Market-Oriented Dispatch Strategies for Wind-Storage Configurations Using Day-Ahead Forecasting Signals

Dimitrios Zafirakis, Georgios Tzanes, John Kaldellis
Soft Energy Applications & Environmental Protection Lab, Dept of Mechanical Engineers
School of Engineers, Univeristy of West Attica
Aegaleo, Greece, 12241
dzaf@teipir.gr, +30-2105381580

***Abstract*—The present work looks at the development of optimum, day-ahead bidding strategies for wind-storage configurations. More precisely, a price-following strategy is devised for wind actors, aiming to determine optimum bidding offers that ensure net revenue maximization on a daily basis, with the support also of optimally, variable-sized storage. In this context, 24h, day-ahead forecasting models are developed for wind power generation and spot prices, with the use of artificial neural networks and support vector regression techniques. Accordingly, the optimization process applied determines the daily-basis optimum storage capacity, assuming among others the possibility of storage capacity leasing, while considering both an ex-ante approach, relying on forecasting results, and a deterministic, ex-post one. Finally, and in order to assess the impact of imperfect prognosis in storage design and operation, storage capacity defined on the basis of the ex-ante approach is evaluated as if operating under deterministic conditions.**

Keywords-forecasting; machine-learning; bidding strategy; energy storage; wind power; electricity markets; spot price

I. INTRODUCTION

The stochastic character of wind power generation entails limitations on the increased shares of wind energy in electricity systems and challenges further market integration of wind power [1]. Moreover, new wind parks are called to cope with more dynamic pricing schemes, with the traditional feed-in-tariffs gradually phasing out. As a result, there is increased interest for advanced bidding strategies that capture the elements of storage and forecasting [2-4].

To that end, in the present paper we evaluate a price-following dispatch strategy for wind-storage configurations, using both day-ahead forecasting results and ex-post, historical data for wind energy production and spot electricity prices. Forecasting results are generated through the training and validation of Artificial Neural Networks (ANNs) and Support Vector Regression (SVR) models. Accordingly, two different approaches apply for the price-following strategy examined, aiming to the maximization of net revenues for the wind-storage configuration on a daily basis. In doing so, the optimum bidding offers and storage size are determined in relation to storage costs' variation. As already mentioned, the first approach (ex-ante) considers day-ahead predictions using the respective profiles generated from the trained forecasting models, while the second one (ex-post) attempts a comparison by considering historical profiles of wind power and spot prices, which is equivalent to the assumption of perfect prognosis.

Finally, an effort is made so as to evaluate the impact of using the ex-ante approach with regards to the expected operation of the storage component. To that end, a selected wind-storage configuration is set to operate under the application of the actual wind and spot price profiles while adopting the ex-ante, optimized day-ahead bidding offers generated previously.

II. METHODOLOGY & CASE STUDY

A. *Methodological Framework*

The adopted methodology is synopsized in the following Fig. 1. As already seen, there are two individual approaches examined; the first one concerns the ex-ante problem solution, employing also appropriate forecasting algorithms in order to produce the respective day-ahead profiles for wind power generation and spot electricity prices respectively. For this purpose, an in-house forecasting software tool, comprising an automated Machine Learning (ML) platform, is employed [5,6]. The range of ML methods currently captured by the forecasting tool include ANNs and SVR.

In this context, one may use different combinations of features-predictions as input in order to form a set of "data cases", which is also automatically extended based on the desired forecasting horizon (length and step), the training and validation partitioning and the historical data (backward data) of each feature to consider. Similarly, for every "data case", the tool generates a set of "model cases", based on the options defined at the user interface. In this way, the performance of different ML methods as well as the effect of each hyperparameter involved can be explored.

After the configuration of the forecasting tool and the training and validation of the forecasting models, the predicted profiles of wind power generation and spot electricity prices are next used to inform an optimization engine. The latter is built in Python programming language employing also the Jupyter Notebook and the Gurobi solver tool in order to achieve maximization of a linear objective function (see also (1)) looking at the net revenues of the wind-storage configuration over the examined period of study which is currently set to be daily. That means that the optimizer generates an optimum storage capacity that varies on a daily basis, enabling the maximization of daily net revenues.

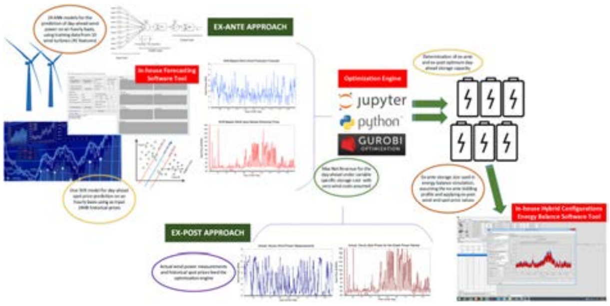

Figure 1. Description of methodological framework.

By daily net revenues "NR" to this end, we currently refer to the sum product of energy delivered to the grid on an hourly basis "ESS^d_i+WP^g_i" multiplied by the corresponding spot price "SP_i", minus the cost of the storage component over the period of study (i.e. every other 24h period). The latter results as the product of the storage capacity "ESS_{cap}", which is also the main output of the optimizer, with the specific storage cost "c_{ESS}" and the hours of operation during the period of study over the entire storage lifespan "h/h_{life}". In this context, the optimizer determines the optimum day-ahead dispatch of the wind park (delivery of wind power to the grid "WP^g_i" or charging of the storage side "ESS^c_i") and of the storage component (charging "ESS^c_i" or discharging "ESS^d_i") on an hourly basis, thus generating optimized day-ahead bidding offers while also determining the optimum storage capacity "ESS_{cap}" on a daily basis.

$$Maximize\left\{\left\{\sum_{i=1}^{h}(ESS^d{}_i \cdot Sp_i + WP^g{}_i \cdot Sp_i)\right\} - \frac{ESS_{cap} \cdot c_{ESS} \cdot h}{h_{life}}\right\} = NR \tag{1}$$

At the same time, constraints of (2) to (5) are also taken into account in order to govern the energy balance of wind power generation and of the storage component operation respectively. To this end, "WP^t_i" corresponds to the total hourly wind power generation, "SOC_{min}", "SOC_i" and "SOC_{i-1}" refer to the minimum (currently assumed to be zero), the current and the previous hour state of charge of the storage system respectively, "η_c" and "η_d" are the storage charging and discharging efficiency (both assumed to be constant and equal to 90%) and finally, "ESS_p" is the storage system maximum charging/discharging power.

In this context, one main variable is currently considered which corresponds to "c_{ESS}", with the power/capacity ratio "ESS_p/ESS_{cap}" of storage component kept constant and equal to 1 (or 1C) and with the optimization process applying for both the ex-ante and the ex-post approach described earlier.

$$WP_i^g + ESS_i^c = WP_i^t \tag{2}$$

$$SOC_i = SOC_{i-1} + ESS_i^c \cdot \eta_c - ESS_i^d \cdot \eta_d^{-1} \tag{3}$$

$$SOC_{min} \leq SOC_i \leq ESS_{cap} \tag{4}$$

$$ESS^d{}_i ; ESS^c{}_i \leq ESS_p \tag{5}$$

Finally, representative results of the ex-ante approach are also used in order to evaluate the impact of imperfect prognosis. More precisely, by selecting a storage size, we let the respective wind-storage configuration to operate under the application of optimized, ex-ante storage bidding curves, facing however the actual wind power generation and spot price profiles. For this purpose, we also employ an in-house simulation tool, used for the sizing and energy balance analysis of hybrid RES and storage configurations [7]. As a result, expected operational results of the ex-ante approach are tested against deterministic conditions.

B. *Forecasting Techniques*

With regards to forecasting techniques, both ANN and SVR models are currently used in order to predict the hourly, day-ahead profile of wind power generation and spot electricity prices respectively. Regarding ANNs, a Feed-Forward Elman network is used, which features an additional layer with neurons, named Context Layer, allowing for the storage of the hidden units' value. The content of the Context Layer is fed back into the Hidden Layer during the next stage of input, providing the network with "memory". Training of ANNs however requires the values of many hyperparameters to be set. As such, besides the network pattern (Feed-Forward, Elman), one must also define the number of hidden layers (i.e. 1 in case of an Elman network), the number of neurons per hidden layer, the activation functions (which are closely related with the normalization field) and the training method together with its properties (see also Table 1).

TABLE I. THE TESTED ANN CONFIGURATION

Property	**Selected Options**
Architecture	Feed-forward / Elman
Training Method	Resilient propagation
Hidden Neurons	70
Activation Function	tanh

Regarding SVR, the main idea is to define a function f(x) that presents a maximum deviation "ε" from the actual training targets for all training patterns. The margin of tolerance "ε" is currently set to 0.1. In order to deal with the non-existence of a function capable to approximate all the training pairs with "ε" precision, SVR models adapt the "soft margin" loss function concept by using slack variables at the constraints of the optimization problem (i.e. finding a hyperplane that splits data, maximizing the distance between the support vectors and the hyperplane). Additionally, a constant "C" is introduced in the objective function, in order to penalize the use of those slack variables. Constant "C" is a hyperparameter that affects function f(x), with its value being subject to trials using logarithmic steps and with the appropriate value being highly dependent on the training set. In case of training patterns separated in a non-linear way at the N-dimensional space, instead of finding a higher degree curve, one may increase N.

This is due to the fact that the formulation requires only the dot product of the training data and thus N, or even a transformation function, is redundant. To this end, one may substitute directly the dot product with a Kernel Function (see also (6)). In the developed in-house tool, the Radial Basis Function kernel, or Gaussian kernel is used, where "x" (test vectors) and "x'" (support vectors) are the vectors to be projected into a new vector space and "γ" is a hyperparameter representing the inverse of the radius of influence of selected support vectors. In this context, and following several trials for the prediction of the day-ahead spot price, the best combination of the "C" and "γ" parameters was 0.001 and 100 respectively.

$$K_{RBF}(x,x') = e^{-\gamma\|x-x'\|^2} \quad (6)$$

C. *Case-Study & Training Dataset*

For the application of the described methodology, an in-operation wind park of the Greek mainland national electricity system is currently used as case study. The wind park examined is located in the interconnected island of Euboea and employs a total of 10 wind turbines of 750kW each (Neg Micon NM44). A detailed dataset of a full year of operation has been made available, including measurements of actual wind energy production together with ambient temperature, as well as wind speed and direction at hub height for all 10 wind turbines. Wind power generation measurements are provided to this end in Fig. 2, with the long-term average wind speed of the wind park estimated at ~9.3m/s, which leads to an average capacity factor exceeding 38%.

The specific set of measurements was properly processed for the training of the different forecasting models used. Out of the available dataset 7,152 hourly values were used for the training of the models (~80%) and 1,632 for the models' validation (~20%). As already mentioned, different prediction horizons applied, i.e. from 1 to 24h ahead, while for the training of the models a total of 41 features were fed into the input layer.

These correspond to measurements registered to each of the 10 wind turbines (i.e. wind speed, wind direction, power generation, ambient temperature) together with an indicator of time. Moreover, and after the execution of several trials, it was decided that an increasing time window should apply for the training of the models, with the same starting and ending point for the input, independently of the prediction horizon, i.e. t+1 (first hour of the day-ahead), t+2 (second hour of the day ahead) and so on. More specifically, the input values correspond to points t-1; t-2 and t-3, which produces a time window of e.g. 4 hours in the case of t+1, 5 hours in the case of t+2, and so on.

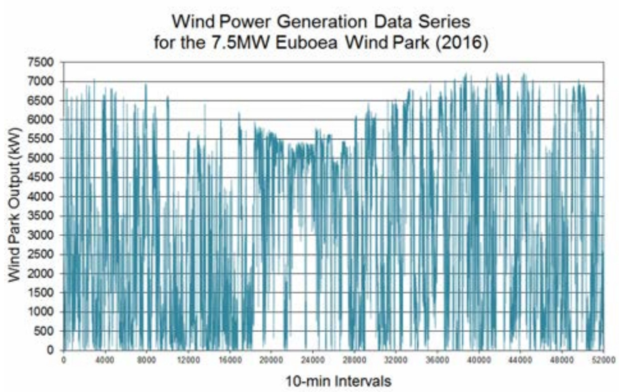

Figure 2. Wind power generation dataset of the examined wind park.

On the other hand, a single SVR model was developed for the prediction of the spot price series, with the training signal produced on the basis of the respective values 24 hours back, acknowledging that the spot price is assumed to follow a relatively consistent pattern, largely dependent on the respective load demand. As such, the time window in that case is always fixed at 24 hours, sliding for every other hour examined. For example, for the prediction of the spot price at 13:00 of D+1, the spot price of D-1 at 13:00 was used, including also an indicator of time, and so on. With regards to the respective data sample, a time series of two years was used (Fig. 3), with 17,544 values kept for the training set and 1,632 for the validation set of the model.

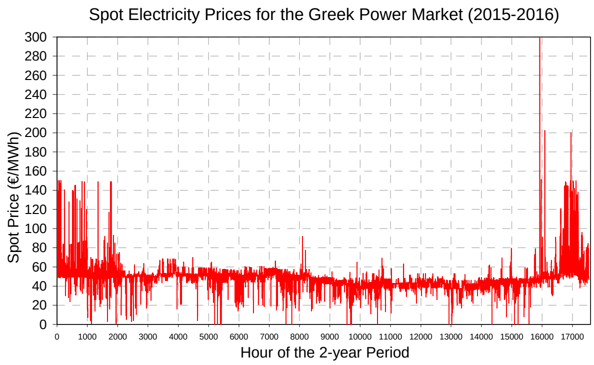

Figure 3. Greek electricity market spot price dataset.

III. APPLICATION RESULTS

A. *Prediction Profiles & Models' Performance*

Following the training and validation of forecasting models for the prediction of hourly day-ahead values, i.e. 24 individual ANN models for wind power and one single SVR model for spot prices, the metrics obtained (i.e. the correlation coefficient R^2 and the index of agreement IA of indicative wind power models and of the SVR spot price model) are given in Table 2.

As one may note, the models' performance for wind power generation gradually decays as the prediction horizon increases. In more detail, the ANN models are found to be sufficiently accurate until 6 hours ahead, with results for 24 hours ahead being determined by an R^2 of ~87% and an IA of ~65%, which, on the other hand, is found to improve considerably in comparison to previous studies based on the use of ANNs [8]. At the same time, the SVR model for the spot price seems to capture the corresponding pattern effectively, with R^2 being 99.7% and IA being 92.6%.

TABLE II. PERFORMANCE METRICS OF THE DEVELOPED MODELS

Method	Parameter	Index	1HA	6HA	12HA	24HA
ANN	Wind power	R^2	99.52%	94.84%	88.94%	87.32%
		IA	99.71%	95.32%	85.85%	64.99%
			24HA			
SVR	Spot price	R^2	99.70%			
		IA	92.59%			

The generated predictions are also presented in Figs. 4 and 5 in the form of time series, allowing for the direct comparison between predicted and ex-post (actual) values. As far as wind power generation is concerned, the predicted curve considers all 24 individual models, i.e. each hour considers the output of a separate model, while in the case of the spot price, the single model developed applies. In this context, ANNs are found to either underestimate (during times of increased generation) or overestimate (during times of low generation) the actual wind power generation, with the models failing to provide an efficient prediction as the forecasting horizon goes beyond 6 hours ahead within the daily cycle.

Moreover, similar is also the behavior of the SVR model, but without the decay in the model's performance as the prediction horizon increases. This is owed to the sliding, fixed time window of 24 hours adopted, which is assumed to take advantage of the cyclic pattern of the spot price profile expected.

Considering the entire period of study, which is narrowed down to 68 days, or 1632 hours of validated predictions, the forecasted wind energy capacity factor "CF_f" is equal to 35.9%, which is only slightly lower than the respective actual one; CF_r=36.4%. This implies that, at least in average, the models seem to balance the overestimation and underestimation noticed earlier. On the other hand, deviation from the actual wind power hourly values is anticipated to have considerable impact on the dispatching of the wind-storage configurations and on the generation of the respective bidding offers (see also following sections).

Next, the average spot price for the same period of study was found to be $Sp_{av\text{-}r}$=64.88€/MWh for the actual values and $Sp_{av\text{-}f}$=57.76€/MWh for the values obtained from the SVR prediction model, reflecting the model inability to capture frequent and also intense spot price spikes (see also Fig. 3).

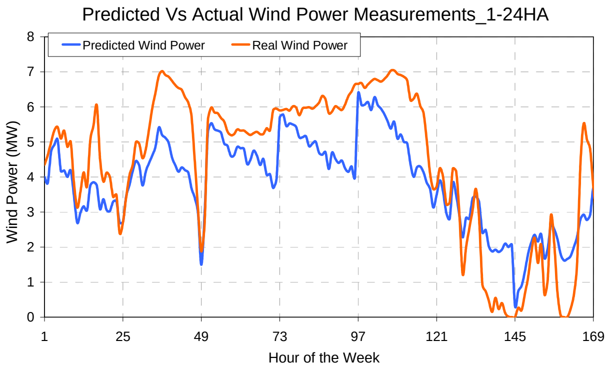

Figure 4. Actual vs day-ahead predictions of wind power generation.

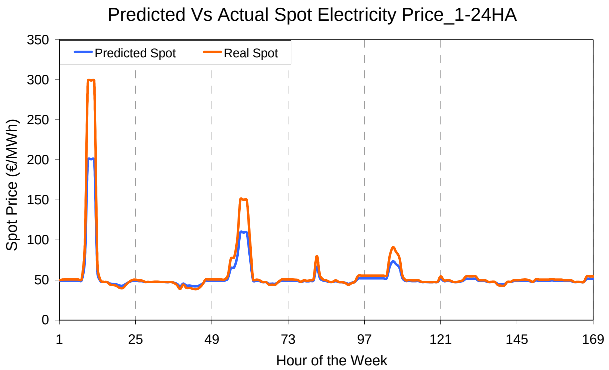

Figure 5. Actual vs day-ahead predictions of spot electricity price.

B. *Optimum Bidding Results*

Accordingly, the generated profiles of forecasted wind power and spot price are fed into the optimization engine, seeking to maximize daily net revenues. An indicative energy balance analysis for a storage cost of 100€/kWh and a period of two consecutive weeks is given in Fig. 6, in order to understand the optimization principle of the solver. As one may see, in view of considerable increase in the spot price, the solver introduces the appropriate storage capacity which is set to fully cycle (charge and discharge) within the given day's time window. At the same time, and owing to the fact that forecasting models developed underestimate the actual wind power generation and spot prices for the examined two-weeks' period, the optimum daily storage capacity becomes higher in the case of applying the ex-post approach, as also demonstrated in Fig. 7, with the full comparison between the ex-ante and the ex-post approach for the entire period of examination provided in Fig. 8.

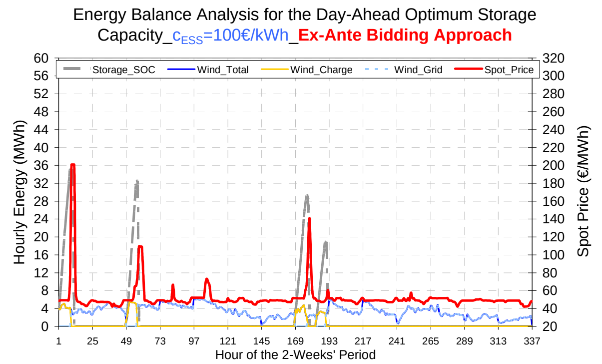

Figure 6. Ex-ante, optimum day-ahead wind-storage bidding profile.

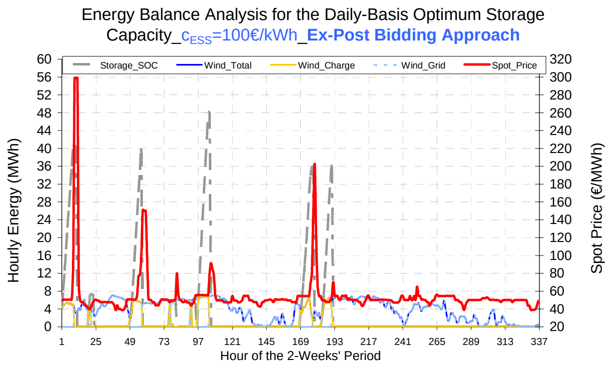

Figure 7. Ex-post, optimum daily-basis wind-storage bidding profile.

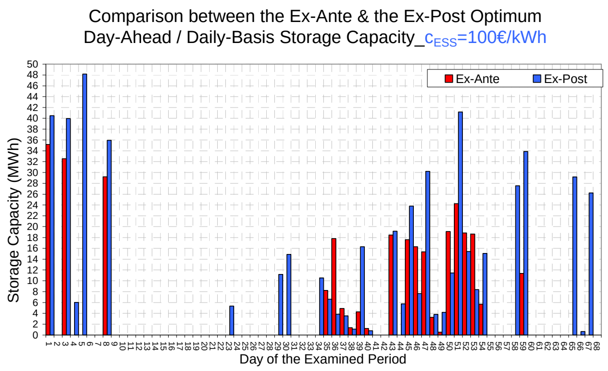

Figure 8. Optimized, daily-basis ex-ante and ex-post storage capacity.

In this context, although for most of the days studied the ex-post approach produces higher storage capacity values, there are instances where due to an overestimation of the actual wind power generation (see for example the last 48 hours of Fig. 4), the inverse behavior is eventually illustrated, i.e. the ex-ante approach produces an optimized daily storage capacity that is greater. What is even more important to stress is the fact that for a considerable number of days, no storage capacity is considered to be necessary, which in turn introduces the question whether leasing of storage capacity (e.g. capacity shares of a large pumped hydro storage plant) that facilitates the daily variation of storage needs could become an option.

To further elaborate on the variation of the optimum storage capacity, even for this limited period of 68 days currently examined, the respective cumulative probability curves of optimized, day-ahead (ex-ante approach) and daily (ex-post) storage capacity values are provided in the following Figs. 9 and 10, letting also "c_{ESS}" vary between 50€/kWh and 250€/kWh, which is equivalent of capturing a broad spectrum of energy storage technologies. To this end, as one may obtain from the two figures, the cumulative probability for zero need of storage capacity is rather important, even in the case of 50€/kWh, relating to the day-ahead scheduling and sizing time horizon as well as to the relatively narrow spot electricity price spreads defining the Greek power market.

At the same time, the impact of introducing higher storage costs is reflected on the restricted storage capacity values obtained, especially for the case of the ex-ante approach, with ex-post results allowing the storage capacity to even exceed 50MWh (~7 times the wind park installed capacity), although for a very limited time share and for the lowest of storage costs examined.

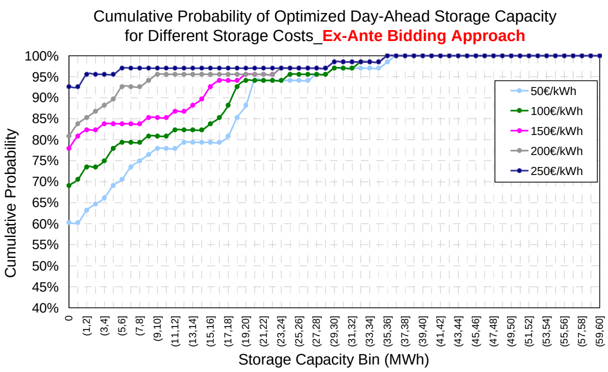

Figure 9. Optimum, ex-ante storage capacity probability curves.

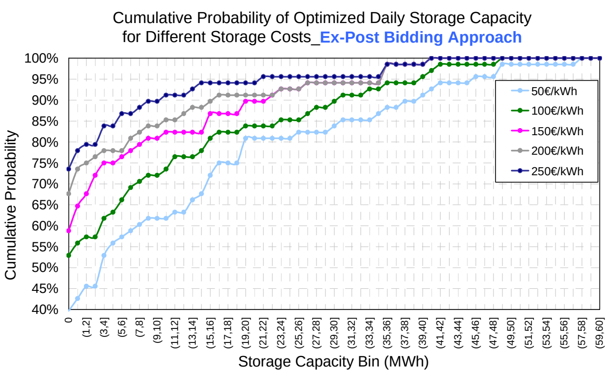

Figure 10. Optimum, ex-post storage capacity probability curves.

Acknowledging the above, the total (for the entire 68-day period) and the specific (€/MWh of energy sold to the grid) net revenue of representative storage cases (fixed storage capacity of 4MWh, 12MWh and 36MWh throughout the 68-day period) is provided in Fig. 11 and Fig. 12, compared also with the case of variable, daily-optimized storage capacity on the one hand, and the case of zero storage (ex-post, wind-only) on the other. As one may obtain from the figures, there is an appreciable difference between the estimated net revenue of the optimum, day-ahead, variable storage case and the respective fixed storage options, which increases with the increase of fixed storage capacity. At the same time, the risk of imperfect prognosis incorporated in the ex-ante approach yields considerably lower revenue expectations and discourages the adoption of higher storage capacity, even in the case of low storage costs. In the same context, high storage costs (250€/kWh) suggest net revenue that is lower than the wind-only case for all fixed storage capacities examined, with the opposite occurring for the ex-post, optimized daily storage scenario.

Similar are also the results for the specific net revenue, with the average spot price of ~65€/MWh and the respective ~63€/MWh revenue for the wind-only scenario challenged only in the case of low-cost storage and variable, daily-optimized storage capacity.

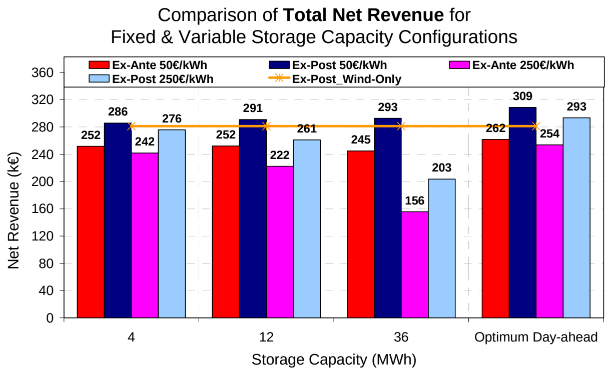

Figure 11. Net revenue for different storage configurations.

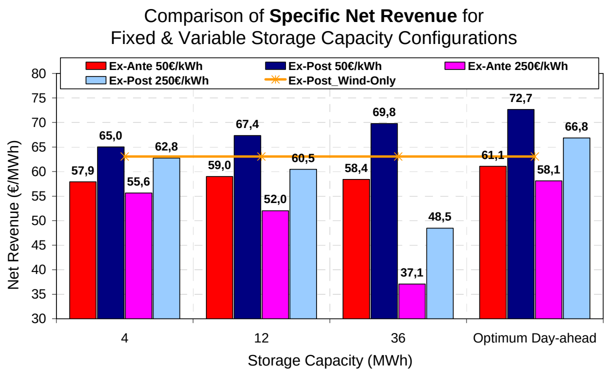

Figure 12. Specific net revenue for different storage configurations.

C. *Impact of Imperfect Prognosis*

Results demonstrated earlier, for both the ex-ante and the ex-post approach correspond to the anticipated, estimated net revenue, which however differs from the actual net revenue in that the latter should assume application of the ex-ante daily dispatch schedule under real operational conditions.

In more detail, in the current paragraph the impact of imperfect prognosis is evaluated by letting the daily, ex-ante generated bidding profile of a given wind-storage configuration to encounter the actual wind power and spot price conditions. To achieve this, we employ an in-house energy balance simulation tool which allows us to obtain the hourly performance of a given configuration, asked to meet a certain dispatch (bidding) profile. The dispatch profile corresponds to the optimized bidding offers obtained from the optimizer under the ex-ante approach. On the other hand, we use the real (ex-post) wind power generation and spot price data and compare the resulting net revenues of the two approaches.

Results obtained to this end for a fixed storage capacity of 4MWh (see also Fig. 13), demonstrate the different cycling of the storage component due to the different wind profile adopted. This also implies the generation of excess wind energy (or curtailments), as well as instances during which the day-ahead (ex-ante generated) bidding offer is eventually not met, which should in turn trigger a penalty (see also Fig. 14).

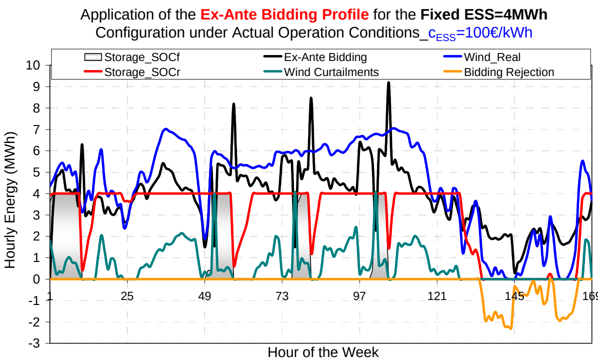

Figure 13. Design vs actual operation for fixed storage capacity of 4MWh.

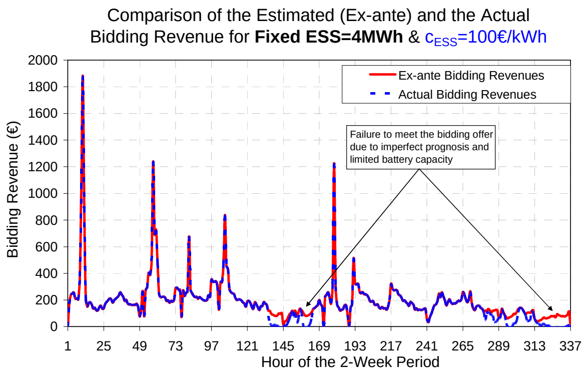

Figure 14. Design vs actual revenue for fixed storage capacity of 4MWh.

As a result, the actual revenues differ from the estimated ones, which is due to both the imperfect prognosis and the limited storage size, dimensioned in accordance with the predicted wind power generation and spot price series. To this end, the net revenue -for the specific example and for the entire period examined- was found to be overestimated by almost 18% on the basis of the ex-ante approach. At the same time, bidding rejections were equal to 17% of the ex-ante bidding offers and wind energy excess amounted to 15% of the actual wind power generation.

IV. CONCLUSIONS

According to the analysis of application results, the following main conclusions may be drawn:

- The spot price spread of the Greek market discourages the use of wind-tied storage with costs exceeding 100-150€/kWh. This seems to completely rule out batteries for the time being.
- Adoption of an ex-ante, 24 hours-ahead approach for the development of bidding offers introduces considerable risk which is not necessarily hedged by an ex-ante optimized storage component, even at the daily interval. Such risk needs to be quantified in order to allow for a rational storage oversizing, evaluating also the trade-off with the penalty cost for bidding rejection.
- Dispatch windows within the day, e.g. intra-day or quarter-day dispatching, may ameliorate the impact of imperfect forecasting, allowing also the minimization of the required storage capacity on the basis of more intense cycling, especially for wind power applications.
- Variable storage capacity on a daily interval challenges the concept of storage capacity leasing, especially in the case of large-scale pumped hydro storage plants.

ACKNOWLEDGMENT

The current study is part of a post-doctoral research supported by the Greek State Scholarships' Foundation, funded by the Action "Support of Post-doctoral Researchers" with resources of the Operational Programme "Human Resources Development, Education and Lifelong Learning" - priority axes 6, 8, 9, co-funded by the European Social Fund - ESF and the Greek State.

REFERENCES

[1] L. Bird, D. Lew, M. Milligan, E. M. Carlini, and J. Miller, "Wind and solar energy curtailment: A review of international experience," Renew Sust Energy Rev, vol. 65, pp. 577-586, 2016.

[2] Ch. Olk, D. U. Sauer, and M. Merten, "Bidding strategy for a battery storage in the German secondary balancing power market," J Energy Storage, vol. 21, pp. 787-800, 2019.

[3] A. Michiorri, J. Lugaro, N. Siebert, R. Girard, and G. Kariniotakis, "Storage sizing for grid connected hybrid wind and storage power plants taking into account forecast errors autocorrelation," Renewable Energy, vol. 117, pp. 380-392, 2018.

[4] S. Li, and C. S. Park, "Wind power bidding strategy in the short-term electricity market," Energ Econ, vol. 75, pp. 336-344, 2018.

[5] D. Zafirakis, G. Tzanes, and J. K. Kaldellis, "Forecasting of spot electricity prices with the use of support vector regression models," Global Conference on Energy and Sustainable Development, December 2018, Edinburgh, UK.

[6] D. Zafirakis, G. Tzanes G., and J. K. Kaldellis, "Forecasting of wind power generation with the use of artificial neural networks and support vector regression models," REM 2018, September 2018, Rhodes, Greece.

[7] K. Moustris, D. Zafirakis, D. H. Alamo, R. J. Nebot Medina, and J. K. Kaldellis, "24-h ahead wind speed prediction for the optimum operation of hybrid power stations with the use of artificial neural networks," 13th COMECAP, September 2016, Thessaloniki, Greece.

[8] D. Zafirakis, G. Tzanes, and J. K. Kaldellis, "An advanced microgrid simulator for stand-alone and market-dependent energy strategies," IEEE International Conference on Environment and Electrical Engineering, June 2017, Milan, Italy.