Levelized income loss as a metric of the adaptation of wind and energy storage to variable prices[☆]

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Abstract

Classifying and categorizing generators according to their financial efficiency is necessary to compare the degree of competitiveness of a generating technology. The levelized cost of energy (LCoE) is arguably the most relevant index for that purpose. It relates the capital and operating expenses to the expected energy output, to encapsulate the financial efficiency into an €/MWh. It is technology-independent, meaning that it can be used for comparing different generator types in a fair basis. However, the LCoE is defined to provide a cost figure under the assumption of a fixed-tariff. It does not make any difference when comparing the performance of an intermittent generating technology in different spot markets. The LCoE does not inherently account for the variability of prices.

This paper details a different approach to classify intermittent renewable generators operating under variable-price tariffs. It shows a levelized income loss as a figure of how the generator allocates the available energy. Ideally, a generator with a production allocated in low-price times would have higher LIL than other with the same production responding to high-price times. Generator location, characteristics, and the market to which the generator delivers the energy make a difference.

This paper shows a methodology to not only obtain the index under uncertain market prices and energy production, but also details a dynamic program to incorporate energy storage systems (ESS). The idea behind this additional investigation is that the re-allocation of the limited energy of a renewable generator might well improve the economic performance. The dynamic program approaches the ESS switching decisions from a stochastic perspective, offering a rigorous evaluation.

Finally, this paper describes the dynamic linear models of several European day-ahead markets and wind datasets to offer a broad valuation of the LIL, and of its possible improvement through the use of ESS.

Keywords: wind energy, energy storage systems, optimization, dynamic programming, stochastic processes, dynamic linear models, economic valuation

1. Introduction

This paper discusses the influence of energy storage systems (ESS) on the improvement in investment efficiency of distributed generators, from the producer perspective. The motivation of this analysis is that renewable distributed generation is progressively moving from a fixed-price to a more competitive variable-price framework. Certainly, renewables have been subject to the problem of fluctuating income as

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a result of the variability of their energy sources. But now, producers face the uncertainty of prices as well, which under also uncertain production leads to the question of whether the maximum generation is "in phase" with the highest prices in order to ensure high revenues. If not, the question is whether delaying energy delivery results in improved revenues. A problem of economical valuation ensues, with implications different to those that follow from fixed-price revenues.

Arguably the levelized cost of energy (LCoE) is the most widely used metric on energy generation costs. The LCoE is the tariff that a power provider would need to charge in order to cover the associated generation costs. Because of its simplicity, but also its comprehensiveness, the LCoE is conceivable the most important factor in many decisions that involve a figure of merit about economic performance. In wind energy literature, for instance, it has been employed in [**? ? ?**] as a part of the objective functions of design optimization problems. The aim was to precisely search for optimized plant layouts [**? ?**] or a optimized structure [**?**] that provided the best economic result; with that economic result encapsulated in one only term. In other cases, it has been employed as a means of comparing different complex scenarios by means of a simple figure, as it was the case in [**?**]; where the authors efficiently defined three different LCoEs summarizing diverse scenarios that otherwise would have been of difficult financial comparison. As another instance, in an interesting approach Lantz *et al.* employed the LCoE to show the cost build-up of deploying several wind technologies with different structural costs to achieve a generation threshold goal [**?**]. In doing so, these authors also took advantage of the comprehensiveness of the LCoE. It encapsulates in one only metric costs and energy. On the whole, the LCoE is a direct way of assessing whether a generation asset can reach commercialization or whether it is competitive compared to other energy generation technologies [**?**].

Still, the LCoE is subject to important criticism when comparing various technologies that have diverse degrees of dispatchability. Any power source is subject to integration problems that Brouwer *et al.* categorized in [**?**] as (i) related to how generators are dispatched, (ii) what economic impact they provoke, and (iii) how they reduce the system security of supply. In the case of renewable generation, the increased uncertainty in their dispatchability provokes a clear economic impact—arising from the dispatch of expensive fuel-based generation units and possible load curtailment, which are specially costly in the balancing markets—and a reduction of the system security. The criticisms on the LCoE are placed precisely on the absence of costs associated to that lack of commitment over time shown by renewable generation, which arguably makes the comparison of fossil and renewable technologies flawed when it is based only on the generator costs [**?**].

To produce a fairer comparison between technologies, some authors have proposed supplementing the LCoE with the "integration costs." This has been extensively discussed in [**?**], where the authors justified the need for additional metrics that served to assess the costs incurred by the system operator. Similarly in [**?**], it is quantified and supplemented to LCoE when the share is above 7%.

Integration costs provide a clearer picture about the *global* generating costs and likewise a better categorization tool for regulators. It penalizes renewable energy uncertainty, to make the comparison with fuel-based generators fairer. From the owner's perspective, however, integration costs do not seem to make an important difference in the perceived profitability. Certainly there are subtle perturbations in the pricing mechanism perceived by the producer when the non-dispatchable generation has an important share in the power mix. Renewable generation—with the best merit order—reduces the spot price, which would affect the producer's profits when a feed-in premium tariff (see below) is in place. Also, the producer should face higher imbalance prices as a result of forecasting errors. Even so, the implications of integration costs appear to be of relative unimportance to the producer when they are not directly attributed to the perturbing generator, and the complexity of their calculation makes this addition certainly difficult and may well be seen as more system-focused.

Lack of integration costs is not the only limitation of the LCoE. By definition, the LCoE is a *constant* breakeven price that the producer must receive in order to cover the costs of acquiring and operating the generator. However, support schemes in several EU countries are moving from fixed feed-in tariffs (FiT) to other variable-price schemes [?]. The change is important for the producers, because it moves from payments on metered output to models of more uncertain payments. For instance, the Contracts-for-Differences (CfD) model specifies a strike price. The producer pays or receives the strike price less the market price. The CfDs with FiTs are an expansion of this support model in that they only pay if there is generation output [?]. And the Feed-in Premium (FiP) are a wholly variable price scheme, in which the producer is granted a premium on top of the wholesale market price—normally a fixed premium, though some authors also expand it to variable values responding to the capacity of renewable generation in the system [?]. In some relevant cases where wind energy has a more than relevant presence, such as Spain, the premium is in most cases set to zero for new generation; which de facto implies that the wind generator is subject to the stochastic evolution of spot prices, as fuel-based generators do. Inherently, the LCoE evaluates the generation costs as compared to a FiT, not to a FiP, and this makes it difficult to assess whether the same generator has better economic performance in one market than in other, for instance. No entry for spot price data is available in the definition of LCoE.

Other authors have proposed metrics devoted to comparing the investment efficiency. Recently in [?], Ritter and Decker have approached this problem in an interesting way, using a wind energy index. This index is a simple measure of the estimated production of energy by a modeled turbine over a given period [?]. The index was employed in [?] to determine the minimum compensation required in a FiT framework to ensure profitability in a large-scale analysis. But then again, the approach was an indirect way of estimating the LCoE from their wind energy index. Petitet *et al.* provided in [?] a formal evaluation through the profitability index defined as the ratio between net present value and investment cost. It is based on estimates of net profit in a long-term basis. The authors addressed the capacity mechanism required to integrate renewable generation, which shows again the perspective of the regulator.

Finally, when ESS is also investigated, the problem becomes more complex. It has been demonstrated that large-scale energy storage might relevantly reduce the costs of integration [?], and that the value of wind generation differs depending on the market [?]. Nevertheless, this paper focuses on the producer perspective, who questions how well tailored to the spot market price a wind generator is—probably endowed with an ESS. In this case, the use of the LCoE as a metric is even more questionable. Here we refer to the critical review made by Lai and McCulloch in [?] where they detailed the flaws of employing it in ESS analyses. These flaws led them to propose a levelized cost of delivery as a measure of the value of ESS integration. This is an approach similar to ours in its scope, certainly, but it has two main differences. First, their approach did not consider the stochastic variability of prices, which is a key driver of the process. Secondly, their approach did not consider the optimality of the ESS switching in the framework. However, a more precise valuation should consider these two elements, in addition, so that the cost figure revealed the best-case scenario. Not considering the optimality of the ESS operation would yield better (in the case that the deterministic price were a better scenario than the stochastic characterization) or worse (in the case that the ESS were not optimally employed) cost results.

To address the above shortcomings about the comparison of generating technologies under varying tariffs, this paper investigates an alternative metric. We define the levelized income loss (LIL) as the accumulated income loss divided by the expected energy output. Or in other words, it is the value of revenues not realized because at a given instant the turbine power may be less than its rated power. The LIL thus define does not incorporate investment and operating expenses, because is meant to serve as a supplementary information about the degree of success that a generator has in collocating or selling its energy in optimal instants. This LIL is accumulated over a determined period, resulting in values that are contingent not only on the output power but also on the instant spot price that the producer receives. LIL is in fact a stochastic process ruled by other two underlying stochastic processes: the wind speed and the spot price. This definition of LIL is indeed in line with what Edenhofer *et al.* claimed in [**?**]: that the LCoE ignores the temporal and spatial structure and forecast errors of generation; and that consequently the marginal value of variable renewables affected by timing and location, that introduce uncertainty in the revenues, should be considered (see also [**?**]).

Regarding the deduction of LIL by storing the energy, this paper considers an optimal switching model that captures the maximum achievable improvement under uncertain prices and wind power. Although the calculation of LIL is straightforward based on a Monte Carlo experiment—once the price and wind stochastic processes have been properly characterized—the introduction of ESS in the analysis complicates the problem considering that the charge/discharge process must be optimal to result in a comparable figure. We approached this problem by means of a stochastic dynamic program that recursively, applying Bellman's optimality principle, aims at reducing the total LIL over an investigated period of time. The algorithm considers at each time step the instantaneous income loss derived from delivering or curtailing energy into the grid, and compares this cost with the probabilistic reduction of losses that would be obtained if the ESS were left to follow from the corresponding state of charge.

In brief, this paper contributes to the existing literature about valuation of renewable distributed generators as follows. (i) This paper investigates the use of the defined LIL as a means of valuing the cost efficiency of a generator which obtains its revenues from a spot market. (ii) To do that, first this paper details how the underlying stochastic processes can be efficiently modeled and simulated by means of dynamic linear models. (iii) These processes are the main inputs to a dynamic program, described in this paper, which we implemented to recursively compute the minimum (optimal) LIL, including ESS activity. (iv) Finally, this paper discusses our results. We designed a series of scenarios in which we mixed different types of wind turbines (with different characteristics speeds) operating in different European spot markets, under different conditions of ESS. As a result, this paper shows that, from the producer's perspective, LIL provides a convenient measure of the economic efficiency, but also that introducing ESS does not make much difference about the economic performance of the generator.

2. LIL calculation

The LIL can be computed by investigating the difference that exists between the realized income—the revenues received from energy sales—and the potential income that could have been received had the generator produced its rated power constantly. In a realistic setting, these losses would vary with time. Particularly they would be subject to (i) the wind variability, (ii) the constraints imposed by the turbine characteristics limiting or even curtailing the production, and (iii) the instantaneous price that the generator receives.

A first approach to the calculation of those losses would be to confront a wind speed realization—indeed the power realization—to a price trajectory over a period of time. The sum of instantaneous products of price and power would give the accumulated income, which divided by the produced energy would yield a figure of the economic efficiency achieved by the generator. This simple calculation, however, implies a deterministic view of the evolution of price and power, which is not the case.

Alternatively a Monte Carlo experiment, in which the calculation is not based on one only realization but on a representative number of possible price and power trajectories, provides a more rigorous valuation of the incurred opportunity losses in an uncertainty framework To that purpose, it is necessary to obtain representative trajectories of price and power. In the next Section, we shall show that this problem can be approached by means of dynamic linear models. The idea is to regress a single realization of the process (wind speed or price), introducing a set of unobserved state space variables that drive the observed model. As a result, we obtain compact observed models that allow us to simulate trajectories that retain the distributional properties of the original single realization of price and power, but describe other probable trajectories. By means of those K simulated paths, the calculation of LIL can then be repeated in K equivalent scenarios, yielding a probabilistic distribution of the losses. This overcomes the flaw of determining the LIL value through an only realization, and it can be used to give a probabilistic value of the economic efficiency of the generator.

In what follows, we further expand the stochastic approach above to include the use of ESS and thus investigate the potential improvement of the system economic efficiency. This of course complicates the problem, because for the valuation to be rigorous it must produce the *minimum loss income* that would be obtained if ESS were considered. That is, it requires computing the optimal switching of the ESS, which would be the most optimistic scenario producing the best economic improvement. Still, this calculation would have to be performed in an uncertainty setting, which must necessarily affect the switching of the ESS.

2.1. Theoretical considerations

Let $\Pi(X_t, u_t)$ be an objective function that indicates at each time step t what the economic result arising from changing the storage level is. This payoff is contingent on the value of observed processes (price and power in our case), which are encapsulated in X_t. It also depends on the control action exerted over the

ESS, u_t, that drives its level from the current level to the next level, over the discretized level space. We identify that target level in this payoff as $\ell_t \in \{1, \ldots, m\}$.

Now let P_{nt} be the generator rated power and π_t the received price at time step t, such that $X_t = (P_{nt}, \pi_t)$. According to our definition of LIL, the objective function is defined as

$$\Pi(X_t, u_t) = [P_{nt} - P_t + u_t] \times \pi_t \times \Delta t, \tag{1}$$

where P_t is the instantaneous generated power.

To compute the accumulated LIL over a given period—which will be related to the energy produced in that period, so that a figure of the economic efficiency can be drawn—we can now proceed as follows:

$$J(X_{\tau_1}, \mathbf{u}) = \mathbb{E}\left[\int_{\tau_1}^{\tau_N} \Pi(X_t, u_t)\,\mathrm{d}t + \zeta(X_{\tau_N}, \ell_{\tau_N})\right] \tag{2}$$

This is an estimate of the accumulated loss when the system evolves from an initial state $(X_{\tau_1}, \ell_{\tau_1})$ to a final state $(X_{\tau_N}, \ell_{\tau_N})$ after a generic sequence of control actions $\mathbf{u} = (u_{\tau_1}, \ldots, u_{\tau_N})$; where the term $\zeta(X_{\tau_N}, \ell_{\tau_N})$ represents the residual loss as a result of the left stored energy at the end of the control period. There is a control sequence $\mathbf{u}^* = (u_t^*)_{t=\tau_1,\ldots,\tau_N}$, however, which is optimal in the sense that it minimizes the accumulated losses. We will denote those losses as

$$V(X_{\tau_1}) = \arg\min_{\mathbf{u}} J(X_{\tau_1}, \mathbf{u}). \tag{3}$$

The aim of the program is, therefore, to find the continuous sequence $\mathbf{u}^*$ that minimizes $V(X_{\tau_1})$.

To solve this problem in practice, we discretize the investigated period into N steps of duration Δt, where we can individually apply (2). Particularly, the optimal switching policy in the interval $[t, t + \Delta t]$ is

$$V(X_t) = \arg\min_{u_t} \{\mathbb{E}\left[\Pi(X_t, u_t)\,\mathrm{d}t + \zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t})\right]\}\,; \tag{4}$$

which is but a transcription of (2) for a single interval using an optimal control action u_t^*.

Because in (4) the optimal control action is selected to minimize the expected cost of operating the ESS along with the wind turbine, the sum of the switching loss $\Pi(\cdot)$ and the residual loss $\zeta(\cdot)$ terms must be minimized. This presents a problem when it is done independently for each interval of the type $[t, t + \Delta t]$, because plainly speaking the optimality found in an interval might lead to a worse value in the next interval. In other words, the optimization must be conducted coherently, considering that all the intervals are chained. It must be taken into account that the action u_t that leads the ESS to a level ℓ_t will necessarily affect the following interval. (In this respect, note that if the ESS were not considered, the optimization would be trivial. It would be a matter of minimizing the loss in each interval, regardless of the optimization in adjacent intervals. In our setting this also amounts to consider $u_t = 0$ for all intervals)

A solution to this problem can be found by recursively computing the optimal control action *backwards*. This procedure observes Bellman's principle of optimality, which states that an optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision [**?** , Ch. 3]. So by proceeding backwards, it can be stated that the residual loss of the previous step in time—the next step in the computation—will equal to the computed (future) minimum loss:

$$\zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t}) = V(X_{t+\mathrm{d}t}). \tag{5}$$

This recursion provides a convenient way of investigating the optimal switching policy following a trajectory of X_t. At any step, the losses caused by all possible control actions are evaluated and added to the residual values that such actions will entail, mindful that those residual accumulated losses have been computed in the previous calculation. In other words, $\zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t})$ is the *continuation loss* incurred from continuing at level $\ell_{t+\mathrm{d}t}$, as a result of a control action u_t that drives the storage to that level, departing from ℓ_t. Importantly, $\zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t})$ is computed *before* all $\Pi(X_t, u_t)$. The optimal control action at each step will be therefore the one that minimizes the sum of all prospective $\Pi(X_t, u_t)$ and their corresponding $\zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t})$.

There is an important caveat to the procedure outlined above, however. By making the direct comparison between $\Pi(X_t, u_t)$ and $\zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t})$, where this latter value is chosen as a result of the investigated control action u_t, we are assuming that we know the loss value of continuing at level $\ell_{t+\mathrm{d}t}$ in advance. We therefore assume that we have perfect foresight, which negates the stochastic framework we are approaching.

To account for the lack of knowledge about the future losses ensuing from a decision, we do not use the value of continuation determined by the prospective u_t, but a conditional expectation. This is the approach employed in the field of approximate valuation of financial and real options in [?] and [?], respectively. Basically, it consists in valuing the decisions at each step by computing

$$V(X_t) = \arg\min_{u_t} \left\{ \mathbb{E}_Q \left[\Pi(X_t, u_t)\,\mathrm{d}t + \zeta(X_{t+\mathrm{d}t}, \ell_{t+\mathrm{d}t}) | \mathcal{F}_t \right] \right\}; \tag{6}$$

where $\mathbb{E}_Q[\cdot|\mathcal{F}_t]$ is the expectation conditional on the filtration at step t. This valuation of (6) can be in practice approximated by means of a regression of the residual values on X_t. Longstaff and Schwartz provide in their seminal work [?] a detailed procedure.

We compared

2.2. *Practical implementation*

Next we formalize a proposal to compute the accumulated loss income through Algorithm 1, following the above theoretical considerations.

As a first consideration, the algorithm requires a complete discretization of the problem. The input to the algorithm are K samples of spot price and generated power, which are discrete time series of N samples. Also, the storage level is discretized into L levels, such that each level corresponds to a determined value of power. If that power is P_ℓ, and the rated capacity and power of the of the ESS are $E_\mathrm{n}^\mathrm{ess}$ and $P_\mathrm{n}^\mathrm{ess}$, then the number of levels is $L = \left\lfloor \frac{E_\mathrm{n}^\mathrm{ess}}{P_\ell} \right\rfloor$ and $\Delta L_\mathrm{max} = \left\lfloor \frac{P_\mathrm{n}^\mathrm{ess}}{P_\ell} \right\rfloor$. Similarly, the price per level should be $\pi_\ell = \pi \times \Delta t \times P_\ell$ and the turbine power $P_\ell^\mathrm{wt} = \frac{P^\mathrm{wt}}{P_\ell}$.

The switching cost function defined in line 4 is a generic function in the sense that it evaluates the cost of implementing a charge/discharge action u when the observed price is π and the wind turbine produces a

Algorithm 1: Computation of the income loss through a dynamic program

1 **Function** `OptimalSwitch`
2 **Input** : $X_t = (P_t, \pi_t)$
3 **Output** : optimal control action and related cost
4 **Define** : $\Pi(X, u) \leftarrow [P_{\text{n}}^{\text{wt}} - P^{\text{wt}} + u] \times \pi \times \Delta t$
5 **for** $t = N - 1$ **to** 1 **step** -1 **do**
6 **for** $\ell = 1$ **to** L **do**
7 **Define** : `ConditionalContinuation` $(X_t) \leftarrow \mathbb{E}_Q\,[\zeta(\mathbf{X}_{t+\Delta t}, \ell)|\mathbf{X}_t]$
8 **for** $k = 1$ **to** K **do**
9 **Define** : U_k is the set of all possible actions leading to level ℓ
10 $\zeta(\mathbf{X}_t, \ell) \leftarrow \arg\min_{u \in U}\,[\Pi(X_{t,k}, u)$ + `ConditionalContinuation` $(X_t)]$
11 **end**
12 **end**
13 **end**
14 **return** $\zeta(\mathbf{X}_1, \ell)$, $\mathbf{u}^*$

power P^{wt}. This function is later employed, in line 10, to minimize the LIL. When the function is called, its inputs are the K realizations of price and power at the time t at which the optimal control action is sought.

The computation proceeds backwards through the N time samples of price and power (starting in line 5). At each time step, the algorithm investigates each of the possible levels, to obtain the LIL incurred at those levels of storage (line 6). Such a loss is computed as the combination of switching cost and continuation accumulated loss. And this is performed for each possible sample of price and power (starting in line 8).

To compute and combine the two related sources of losses in line 10, we define a conditional expectation function in line 7. This is a regression at time step t of the K states (prices and powers) with the accumulated LIL so far as the independent variable. As a result, when the minimization is run, in line 10, an estimate of the accumulated LIL can be employed, therefore avoiding the perfect foresight flaw.

In line 9 we define the set of possible actions that can drive the storage level to the investigated level ℓ. The set, U, includes all possible charge/discharge conditions, provided that the origin level from which the action starts is within bounds—not exceeding the maximum capacity of the ESS or being negative—and that the amount of charge traded is below $\Delta L_{\max}$ in absolute value. Those values of $u \in U$ constitute the search space in which the LIL is minimized. Note importantly that U changes as a function of ℓ.

As a result of the minimization conducted at each step, level, and sample, we obtain a $K \times N \times Ł$ array of optimal decisions that determines which would be the optimal charge/discharge path starting at a proposed level of charge. Also, a last value of accumulated LIL are obtained that provides—again after deciding the initial charge of the ESS—the K realizations of LIL.

To compare our approach to a constrained optimization method and thus validate the results, we solved the following interior-point problem:

$$\min_{\mathbf{u}=(u_1,\ldots,u_T)} \quad (P_{\text{n}} - \mathbf{P} + \mathbf{u})^t \times \boldsymbol{\pi} \times \Delta t \tag{7}$$

$$\text{s.t.} \quad \sum_{k=1}^{T} u_k = 0, \tag{8}$$

$$\sum_{i=1}^{k} u_k = \ell_k, \tag{9}$$

$$0 \le \ell_k \le 1, \quad \forall k \in [1, T]. \tag{10}$$

This is a deterministic problem to find the optimal policy $\mathbf{u}$ in a given horizon of length T when the price and power processes, $\boldsymbol{\pi}$ and $\mathbf{P}$, are given. The results obtained by means of this approach were the same as those produced by our dynamic-programming approach in the deterministic case. These are different approaches, with one major difference in the number of decision variables employed. Whereas in the dynamic-programming approach the number of decision variables is equal to the number of storage levels L, in the case of the constrained-optimization approach the number is equal to T. In both cases, this number is multiplied by the number of simulations employed, K.

In the case of stochastic optimization, the results are not easily comparable. The constrained-optimization problem would be expanded to account for K different paths of price and power simulations. These could be solved independently and the results would be averaged to obtain an optimal storage switching policy. To be rigorous, however, this approach incurs in the perfect foresight flaw, because every decision is made by assuming that the path investigated is perfectly defined. This could be remedied by means of multi-stage optimization, which certainly would complicate the problem. In our dynamic-programming proposal, this flaw is more simply approached by incorporating the conditional expectation calculation proposed by Longstaff and Schwartz in the context of real options. Particularly, the decisions about storage charge/discharge are based on the calculation of the conditional expectation about the future evolution of the prices and power. That is, the value of the price at the next time step is not known with certainty before the decision, and this uncertainty is readily incorporated at the same stage.

In a 64-bit Intel(R) Core(TM) i7-4712HQ CPU 2.3GHz, with double core and 6 GB of installed RAM, optimizing the ESS switching sequence of $K = 100$ samples of a one-year period (8760 hours), employing a discretization of the SoC into 100 levels, the calculation took around 15 seconds.

3. Characterization of the stochastic processes

Uncertainty in the energy production is the main driver of our analysis. We describe in what follows how we model the electricity and wind energy availability under an uncertain evolution of the processes. Prices and wind speed have distinctive stochastic characteristics, but we model them by using the same approach, based on the structural characterization of their time series in a dynamic linear model (DLM).

3.1. DLM of electricity price

A major characteristic of day-ahead electricity prices is that they are non-stationary stochastic processes. They exhibit a marked variability as a consequence of uncertain changes in predictors such as weather-sensitive loads, generation outages, the fuel cost variations, or the transmission congestions, to cite some [**?**].

In general day-ahead prices can be represented by means of multifactor models [**? ?**], where prices are broken down into deterministic and stochastic processes. The deterministic part can be represented by a number of methods that include among others the use of dummy variables and indicators [**? ? ?**] or sinusoidal functions to adjust for seasonality [**? ?**], and differencing for filtering the trends [**?**]. The stochastic part is often described as a mean reverting process of the type Orstein-Uhlenbeck [**? ?**], which in turn can be expanded to a extended Vasicek model [**?**].

In [?], Durbin and Koopman analyzed in detail the formulation of time series by means of structural dynamic linear models. These structured models consist of a number of submodels that together define the entire stochastic process. Consequently, DLMs follow the same conceptual approach as the multifactor models above, because they break down the total signal into a number of simpler models. However, there are some relevant differences in their characterization compared to other modeling procedures. First, the structural DLMs in [?] are based on unobserved states that are readily formulated by autoregressions in matrix form. Therefore, seasonality, trends, cycles, etc. are easily characterized as a number of block models stacked in matrix form, using the unobserved states—hence its *structural* definition. Second, in the cases in which ARMA are employed to describe the stochastic component, the original series must be *pre-conditioned* before fitting a model. ARMA models (and Orstein-Uhlenbeck models are but an AR(1) model [?]) refer to stationary series, and therefore the series must be previously deseasonalized and detrended [?]. This is a complex process that requires trial and error procedures to provide the stationary series. Differently, DLMs are formulated to account inherently for these components. That is, rather than detrending and deseasonalizing the series *ex ante*, the terms are extracted *ex post* as a result of the fitting procedure.

This approach facilitates in our opinion the fitting and subsequent simulation of time series such as the electricity spot prices. The procedure consists of three main stages, extensively explained by Durbin and Koopman in [?]. First a model, a structure, of the price series must be proposed—a trend component depicting the major upward or downward trends of the series, a seasonality embodying the daily and weekly event "repetitions", and an ARMA component that includes (with varying parameterization) the autocorrelation between past and current prices (recall that Orstein-Uhlenbeck models are a particularization of ARMA models). This first stage is not difficult, indeed, because it can be achieved by building a set of well-defined structures. In general, the model is

$$\mathbf{x}_t = \mathbf{G}_t\mathbf{x}_{t-1} + \mathbf{w}_t, \quad \mathbf{w}_t \sim N(0, \mathbf{W}_t), \tag{11a}$$

$$y_t = \mathbf{F}_t\mathbf{x}_t + \mathbf{v}_t, \quad \mathbf{v}_t \sim N(0, \mathbf{V}_t). \tag{11b}$$

In this equation, y_t are the observations, i.e. the electricity price, at time $t = 1, \ldots, N$. The vector $\mathbf{x}_t$ contains the unobserved states that define the process. Its entries or elements will correspond to various components of the pursued structured model, such as trend and seasonality. It is assumed that they evolve linearly, ruled by the system operator $\mathbf{G}_t$ that correlates the current states with a previous occurrence. The linear combination of the states $\mathbf{x}_t$ obtained using $\mathbf{F}_t$ provides the value of electricity price, which is observed in y_t. In both parts, observation and state equations, additive Gaussian errors with covariance matrices $\mathbf{V}_t$ and $\mathbf{W_t}$ account for unknown, uncertain deviations.

The structured model is achieved by building a matrix $\mathbf{G}_t$ that progressively grows as it incorporates blocks that represent each component. For instance, the level trend of the prices can be described by means of

$$\alpha_t = \alpha_{t-1} + \epsilon_{\text{trend}}, \qquad \epsilon_{\text{trend}} \sim N(0, \sigma^2_{\text{trend}}) \tag{12a}$$

$$\mu_t = \mu_{t-1} + \alpha_{t-1} + \epsilon_{\text{level}}, \qquad \epsilon_{\text{level}} \sim N(0, \sigma^2_{\text{level}}) \tag{12b}$$

$$y_t = \mu_t + \epsilon_{\text{obs}}, \qquad \epsilon_{\text{obs}} \sim N(0, \sigma^2_{\text{obs}}). \tag{12c}$$

and put in the form of (11) if we set

$$\mathbf{G} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}, \quad \mathbf{F} = \begin{pmatrix} 1 & 0 \end{pmatrix}, \quad \mathbf{x}_t = \begin{pmatrix} \mu_t & \alpha_t \end{pmatrix}^T. \tag{13}$$

Similarly, ARMA and seasonality components can be cast into the formulation of (11). For instance, an AR(3) process

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \phi_3 x_{t-3} + \epsilon_{\text{AR}}, \qquad \epsilon \sim N(0, \sigma^2_{\text{AR}}) \tag{14}$$

can be cast into the form of (11) if we set

$$\mathbf{G} = \begin{pmatrix} \phi_1 & 1 & 0 \\ \phi_2 & 0 & 1 \\ \phi_3 & 0 & 0 \end{pmatrix}, \quad \mathbf{F} = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix} \tag{15}$$

(See [**?**], for a more detailed analysis of the ARMA case.)

These structural components can then be stacked (diagonally) in an inclusive matrix $\mathbf{G}$, while expanding the vector $\mathbf{x}_t$ and observation matrix $\mathbf{F}$. In this process of defining the model, some of its parameters will be left as unknowns to be determined through the fitting procedure, such as the ARMA components ϕ_i or the variance of each model σ_i.[1]

In the second stage, the unknown parameters are worked out by fitting the model to the original series. In our model, we perform this step by minimizing the negative likelihood to find the estimates of the parameter using the Kalman filter. The fitting procedure must pass a number of goodness-of-fit procedures, which basically are conducted on the residuals (i.e., on the difference between the original time series and the step-ahead forecast obtained by again applying the Kalman filter to the fitted model). They must show a Normal distribution and a lack of autocorrelation. That is, the residuals must be uncorrelated normally distributed events. If not, another prospective model has to be tried.

Finally, if the goodness of the parameter estimates is acknowledged, we shall obtain simulation and (if needed) forecast samples.

The result of this three-step procedure is exemplified in Fig. 1. In this case, the original series was broken down into three components: local trend, seasonal, and ARMA components. For this time series—TenneT price in 2017—we obtained the best fit after proposing a model with local level trend (polynomial of order zero), a daily seasonality, and an ARMA(p, q) process with $p = 1$ and $q = (1, 2, 24)$. In all,

[1] In R, for instance, a number of specialized packages allow for this type of modularization or, in the words of Durbin and Koopman, structural composition. See for instance `KFAS` or `dlm`. Also Matlab includes in its more recent versions the `ssm` class as part of the Econometrics Toolbox, which follows this same structured "stacking" philosophy.

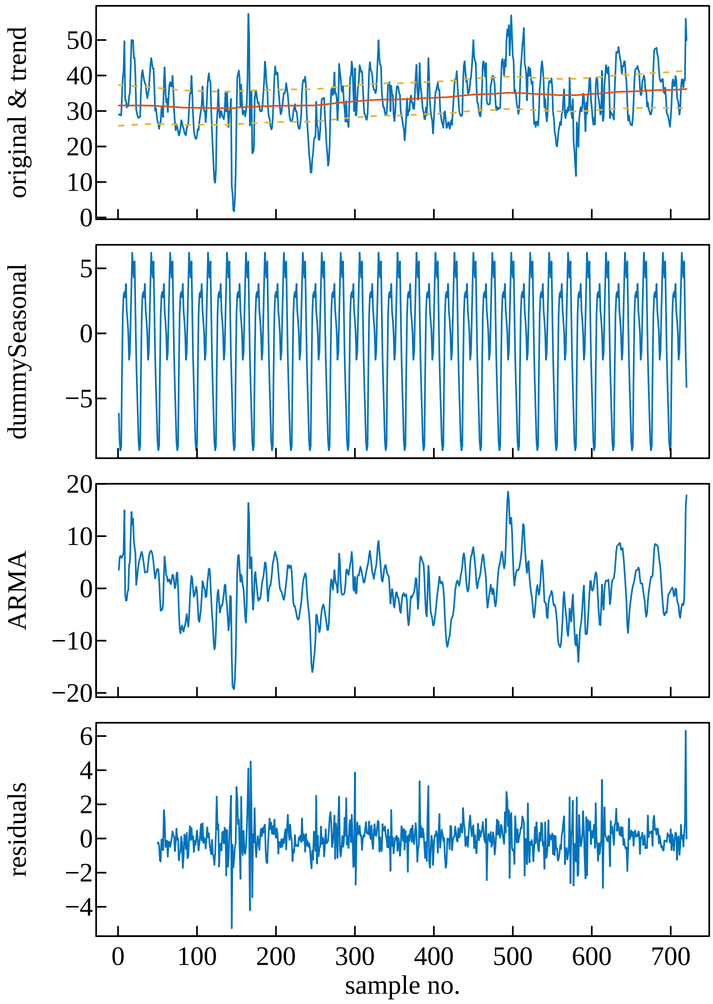

Figure 1: Four-week sample of spot prices of TenneT. From top to bottom: original time series and computed level trend (in red), seasonal component, ARMA component, and residuals.

the model had 8 unknowns (the ARMA coefficients plus the variance of each structural component). As a result, from the only available realization of prices represented in the top panel of Fig. 1, the model can be decomposed into the components represented in the other panels, with the computed variances accounting for the uncertainty in the prices. This allows obtaining other paths of the prices that would also have been possible in this setting if the errors in the process defined through their Gaussian distributions were considered. This is shown in Fig. 2, where the underlying components of the original series can be appreciated, though distorted by the additive random errors.

3.2. *DLM of wind speed*

For wind speed, we conceptually proceeded as we did with electricity prices. The structure we defined was different, however, because we found unnecessary to employ a seasonal component. Significantly, the

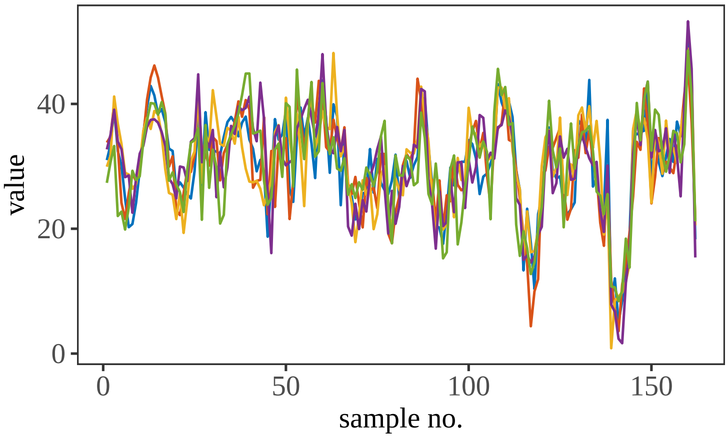

Figure 2: Simulation of the model calibrated using the time series shown in Fig. 1. For clarity only five paths and the first week (168 samples) are shown.

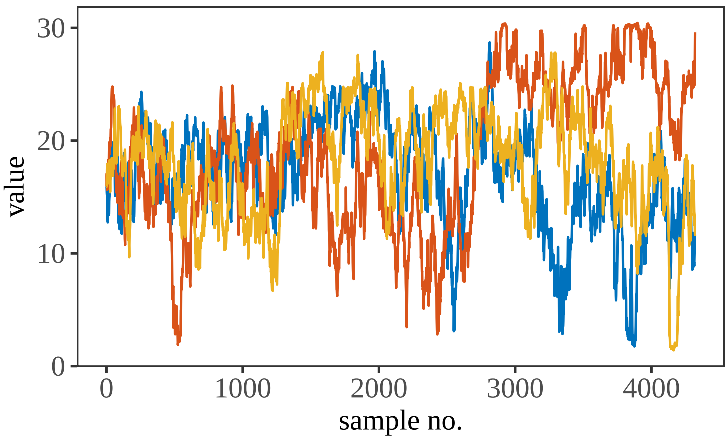

Figure 3: Simulation of four-week wind speed for site 24618 of NREL dataset. A sample of three paths is shown.

most parsimonious models we obtained were comparatively high-order models. For instance, the model that produced the simulations in Fig. 3 had, in addition to a local level trend, an ARMA(p,q) with $p = 1$ and $q = (1,\ldots,5)$.

4. Results and discussion

4.1. Deterministic analysis

In what follows we present an analysis of a switching sequence following three scenarios, in order to clarify our approach to quantifying the cost of energy production. Because we are interested in analyzing the main features of the switching sequence and the ensuing opportunity cost, we focus on a deterministic case (only one price path and wind speed path), in a brief two-day setting. The day-ahead price evolution for that period is shown in Fig. 4a. We have purposely selected a price sample from the Spanish spot market that exhibits an upward trend, rather than an oscillating pattern, to simplify the analysis.

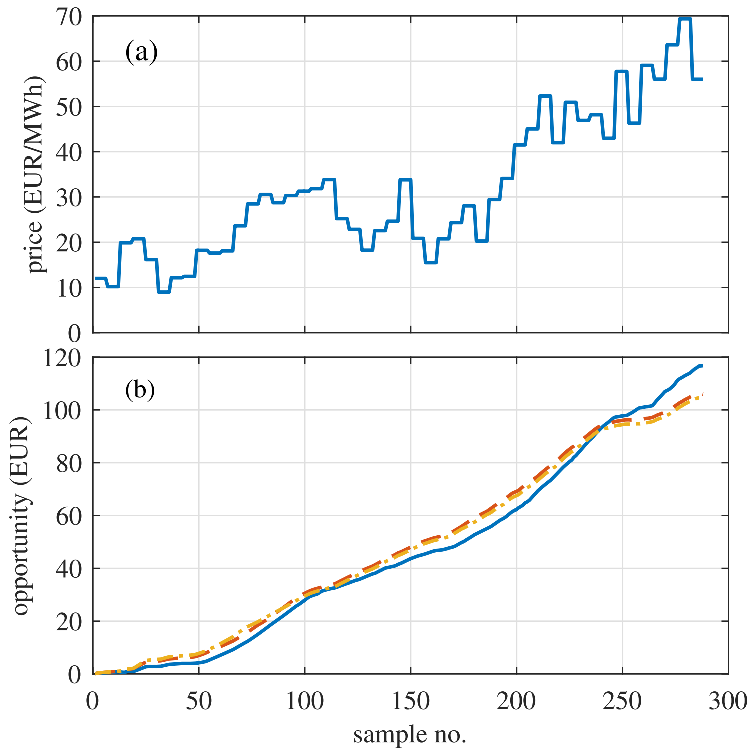

Figure 4: Top: Sample of day-ahead electricity price (Spanish spot market). Bottom: cumulative opportunity costs for the three considered scenarios of Fig. 5 (solid blue line), Fig. 6 (dashed red line), and Fig. 7 (dash-dotted yellow line).

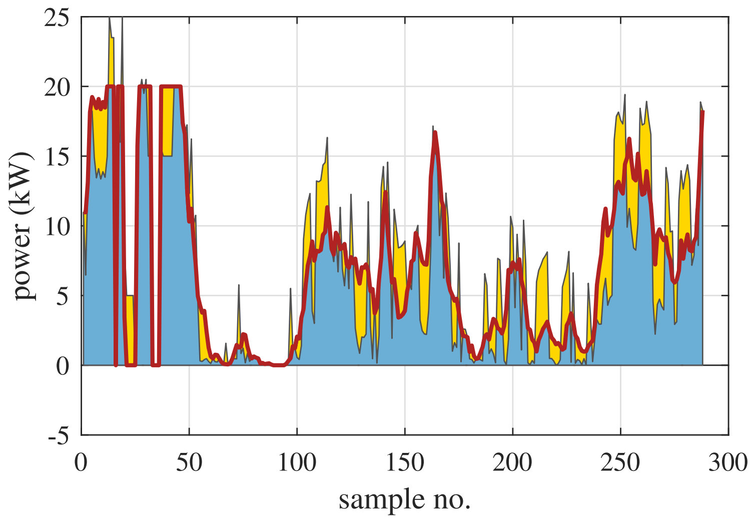

Figure 5: Two-day analysis of wind power supported by ESS of 40-kWh capacity and 40-kW rated power. Blue area: power delivered to the grid by the wind turbine. Yellow area: power managed by the ESS, stacked on top of the power delivered to the grid. Red thick line: wind power.

Figs. 5–7 show how the algorithm selects the ESS charging and discharging periods, based on the price and on the available wind power. The turbine is a Jacobs J31-20 of 20 kW rated power. Remarkably, it is difficult for this turbine to be at its rated power, because of the narrow range at which that power is

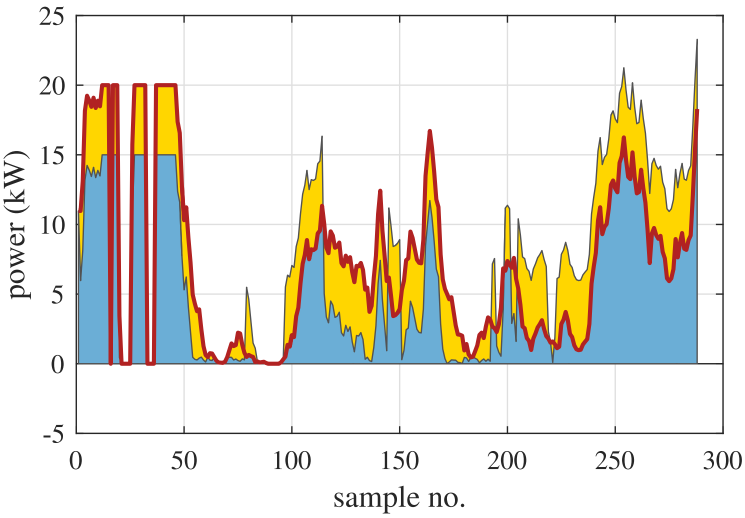

Figure 6: Same as Fig. 5, but with ESS capacity equal to 400 kWh.

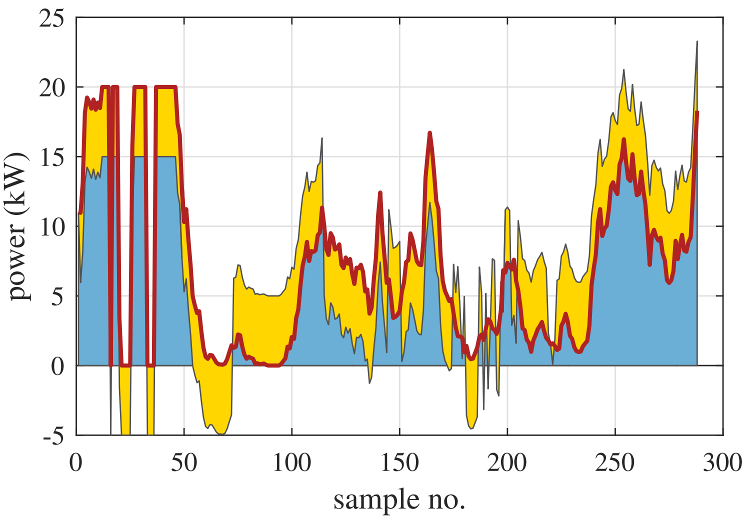

Figure 7: Same as Fig. 6, but with additional support of the grid.

produced: the turbine rated speed is 12 m/s and its furling speed is around 14 m/s. This provides a more oscillating power than that of other turbines with wider rated production, introducing in turn a richer switching sequence of value in our analysis. The generated power is represented by a thick red line in Figs. 5–7.

The first scenario, Fig. 5,is meant to analyze the switching sequence when the wind turbine is supported by a 40-kWh ESS. This capacity would allow the turbine, constantly producing the rated power, to completely charge the ESS in two hours. Or, conversely, would allow the ESS to substitute completely the wind turbine over a two-hour period. In our analysis this is the scenario of low ESS capacity. The second scenario ESS capacity was of 400 kWh, meaning a complete charge in 20 hours at rated power (or a complete replacement over 20 hours). The results are represented in Fig. 6. This is the large capacity

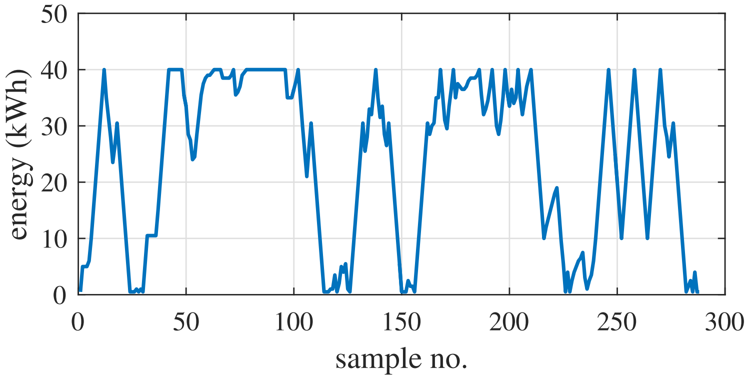

Figure 8: Energy stored by the ESS in the switching scenario represented in Fig. 5.

scenario.

In both cases, the interpretation of the results is simple if the thick red line—the wind power—is compared to the yellow area, which stands for the ESS operation.

- Particularly, when the yellow area is *above* the wind power line, it means that the ESS power is supplementing that of the wind turbine. It therefore means that the ESS is discharging. In this case, the blue area matches with the wind power line, meaning that all the power generated by the wind turbine is delivered to the grid. Or in other words, the grid is receiving the full turbine power plus the ESS discharged power.
- When conversely the yellow area is *below* the wind power line the ESS is charging. The power delivered to the grid is the power produced by the wind turbine less the power required by the ESS. This produces a blue area—the power delivered to the grid coming from the wind turbine—that does not match bounded by the thick red line.

With this convention in mind, it can be readily interpreted from Figs. 5–7 how the algorithm computes the optimal switching. To start with, over the first 50 samples the turbine is subjected to high wind speeds that drive its power through successive sequences of maximum and null power. The algorithm decides that the operation must consist of a series of charge/discharges, see Fig. 8, to supplement the null power production intervals in these first 50 samples (see the notches approximately at samples 30 and 40 in Fig. 5, which are filled by the ESS). From samples 50 through 100, with almost null generated power, the algorithm results show an almost idle ESS, waiting a discharge in sample 100. This is slightly different in the 400-kWh ESS case. Because of its high capacity, the ESS will be continuously charging up to sample 50. Yet it will be again almost idle over the next 50 samples of null wind power, and will provide a power supplement for the next 20 samples, starting at sample 100.

This is indeed a correct solution to the problem; in both cases. When it comes to the low-capacity ESS, the operation is restricted by the reduced operational horizon. The ESS restricts its actions—supplementing the wind power at the cost of previously subtracting some of it—to shorter periods. This makes it interesting for the ESS to operate in the notches at samples 30 and 40. It does not make any sense for the ESS to remain idle awaiting for higher electricity prices, when the it can be readily fully charged again. However, the high-capacity ESS operates in longer period scales. This is correctly detected by the algorithm, which provides a less frequent switching. Indeed, it only produces two relevant discharges: 90 kWh starting at sample 100, and a full discharge of 400 kWh starting at sample 200. It is indicative how the algorithm then divides the representation shown in Fig. 6 into two well-defined periods. Leading up to sample 200 the operation is charging or idle (except for the brief spell at sample 100, where the ESS discharges at a cumulated relative maximum price to make room for a complete charge thereafter), represented as the yellow area below the thick red line. From sample 200 through the end, the yellow area is always above the thick red line. So in both scenarios, the solution produced by the algorithm is coherent; showing a preference for charging when it is less profitable to deliver power to the grid, and charging in the last samples where the prices for delivered power are higher. In both cases, the solution follows this pattern, only changing the operational horizon.

Fig. 7 provides an expanded view to the solution shown in Fig. 6. In this case, we did not define the negative values of the cost function to be negative infinite. And in doing so, we did not prevent the algorithm to consider "purchasing" energy from the grid at some periods. As a result, the algorithm visibly changes the solution following a sound rationale. Now the periods of low power production by the turbine are employed to draw charging power from the grid. Hence the negative value of powers in Fig. 7 with the yellow area *below* the thick red line. The solution is quite similar to that shown in Fig. 6. But now, an arbitrage capability is enforced by purchasing low and selling high—see the operation in the period going from samples 50 through 100—now that the charging power comes from the wind turbine *and* the grid (although at a cost).

Over the calculation period eventually the opportunity costs accumulate, as a figure of the lost profits due to the lack of wind power. That is shown in Fig. 4b, existing periods of fast cost growth due to little injected power into the grid, which alternate with other periods in which the injection reduces the cost—even being zero if the power injected is equal to the rated power. The curves of cumulated costs are in general increasing functions, though not necessarily monotonically. It might occur that, given the necessary conditions, a discharge of the ESS were added to the produced wind power producing a total power greater than the turbine rated power. In such a case the cost would be negative, breaking the upward trend of the curves in Fig. 4b.

It is therefore important in the representation of Fig. 4b to analyze the final values of the functions, because they reflect the accumulated cost through the ESS and turbine combined operation. In the analysis presented here it is evidenced that an increase of the ESS capacity results in a final reduction of the opportunity cost. But moreover, the analysis of the cumulated cost history also shows that the short- versus long-term strategies discussed in the analysis of Figs. 5 and 6 also result in a solution that makes the best of the charged energy at the end of the period—when the prices were higher—when the ESS has a larger capacity.

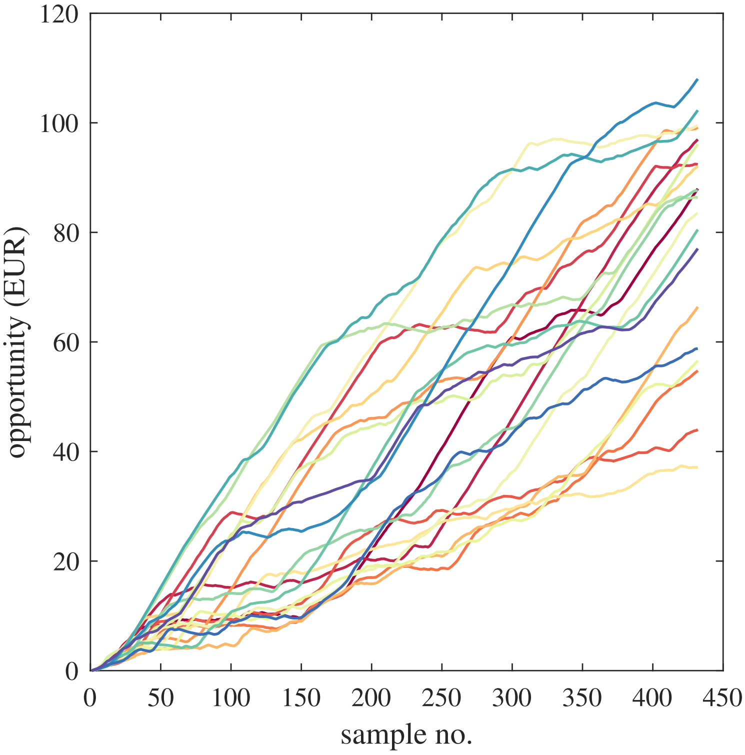

Figure 9: Evolution of the opportunity cost through a three-day evaluation. Because samples are observed every ten-minute period, the number of samples shown is 432. Only 20 paths are rerepresented.

4.2. Bootstrapping

Each simulated path produces different switching strategies that entail different accumulated opportunity costs. This is represented in Fig. 9. The paths are visibly diverse, alternating periods of relative rapid rise with some periods of moderate increase at different stages of the simulation. In some cases, the trend is even downwards, reflecting a brief period in which the sum of power generated by the turbine and power discharged by the ESS was above the rated value of the turbine.

Initially it seems difficult to observe a trend in the mean value of lost opportunity, in view of those paths in Fig. 9. To clarify this issue, we performed a bootstrap of the mean value at every stage of the calculated results. This would allow us to infer a measure of accuracy to the opportunity cost estimates. We did 1000 resamplings at each step of the switching calculation, and to detrend the bootstrapped statistics we divided them by the sample number. This procedure produces graphics like the two in Fig. 10, where the mean is represented along with the 95%-confidence interval for two different cases involving different wind regimes. In both cases, like in all the others we examined involving diverse simulation conditions, the mean value of the opportunity cost tends to stabilize to a final value after an initial growing short period. This is an important result, because it definitely allows for a simplification of the calculation. It allowed us to solve one-year optimization problems, thus reducing the computational burden. If this were not the case, if the mean value of the opportunity cost were not approximately constant, the calculation of the annual opportunity—which should eventually be integrated into the LCOE calculation—would require

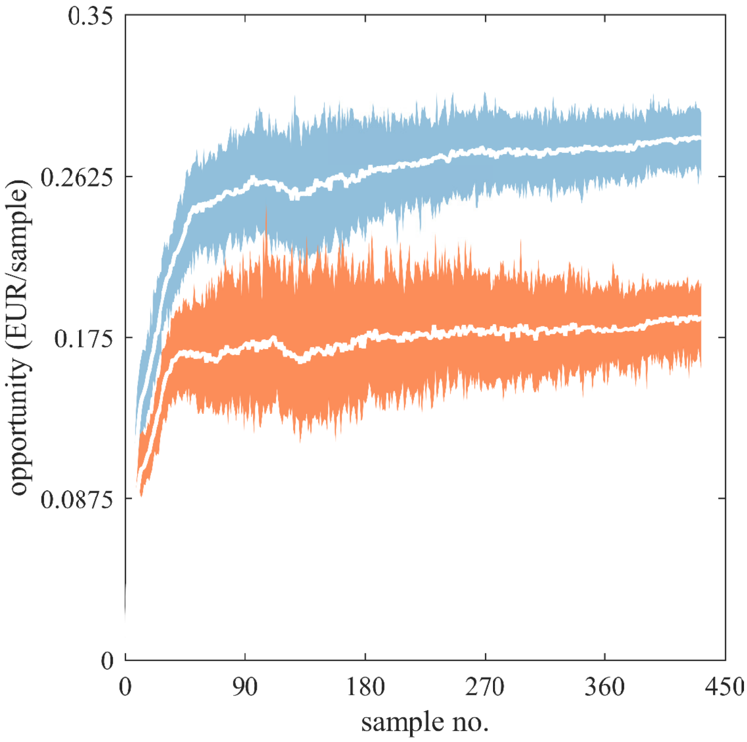

Figure 10: Bootstrapped means relative to the sample number. The shaded areas delineate the 95% confidence interval. Top blue plot is for the NREL wind dataset 26798, and bottom orange plot for the 1775. Both cases were processed using the 53-kW wind turbine Bergey BWC XL.50/14.

longer simulations, recording the entire switching policy over the year. But our results show that the mean opportunity can be inferred through a more reduced simulation. Thus for instance, in the case represented in Fig. 10, the opportunity costs are approximately 27 and 17 c€/sample. These are a results for $6 \times 24 \times 3 = 432$ samples. For an entire year, the mean opportunity cost could be approximated as $6 \times 24 \times 365 \times 0.27 = 14200$ € for the first case.

4.3. *Stochastic analysis*

In a feed-in premium setting, incomes are affected not only by the wind regime, but also by the variation of prices. The top panel of Fig. 13 shows the box plots depicting a group of European electricity prices. These are prices with remarkably different characteristics: mean prices ranging from TenneT's 33 €/MWh through Elia's 73 €/MWh; standard deviations also varying on a wide spectrum, from NO5's 1.3 €/MWh through Elia's 29.7 €/MWh; and noticeably different degrees of skewness, from almost null in REN's prices to Fingrid's 2.9.

The middle panel of Fig. 13 shows a comparison of the realized income for the five turbines described through the curves of Fig. 11, subject to the market price distributions shown in the top panel. The difference between markets is clearly observed in the resulting incomes. Markets exhibiting relative high prices (Elia, REN, and Swissgrid) induce relative high incomes. This is obvious. However, it is interesting to observe a particular result regarding the comparison of turbines in each single market. The average income is

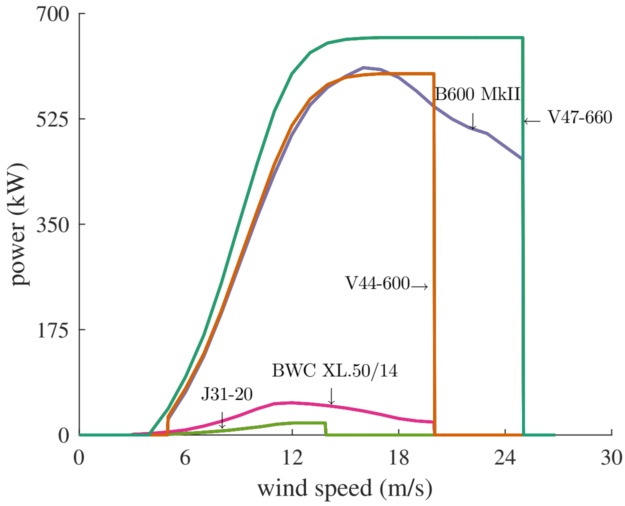

Figure 11: Wind power characteristics of Vestas V44-600 and V47-660, Bergey BWC XL.50/14, Jacob J31-20, and Siemens B600 MkII.

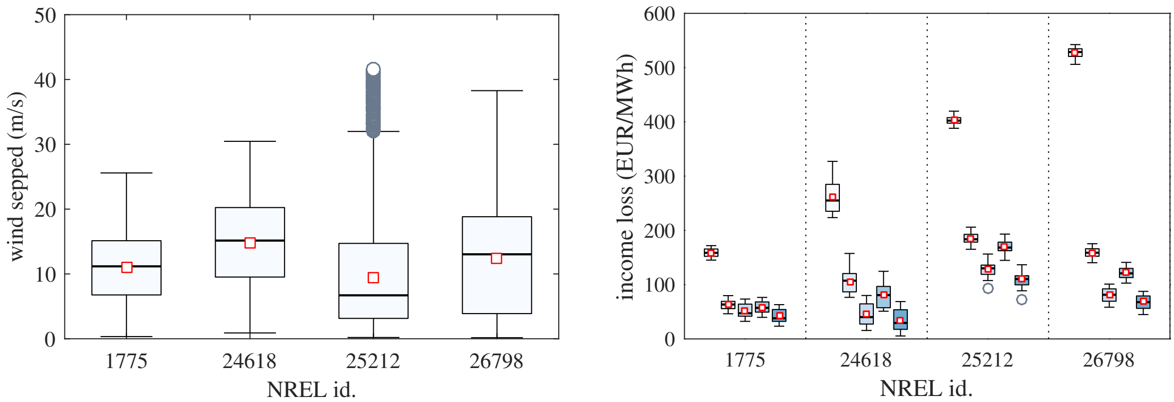

Figure 12: Influence of wind speed and turbine model on the LIL. Left panel: wind speed distribution for four investigated NREL sites. Right panel: loss income for the five turbines in Fig. 11. The different shades of color correspond to (from lightest to darkest, or left to right in the same category) Jacob J31-20 (T1), Bergey BWC XL.50/14 (T2), Siemens B600 MkII (T3), Vestas V44-600 (T4), and Vestas V47-660 (T5).

particularly constant in a given market, regardless of the turbine type. Other statistics, such as the median and most importantly the quartiles do change appreciably; but no so the mean, which is most of the times considered as the definitive statistic in making a valuation.

On the other hand, the results do not seem to be appreciably affected by the tails of the price distributions. See for instance REN and Swissgrid. REN's mean absolute deviation—which measures the average absolute distance between prices and the mean—is 11.4 €/MWh; whereas Swissgrid's, with visible outliers, is 17.5. If we look at the realized income, however, the differences between the performance of the five turbines in the two markets are hardly perceptible.

Now we turn our attention to the valuation of the LIL, which is represented in the bottom panel of Fig. 13. It is readily observed that the picture is visibly different compared to that of the realized income:

- In the middle panel of Fig. 13, T1 has similar economical performance to that of the other four

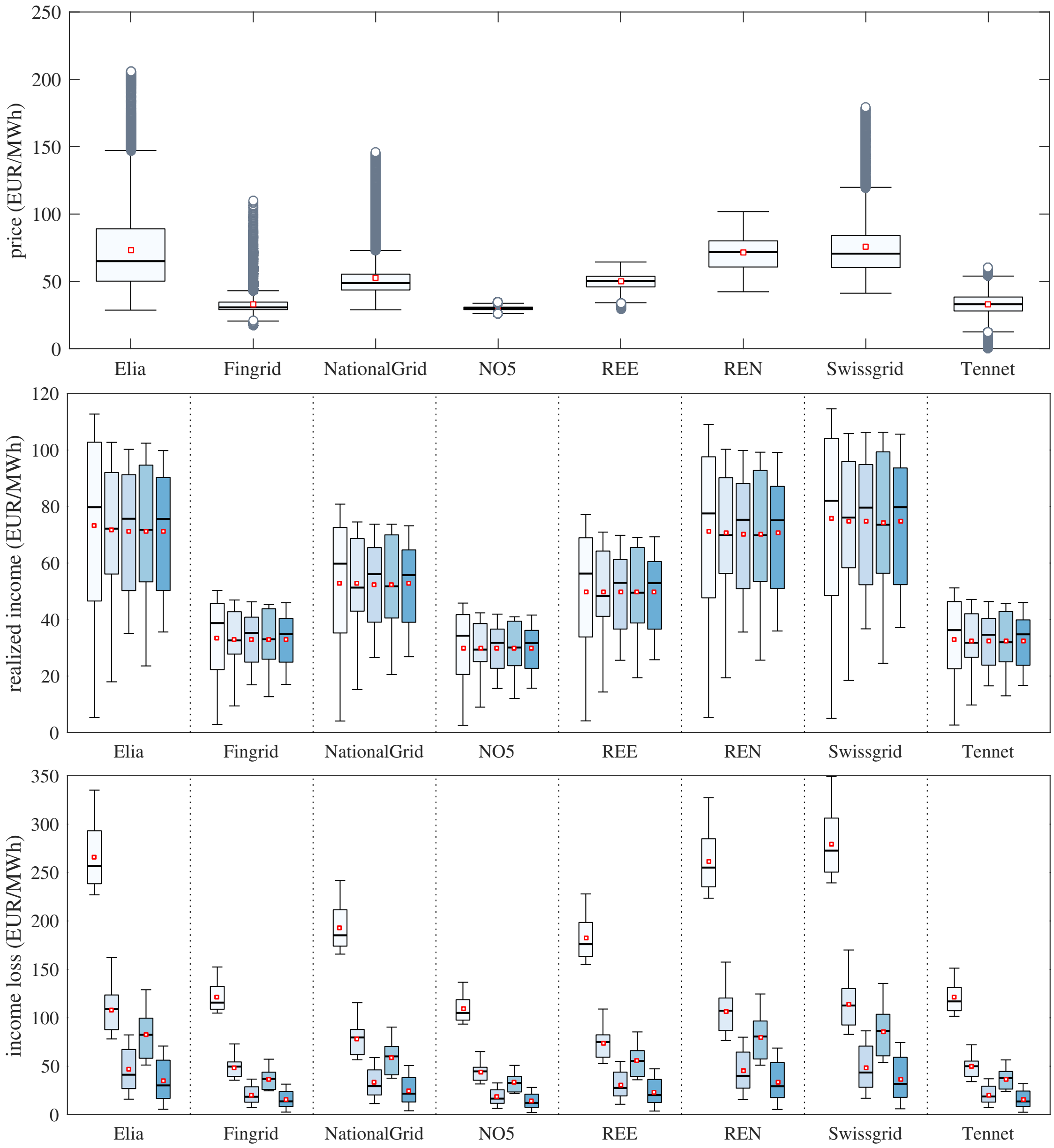

Figure 13: Analysis of the relationship between day-ahead price and turbine characteristics (see color code explanation provided in Fig. 12), using the wind profile of NREL site no. 24618. Top panel: reference prices for eight investigated spot markets. Middle panel: actual income for those markets. Bottom panel: LIL in the conditions proposed in the other two panels.

turbines. The mean price obtained for MWh is even slightly higher. It is true that, on the negative side, the risk—if we consider it to be the negative deviation from the mean—is higher in T1 than in any other turbine of the set. Therefore, for a risk-averse producer, turbines T3 and T5 would represent the best choice. But if only the mean value were considered, a producer would end up selecting T1 as the best turbine of the set. (Note that this is an oversimplified explanation about the selection of the turbine. No CAPEX or OPEX are considered in the analysis.)

- The bottom panel provides significantly more information. It shows that turbine T1 is really ill-suited, because in each market its LIL are markedly superior to those of the other turbines. In some sense, the calculation of the loss provides a clearer insight about the risk of realizing lower incomes, because T1 is likely to be idle significantly longer than any other turbine in the set. This is equivalently translated into a higher probability of producing lower incomes because it misses more generation opportunities. In the middle panel this is not so obvious.

  The LIL figure also allows classifying the other four turbines. Again the speed regulation makes the turbines T3 and T5 more competitive, and in this case it is clear that turbine T5 is the best option in all the markets.

  Finally, the LIL may also capture the existence of outliers. It is not so evident as in the case of the differences between two turbines in a given market, but for instance it shows how T1 may more likely miss the existing price spikes in Fingrid compared to NO5 (see the slightly higher mean LIL in the bottom panel). In other words, it reflects how T1 has a lower joint probability of producing its rated speed at a time of high prices.

On the whole, the calculated loss reflects how a wind generator misses opportunities of increasing its economic revenues. It is a result of the combination of the characteristics of the electricity prices (*extra-constant* prices such as NO5 inherently reduce the probability of missing good selling opportunities, because there are not such *good* opportunities, whereas more volatile markets such as Elia increase that probability) with the characteristics of the wind turbine and the wind speed regime (turbines with high likelihood of idleness obviously have more chances of missing those good opportunities).

The LIL combines these three crucial factors into a single figure, which conceptually differs from the realized income. If we look at the middle panel of Fig. 13, we see that the range of realized income is *obviously* below the maximum price payed for MWh by the market. However, this is not so for the LIL (see bottom panel). The loss could be hypothetically infinite. It would be the case of a continuously stopped turbine missing all the prices in the considered period. From the point of view of a prospective analysis about the matching between wind power production and received price, it would be serve as an opportunity cost.

This means that the LIL acts as a figure of penalty, allowing us to classify the turbines regarding their capability of making the best of the operational prices and wind speeds. And in doing so, the LIL also serves as a measure of the impact that the generation of energy has on the system, indirectly. That T1 shows the highest losses in any market and wind regime means that it will be less reliable; that it too often will miss the highest prices, which in turn are a translation of the stress of the power system as a whole.

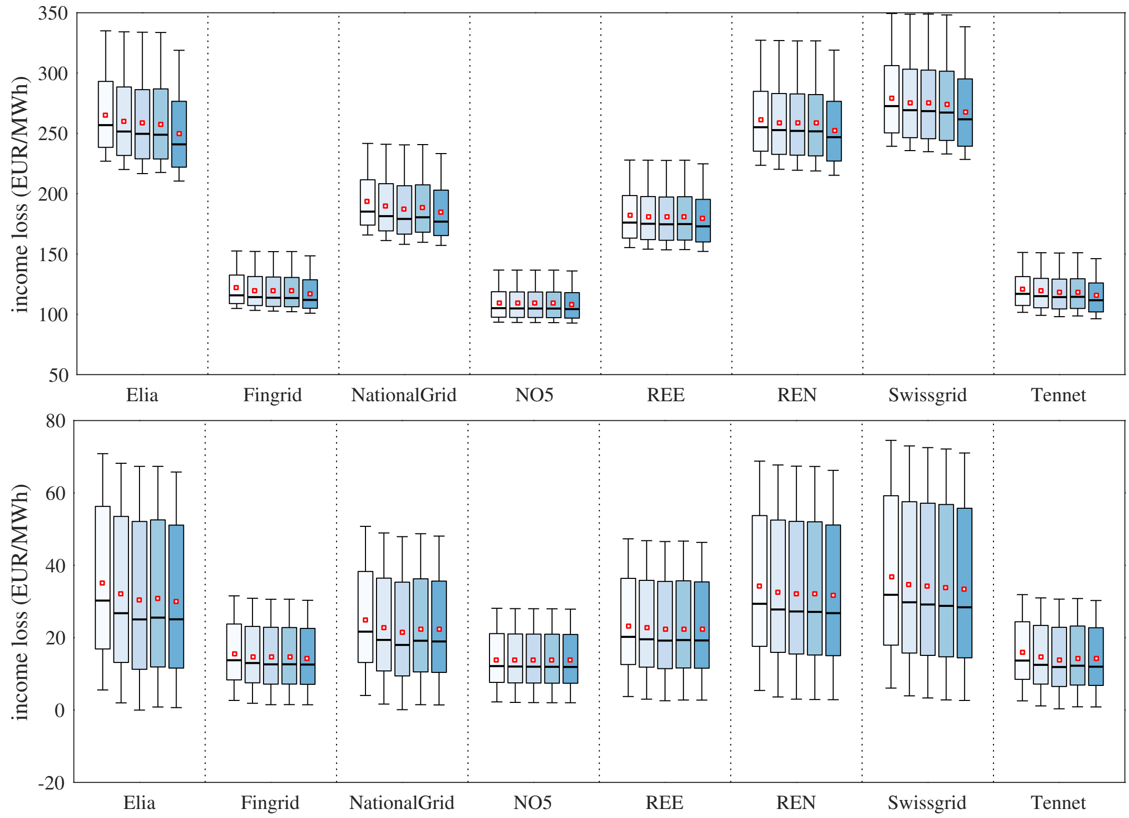

Figure 14: LIL in an analysis of energy storage using data from NREL dataset 24618 and 23-kW turbine Jacob J31-20 (top) and Vestas V47-660 (bottom). Table 1 provides the explanation to the different color shades.

Table 1: Meaning of boxes (from left to right, or from lightest to darkest) in Fig. 14.

	lightest	...	...	...	darkest
ESS power (p.u.)	0.00	0.25	1.00	0.25	0.25
ESS capacity (p.u.)	0	5	5	20	20
grid arbitrage	no	no	no	no	yes

Consequently, the relative high loss figure will indicate the relatively higher need for backup generation to support the lack of reliability (in this case of T1).

To conclude this analysis the question that remains is: Does energy storage significantly reduce the loss of income? A summary of the results obtained after employing several storage scenarios is presented in Fig. 14, showing that the answer is that it does not contribute to appreciably mitigate the opportunity cost. We proposed several possible scenarios, employing the turbines characteristics and wind speed turbines above described, with similar results. Fig. 14 shows just two of these analyses, of wind generator J31-20 (top) and Vestas V47-660 (bottom) along with wind regime modeled following NREL dataset id. 24618. The scenarios are described in Table 1. Power is in given as a fraction of the rated powers of the generators, and capacity as a fraction of the rated power sustained over an hour by the generator. Thus for instance, ESS power equal to 1.00 p.u. means that the ESS can at most provide a power equal to that of the generator to which it is attached. This would be the value of ΔL_{max} above. A capacity of 5 p.u. means that the ESS could sustain the rated power (if allowed in the scenario) over five hours. This would define the value of L above, once P_ℓ is defined. The scenarios were aimed at investigating:

- What the influence of using ESS is: lightest boxes in each market in Fig. 14 show the benchmark resuts *without* ESS, and the second box from the left shows a first case of ESS installation.
- What the result of increasing the ESS power is, which is summarized in the second box of each market.
- What the results of increasing ESS capacity are: the fourth box was obtained by increasing also four times the capacity of the second case.
- Finally, what the result of allowing for energy arbitrage with the grid is.

The results obtained justify the following conclusions:

- First, LIL is reduced when ESS is used. In highly volatile markets such as Elia, a reduction is observed, though visibly minor. In stable markets such as NO5, however, it really does not make any difference introducing an ESS. The constant prices in NO5 makes delaying energy delivery advantages almost inexistent.
- Increasing the power or capacity of the ESS does not seem to provide an added reduction of the LIL. Only allowing for grid energy arbitrage capability appears to improve the economic efficiency. Yet this improvement is again only observed in high-volatility markets.

On the whole, it seems that the LIL, as a figure of the economic efficiency of a generation asset, allows obtaining a clear categorization of generators. We have shown in Fig. 12 that wind turbines that have reduced generation capability show distinctive high LIL values. Also, this occurs when comparing relatively "bad" wind regimes, since the LIL again makes the less efficient generators to stand out.

Regardless, it could be argued that the simplest LCoE already penalizes lowly efficient generation, when comparing different methods of generation. And this appears to be true in some comparisons, indeed. To verify it, consider the definition of LCoE as the net present value of the unit-cost of electricity over the lifetime of a generating unit. If CAPEX is the overnight investment expenditure, and OPEX_t and E_t the O&M expenditures and the energy generated in the year t, at a discount rate r over an expected lifetime of n years, a formulation of the LCoE is [**?**]

$$\text{LCoE} = \frac{\text{CAPEX} + \sum_{t=1}^{n} \frac{\text{OPEX}_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}. \tag{16}$$

If we approximate the O&M expenditures and the energy generated to be constant over the years, and define the capital recovery factor as CRF= $\sum_{t=1}^{n}(1+r)^{-t}$, it follows that

$$\text{LCoE} = \frac{\text{CAPEX} \times \text{CRF} + \text{OPEX}_t}{\text{CF} \times E_\text{n}}, \tag{17}$$

Table 2: Capacity factor of scenarios shown in Fig. 12

	1775	24618	25212	26798
T1: Jacob J31-20	0.310	0.215	0.151	0.119
T2: Bergey BWC XL.50/14	0.569	0.432	0.299	0.331
T3: Siemens B600 MkII	0.592	0.629	0.362	0.476
T4: Vestas V44-600	0.551	0.475	0.297	0.370
T5: Vestas V47-660	0.632	0.682	0.395	0.512

where CF is the capacity factor, and E_n is the rated energy. (Note that the expression CAPEX $\times$ CRF is but the equivalent annuity of the capital expenditures, so that the entire expression refers to yearly cost and production data.)

In (17), all the LCoE components can be approximated as constant, except the capacity factor. The LCoE measures the minimum *constant* price that the generator must receive to cover its investment and production costs. The capacity factor measures actual production relative to possible production. So a low CF means that the generator is performing relatively poorly, and it will require a higher selling price of its energy. So eventually, the LCoE is also an indicator of the generator economic efficiency. This is corroborated through a comparison of Table 2 with Fig. 12: the scenarios with high CF (low LCoE) are also those with low loss income.

However, this equivalence is not so valid when the received price is varying. In such cases, the LCoE does not yield useful information about the matching between price, wind turbine, and wind speed; as a quick inspection of (17) reveals. However, the LIL does provide an indication of how diverse turbines adapt differently to market structures (see Fig. 13).

5. Conclusion

In our approach, the dynamically computed LIL evaluates the missed opportunities for obtaining higher revenues from a given wind and price scenario. It is therefore a measure of how the turbine production deviates from an optimal value, which would have occurred had the wind conditions being optimal—wind speed between the turbine rated and cut-off speeds—when the received electricity prices were non null. Consequently, it is a measure of how a turbine is tailored to the particular characteristic of its location and market. But indirectly, it is also a measure of the power system backup needs; because turbines with higher LIL—an unwanted situation for the producers, who would not get as high revenues as they would through a fully dispatchable generator—also require more replacement generation.

Thus defined the LIL provides a valuation of the economic inefficiency of the generator, which obviously must be minimized when possible. This paper has detailed a dynamic programming approach to provide an assessment of the role that ESS play in that minimization. The program considers two main factors: uncertainty of price and wind, and optimal re-allocation of energy to minimize the income loss under those conditions.

The LIL has proven to be a convenient and sensible metric to categorize the matching of wind speed, wind turbine characteristic, and market spot price, regarding the economic results. Our results show that without ESS the LIL index visibly categorize different scenarios. Turbines with inferior specifications stand out remarkably. When the ESS is introduced in the analysis, our results show that the LIL is only marginally improved. Only in relatively highly volatile spot markets the reallocation of energy in time could serve to make a visible difference, but as low as a 4%. Re-allocating the energy by using the ESS could bring at best a mean improvement of around 11 €/MWh, according to our results; which could be attained if the ESS could charge from the grid.

It seems reasonable to think that the combination of low capacity factor and price differences reduces the extent to which the ESS can provide advantages. It also seems reasonable, planning for future research, that a combined operation of the ESS in other markets—intra-day and possibly balancing markets—might improve the value of energy storage. That would be a case of valuation, different from the scope of this paper, but with several aspects in common with the methodology shown here. It would be necessary to upgrade the DLM and the dynamic program to accommodate market prices other than day-ahead prices. And in the case of the dynamic program, the approach we have presented is flexible enough to incorporate the cost analysis in the objective function, while the recursive stochastic computation—the core of the program—remains unchanged. Consequently, analyzing such cases would be a matter of defining a proper cost function and, as in this paper, possibly a classifying index.

References