constraints (i.e. $P_{grid,k} \leq P_{max}$) while Heuristic H_Tlim considers a temperature constraint (i.e. $\theta_k \leq \theta_{max}$ via a dynamic power constraint).

These heuristics are compared to their SDP-based counterpart (SDP_Nolim, SDP_Plim and SDP_Tlim), which consider the same set of constraint but aim to optimize the objective function over a certain time span.

IV. CASE STUDY

1) *Cable and soil characteristics:* We had access to the geometry and materials characteristics of an anonymized 3-core submarine cable, whose cross-section is equal to 1000 mm² and whose rated voltage U to 225 kV. We assumed a power factor equal to unity, which is a first-stage hypothesis, as submarine cables generally generate reactive power. The maximum allowed temperature is equal to 90°C for this type of cable insulated with XLPE. The power for which this maximum temperature is reached under steady-state conditions is equal to 336 MVA.

2) *Wind power production and forecast data:* Measured power profiles of real offshore wind farms connected to the network of Belgian TSO Elia were used in this study [23]. Day-ahead forecasts were also provided by this operator and used in this study as well. They are provided in the form of quantiles (namely P90, P50 and P10), where PX represents the power level that has X% chance of not being exceeded.

The measured and forecast power data corresponding to one year (from 13 January 2016 to 13 January 2017) was used. The

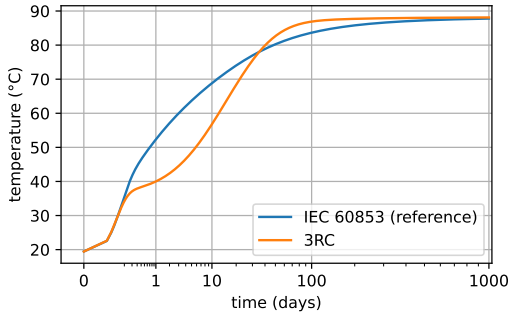


Fig. 2. Step response of 3-RC model compared to the step response of the reference IEC model. The horizontal scale is polynomial (instead of logarithmic) in order to be able to represent $t = 0$.

aggregated power capacity of the wind farms stayed constant, and equal to 800 MW. In order to simulate overplanting for an offshore wind farm, both the measured and the forecast data were scaled up proportionally from 336 MVA (overplanting rate $\alpha = 1$) to 537 MW ($\alpha = 1.6$). Fig. 3 shows the power profile considered in this work, with $\alpha = 1.3$. It must be emphasized that proportionality method is approximate, as it does not consider any change in the power profile shape as the overplanting rate increases.

3) *Energy storage unit characteristics*: Energy storage is realised thanks to an ideal storage device of rated capacity linearly scaled up with overplanting (starting with 400 MWh for $\alpha = 1$): it has no constraint on charge/discharge power, and its energy conversion ratio is equal to unity.

4) *SDP implementation*: The strategy that needed the widest state space was SDP_Tlim with a dimension of 5. We chose a corresponding state-space discretization with a total of 495,495 state points per time step. For each SDP-based strategy, and each overplanting ratio α , we ran the SDP algorithm once on a 30 days horizon (which represents 2,880 time steps and corresponds to the first 30 days of our dataset), and applied the computed control law for the same time span. This implies a total of 1,427,025,600 state points to consider for SDP_Tlim and each α , and as many optimizations to perform. To speed up the computations, SDP has been implemented on an NVIDIA RTX 3080 GPU with OpenCL.

V. RESULTS AND DISCUSSION

A. Thermal model

1) *Step response*: In order to evaluate the performance of our thermal model, we compared its step response to the one of the IEC reference model (see Fig. 2).

The proposed 3-RC model achieves its goals: the short-term prediction (up to about an hour) is relatively close to the reference model, and the steady state temperature –attained after no less than 3 years– is perfectly matched. However, as expected from its highly reduced order, the error is very noticeable for time scales in between and goes up to 16°C around 3 days, which shows that it is not meant for temperature prediction on this time scale.

Still, thanks to the short-term accuracy, the model can reliably be used to enforce the temperature limit during the optimization process, as we show next.

2) *Use for control*: Fig. 3 shows transmitted power and cable temperature with $\alpha = 1.3$ for two management methods based on SDP: SDP_Plim (static rating) and SDP_Tlim (dynamic thermal rating). Commitment and available power (P_{prod}) are also shown, as well as the power and thermal limits. The thermal constraint is always satisfied, thanks to the properties of the thermal model.

B. Comparative analysis of the strategies

Fig. 3 highlights the difference between SR and DTR, in terms of transmitted power and attained temperature; while showing how SDP handles a difference between commitment and available wind power. We can see that DTR fills its purpose allowing more power to be transported. We can also see how SDP anticipates the near future: it attempts to smoothen the difference between commitment and transmitted power, as it is the behavior that minimises the value of our cost function.

Fig. 4 shows the minimized objective function for the six studied strategies (i.e. the three heuristics and the three SDP-based ones, each considering no power export limitation, and power export limitations in the form of a power constraint or of a temperature constraint).

The most important parameter at play is the set of constraints: the lower cost is associated with no cable constraint (dotted lines on the figure), while the higher cost is due to SR which dramatically restrains the transmitted power (dashed lines). Because the temperature constraint must be satisfied, the lower achievable cost is attained with DTR (plain lines).

The cost advantage of using SDP (blue lines) versus a greedy heuristic (orange lines) is less important. However for an overplanting ratio of 1.2 and with dynamic thermal rating, the heuristic still induces a 20% increase in cost.

Finally and for reference, with our machine, the total computation time was close to 2 hours and produced 13.8GB of data (essentially the control laws).

VI. CONCLUSION

This paper presented a strategy for energy management of an overplanted wind farm with storage and dynamic thermal rating, and compared it with simpler strategies, some of them implying static rating. Focus was on on-line management, when commitment has already been decided, and with simple hypotheses regarding the cable (notably, reactive power was omitted). A simplified thermal model of the cable has been introduced, in order to comply with the requirement of the used optimisation method (Stochastic Dynamic Programming). Between the six considered strategies, two were not applicable to an overplanted farm. The ones implying dynamic thermal rating performed better than the ones based on static rating. With DTR, the best result was obtained using SDP. Future work could compare these strategies to an MPC based one, or aim to improve the thermal model used for the optimisation.

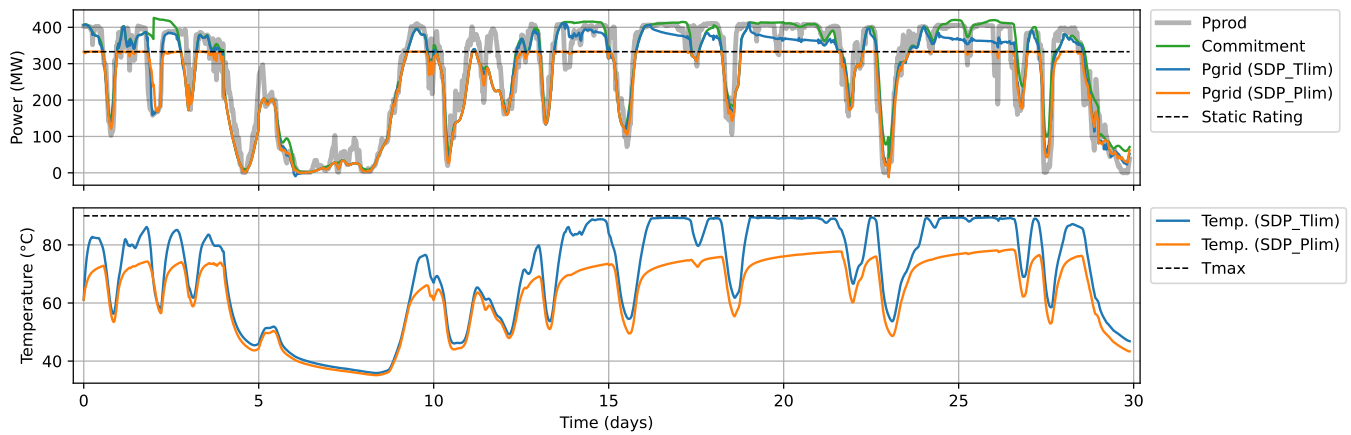


Fig. 3. Power and temperature over time for two SDP-based strategies (with static and dynamic thermal rating) for $\alpha = 1.3$.

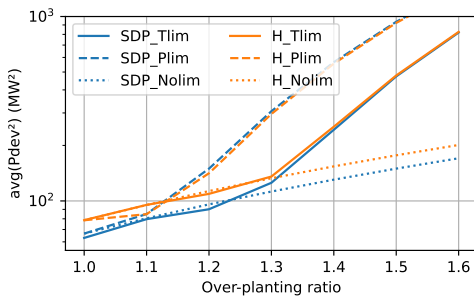


Fig. 4. Cost function versus overplanting rate for the six studied strategies.

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