Store or Sell? A Threshold Price Policy for Revenue Maximization in Windfarms with On-site Storage

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***Abstract*—We consider the problem of maximizing the revenue of a windfarm with on-site storage, and propose and analyze a scheme for a windfarm to store or sell energy based on a threshold price. The threshold price is calculated based on long-term distributions of the electricity price and wind power generation processes, and is chosen so as to balance the energy flows in and out of the storage-equipped windfarm. We apply our method on real time data from a windfarm in New York, along with real time electricity prices from NYISO for the same region and time period. Comparing it with the optimal policy that has knowledge of the future, we observe that the revenue obtained by our threshold policy increases as the storage capacity is increased, and is approximately 90% of the maximum attainable revenue at a storage capacity of 10−15 times the power rating.**

I. Introduction

Real-time prices in modern deregulated power markets fluctuate every 5 to 10 minutes. The price at a particular time interval at a location depends on various factors such as the current generation capacity, the current load, the congestion in the system etc. Typically, windfarm owners want to maximize their profit by selling the wind power during high price hours. However, the availability of wind need not move synchronously with the price variations. It is possible that the Locational Marginal Price (LMP) is low when abundant wind is available, and it may be high when wind power is scarce.

One way to deal with this issue is on-site storage at the wind generation facility. Wind power generated at a time when the price is low, can be stored in the energy storage system (ESS) and sold later when the price is high. However, the terms "high price" and "low price" need to be defined precisely and quantitively towards developing an implementable policy that can maximize the revenue of the ESS-equipped windfarm. In other words, the question that we seek to address is: at any given time, what price is high enough for the windfarm to sell energy? In general, the optimal choice of this *threshold* price (beyond which the windfarm should sell the energy at the current time) will depend on the current system conditions such as the amount of energy stored in the ESS, and the state of the wind generation and energy price processes. Even if the wind generation and electricity prices are well modeled, determining the optimal time-dependent price threshold to sell would require solving a complex stochastic decision problem. Under Markovian assumptions on the wind generation and electricity prices, the problem can be posed as a Markov Decision Process (MDP). Such an approach is often too complex to implement in practice due to large state-space, and could also be prone to modeling and prediction errors.

The approach that we take in this paper towards solving the above problem is motivated from practical considerations. Firstly, we note that while the the wind generation and electricity prices may be difficult to model (in terms of short-term evolution at least), the statistics of these processes (in the medium to long term) are relatively stable and therefore can be well estimated through measurements over an appropriate time window. Secondly, the availability of storage in the system can allow us to "ride over" (at least partially) the short-term variations in these processes. This motivates us to consider decision policies that would be optimal in the *long term*, in presence of *sufficient* storage. This allows us to develop a *time-independent* price threshold that ensures a balance of energy flow in the system, i.e., the chosen fixed threshold price is just enough to sell all wind power generated in the real-time market, in the long run. In practice, the presence of storage capacity constraints may not allow us to implement the threshold policy (developed under the assumption of unlimited storage capacity) as is; nevertheless, we attempt to emulate it as closely as possible. The corresponding policy, which applies to a limited-capacity ESS equipped windfarm as well, is termed the *Energy-balancing Threshold Price (ETP)* policy. Calculation of this threshold price requires knowledge of the statistics of the wind power generation and electricity prices, and that these statistics remain stable over the optimization period. However, it avoids complex modeling of these power generation and price processes; the required distributions can be obtained through measurements.

Previous literature on this topic has tried to address these questions in both stochastic and deterministic frameworks. In [1], energy storage is used to minimize the deviations in day-ahead contracts. [2] and [3] focus on the joint optimization of wind generator and pumped-hydro storage through a two stage stochastic optimization scheme. In [4], two energy storage units are used to optimize a windfarm dispatch. [5] maximizes the predicted windfarm profit by finding the optimal strategy for combined operation of a wind power plant and on-site pumped hydro storage. In [6], the day ahead operation of windfarm with on-site storage is optimized using a continuous-state Markov decision process and approximate dynamic pro-

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gramming. [7]–[9] are other similar studies that address the optimization of operation of windfarms with on-site storage, but from different perspectives.

In this paper, we propose and analyze a simple fixed price-threshold policy towards optimizing the long-term revenue of the windfarm with on-site storage. Our choice of the "energy-balancing" threshold price is motivated by our prior work on designing a near-optimal activation policy for rechargeable sensors [10]. A novel feature of our approach over existing work is its simplicity, and its reliance on only the statistics of the power generation and price processes (assumed to remain stable over the optimization horizon). We also observe that under more realistic constraints of limited energy storage capacity (say $10-15$ times the power rating of the system) and optimization window (say a 4-week period), the performance attained by our ETP policy is approximately 90%, when compared to the optimal *prescient* policy that possesses full knowledge of the future evolution of power generation and price processes.

The rest of this paper is organized as follows. In Section II, we describe the system model and formulate the optimal prescient policy (against which our ETP policy will be compared with) that assumes exact knowledge of the future in optimizing the system. In Section III, we describe the ETP policy, and derive the expression for the energy balancing threshold price for both cases of with and without efficiency loss in the ESS. In Section IV, we present and discuss the results of our method on actual wind and price data sets obtained from NREL Eastern Wind Integration Study (EWIS) and NYISO. We conclude in Section V.

II. System Model and Upper Bound on Revenue

We consider a wind power plant with an ESS as shown in Fig. 1. The power rating of the windfarm is d MW; the power rating of the ESS is also d MW. The output of windfarm and ESS are coupled with a converter or a transformer of the same power rating. So the maximum amount of power that can be supplied by the system is d MW.

An upper bound on the revenue that can be earned by the windfarm could be obtained by an economic dispatch under *perfect forecast* of the future wind and price data. We will use this for bench-marking the performance of the proposed ETP policy. This can be posed as a linear program (LP) as desribed below. Let $t \in \{1, 2 \ldots T\}$ be the time window over which the revenue has to be optimized. Also, let Λ_t and G_t represent the price and available wind generation at time t, respectively.

The maximization objective is:

$$\max(\sum_{t=1}^{T} \Lambda_t \times P_t), \quad (1)$$

where P_t is the power dispatched in period t. The state of the ESS evolves as follows:

$$S_t = \begin{cases} S_{t-1} + G_t - P_t & 0 \le P_t \le G_t, \\ S_{t-1} + \left(\frac{G_t - P_t}{\eta}\right) & G_t < P_t \le d. \end{cases} \quad (2)$$

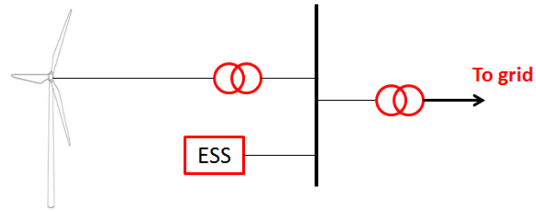

Fig. 1. Windfarm and ESS system.

where S_t is the amount of energy available in the ESS at end of time interval t and η is the efficiency of the ESS.

Additionally, the maximization must be performed under the applicable power rating and availability constraints,

$$0 \le P_t \le \min(d, S_t + G_t), \quad (3)$$

as well as the storage capacity constraints,

$$0 \le S_t \le C, \quad (4)$$

where C is the capacity of the ESS.

For $\eta = 1$, the constraint in (2) becomes a single equation. The maximum possible revenue, i.e., an upper bound on windfarm revenue can be obtained by maximizing the objective function in (1) subject to the constraints in (2) $-$ (4) with accurate knowledge about the future wind and price data.

III. Energy-balancing Threshold Price policy

While it is not possible to obtain accurate future data, it is likely that reasonably accurate statistics for price and wind in medium to long term time frames can be obtained using historical data and other forecasting techniques. In this section, we will present a policy for obtaining near optimal revenues based on a threshold price, and also derive expressions for the calculation of the threshold price level R_β.

A. The threshold price policy

We start by assuming that the ESS has an infinite capacity to store energy. Suppose the price can take on m discrete values from $(R_1, R_2 \ldots R_m)$ such that:

$$R_1 < R_2 < \ldots R_{m-1} < R_m$$

The windfarm would like to sell the generated energy in the highest priced hours to maximize its profit subject to its power rating d. We consider a threshold price level R_β and propose the following method for the amount of power P_t, sold in interval t:

$$P_t = \begin{cases} \min(d, S_t + G_t) & \Lambda_t > R_\beta, \\ \min(d, S_t + G_t) \text{ with probability } q & \Lambda_t = R_\beta, \\ 0 & \Lambda_t < R_\beta. \end{cases} \quad (5)$$

Now to obtain the expressions for R_β and q, let us model the windfarm power and electricity prices as Markovian processes. Suppose that there are N discrete levels of power that can be generated by the windfarm $(W_1, W_2 \ldots W_N)$, with W_N being the maximum power rating of the windfarm, i.e., $W_N = d$. If the Markov process modeling the wind generation is irreducible and aperiodic, then the stationary distribution $\boldsymbol{\lambda}$ can be calculated as [11]:

$$\boldsymbol{\lambda} = \mathbf{1}^N (I - \boldsymbol{W}^{N\times N} + \mathbf{1}^{N\times N})^{-1}. \tag{6}$$

where $\{\lambda_1\lambda_2\ldots\lambda_N\}$ are elements of $\boldsymbol{\lambda}$ and represent the stationary distribution probability of having wind power generation as $\{W_1, W_2 \ldots W_N\}$. $\boldsymbol{W}^{N\times N}$ is the probability transition matrix for wind power generation, with element W_{ij} given as:

$$W_{ij} = Prob(G_t = W_j \mid G_{t-1} = W_i).$$

The total expected wind generation can be given as:

$$E_W = \sum_{i=1}^{N} \lambda_i W_i = \mu. \tag{7}$$

Similarly, if the Markovian process modeling the electricity price is also irreducible and aperiodic, we can calculate the stationary distribution vector $\boldsymbol{\pi}$ for LMPs as:

$$\boldsymbol{\pi} = \mathbf{1}^m (I - \boldsymbol{R}^{m\times m} + \mathbf{1}^{m\times m})^{-1}, \tag{8}$$

where $\{\pi_1\pi_2\ldots\pi_m\}$ are elements of $\boldsymbol{\pi}$ and represent the stationary distribution probability of having LMPs as $\{R_1, R_2 \ldots R_m\}$. $\boldsymbol{R}^{m\times m}$ is the Markovian probability transition matrix for LMPs with elements R_{ij} given as:

$$R_{ij} = Prob(\Lambda_t = R_j \mid \Lambda_{t-1} = R_i).$$

B. Threshold price with no efficiency loss

During the total time window T, the expected time over which the windfarm can supply power at a rate of d is $\frac{\mu T}{d}$.

Let

$$\beta = \max_k \left(k : \left[\sum_{i=k}^{m} \pi_i \; - \frac{\mu}{d} \right] \geq 0 \right), \tag{9}$$

$$\phi = \sum_{i=\beta+1}^{m} \pi_i. \tag{10}$$

The windfarm owner wants to sell the energy in hours with the highest price levels. With an infinite energy storage capacity, it is possible to store energy for an indefinite period of time and sell it when the price is high. If we equate the expected amount of energy generated with the expected amount of energy sold, we have:

$$\mu T = T \left[d\,\pi_m + d\,\pi_{m-1} + \ldots d\,\pi_{\beta+1} + d\,q\pi_\beta \right], \tag{11}$$

$$q = \frac{\mu - \phi d}{d\,\pi_\beta}, \tag{12}$$

where q is the probability at which the windfarm owner will sell if the price is equal to the threshold value of R_β as mentioned in (5). It can be shown that with a price threshold R_β, we get a revenue that is no less than the revenue obtained by using any other threshold price R_i, $\forall i \neq \beta$.

C. Threshold price with efficiency loss

In order to find the threshold price when there is efficiency loss due to the storage device, we will reduce the amount of expected wind energy to account for the losses due to ESS inefficiency. Let the ESS have an efficiency of η. Suppose $0 \leq \rho \leq 1$ is the fraction of time the windfarm owner sells the energy in the market. Some of the wind energy is sold directly without any efficiency loss and the rest is stored in ESS to be sold later. This would reduce the expected available wind energy due to ESS inefficiency. Then, under the assumption that wind generation and prices are independent events, the expected available energy over the time window under consideration can be represented as:

$$[\mu\rho + \mu(1-\rho)\eta] \times T. \tag{13}$$

Now, if we equate the expected amount of energy generated with the expected amount of energy sold, we have:

$$[\mu\rho + \mu(1-\rho)\eta] \times T = \rho \times T \times d. \tag{14}$$

$$\rho = \frac{\eta\mu}{d + \eta\mu - \mu}. \tag{15}$$

For this case, let

$$\beta = \max_k \left(k : \left[\sum_{i=k}^{m} \pi_i \; - \frac{\eta\mu}{d + \eta\mu - \mu} \right] \geq 0 \right). \tag{16}$$

$$\phi = \sum_{i=\beta+1}^{m} \pi_i. \tag{17}$$

Since ρ is the fraction of time the windfarm sells power in the market,

$$\rho = \phi + q\pi_\beta. \tag{18}$$

where q is the probability at which the windfarm owner will sell if the price is equal to the threshold value of R_β. This can be calculated from (15) and (18) as:

$$q = \frac{1}{\pi_\beta} \left[\frac{\eta\mu}{d + \eta\mu - \mu} - \phi \right]. \tag{19}$$

IV. Simulation Results

In this section we will compare the revenue from ETP with the maximum revenue that can be obtained under perfect forecast, and show that revenues from ETP are near optimal. We apply our proposed ETP policy on a windfarm from NREL EWIS [12] in Capital region of New York state. We use wind power data for 4 weeks from July-1-2006 to July-28-2006 and normalize the wind generation values to a windfarm power rating of 1 MW ($d = 1$). We start the operation of windfarm and on-site storage system of power rating 1 MW at 00:00 Hrs on Saturday July-1-2006 and end it after continuous operation for four weeks at 00:00 Hrs on Saturday July-28-2006. We use the 5-minute real time LMP data from NYISO for the same region and time period [13]. We use this data to obtain the statistics (distributions) for wind generation and prices. We consider three cases in our analysis. In Case 1, we have no efficiency loss, i.e., $\eta = 1$. In Case 2, we consider a 90% efficiency loss, i.e., $\eta = 0.9$. In Case 3, we consider no efficiency loss (i.e., $\eta = 1$), but we use imperfect statistics for wind and price, obtained from the wind and price data for the same month in the past two years. For all cases, we calculate the revenue earned by the windfarm using our policy and also observe the level of energy storage during that period. We also obtain the upper bound on revenue by maximizing the objective function in (1), subject to constraints in (2) $-$ (4) for all cases. We do these calculations for different storage sizes.

A. Case 1: No efficiency loss

In this case, we assume that there is no efficiency loss in the ESS, i.e., $\eta = 1$. We use the wind and price data to obtain the corresponding distributions. We then calculate the threshold price R_β and the selling probability q at the threshold price, using (9) and (12). We first run our policy with an unlimited storage capacity. The storage levels reached with an unlimited storage capacity for the entire period are shown in Fig. 2. It can be seen that one would need a very high storage capacity of about 45 MWhr i.e., 45 times the size of windfarm capacity for implementing the policy over a duration of four weeks. In order to observe the effect of limited storage capacity, we run our policy on the same windfarm and same price data with different capacities for on-site storage.

We also run a linear program to maximize the objective function in (1) subject to the constraints in (2) $-$ (4) with the actual wind and price data to obtain the upper bound on revenues with $\eta = 1$. The storage levels reached during this optimization are shown in Fig. 3 for unlimited storage capacity. The revenues from our policy and the upper bound values for different storage capacities are shown in Table I.

B. Case 2: 10% efficiency loss

In this case, we assume that there is a 10% efficiency loss in the storage device, i.e., $\eta = 0.9$. Using the same data from Case 1, we calculate the threshold price R_β and the selling probability q at the threshold price, using (16) and (19) respectively. We run our policy with unlimited storage capacity. The storage levels required in this case at different times are shown in Fig. 4. We then use the same threshold price level on limited storage capacities and run our policy. The results of revenues obtained for different storage sizes are shown in Table II.

Similar to Case 1, we also maximize the objective function in (1) subject to constraints (2) $-$ (4) with $\eta = 0.9$ for actual price and wind data. We do this for both unlimited and limited storage capacities. The storage levels reached to achieve the upper bound revenues when the storage capacity is unlimited are shown in Fig. 5. These upper bound revenues for different storage sizes for Case 2 are shown in Table II.

C. Case 3: Imperfect statistics

In this case, we assume that there is no efficiency loss in the ESS, i.e., $\eta = 1$. However, we obtain the statistics for wind power and LMPs from the historical data of the same

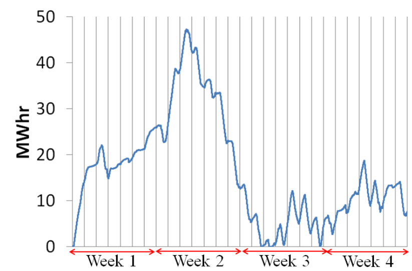

Fig. 2. Storage levels in MWhr when a 1MW windfarm and ESS with unlimited capacity are operated using ETP for Case 1, ($d = 1$MW, $\eta = 1$).

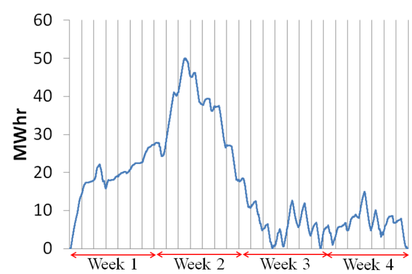

Fig. 3. Storage levels in MWhr when a 1MW windfarm and ESS with unlimited capacity are operated using a linear program to achieve upper bound revenues for Case 1, ($d = 1$MW, $\eta = 1$).

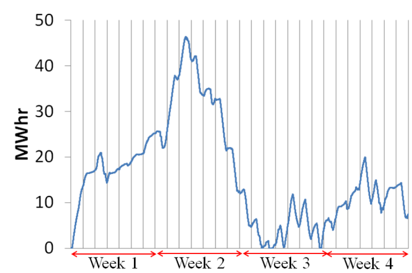

Fig. 4. Storage levels in MWhr when a 1MW windfarm and ESS with unlimited capacity are operated using ETP for Case 2, ($d = 1$MW, $\eta = 0.9$).

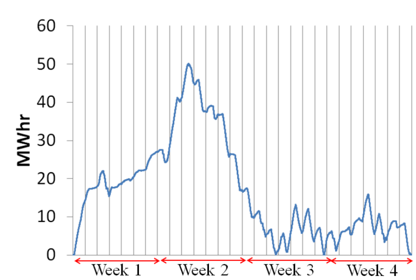

Fig. 5. Storage levels in MWhr when a 1MW windfarm and ESS with unlimited capacity are operated using a linear program to achieve upper bound revenues for Case 2, ($d = 1$MW, $\eta = 0.9$).

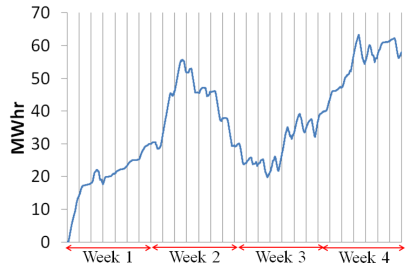

Fig. 6. Storage levels in MWhr when a 1MW windfarm and ESS with unlimited capacity are operated using ETP for Case 3 i.e., using imperfect statistics, ($d = 1$MW, $\eta = 1$).

time period during the last two years. Using this imperfect forecast we calculate the threshold price according to the same principles as Section III. We use the threshold price from imperfect statistics in our policy on the same time period and observe different results. The storage levels reached with an unlimited storage capacity for the entire period are shown in Fig. 6. It can be seen that the requirement on the storage size has increased significantly because the statistics were not perfect. The revenues for different storage sizes with this threshold price are shown in Table III. The corresponding upper bound revenues for Case 3 are same as the upper bound revenues for Case 1 (note that $\eta = 1$ in both cases).

D. Discussion

The threshold prices and maximum storage levels for all cases are listed in Table IV. It can be seen from Figs. 1−4 and Table IV that one would need a very high storage capacity of about 45−50 MWhr, i.e., 45−50 times the size of windfarm power rating for operating consecutively for four weeks and also for achieving upper bound revenues. The results from Table I and II show that as the storage size is increased, the revenues from the ETP approach the upper bound obtained with perfect knowledge of the future data. For ESS with a capacity of about 10 times the power rating, one can obtain revenues about 90% of the upper bound.

It should be noted that the upper bound on the revenues is calculated assuming perfect knowledge of the future wind and price data for four weeks. On the other hand, the ETP policy which only uses knowledge about the distribution statistics of price and wind provides about 90% of the upper bound revenue when the storage capacity is about 10 to 15 times the power rating, which seems to be a realistic storage size in practice. Any increase in the storage capacity above these levels results in only a minor increase in revenue as it approaches the upper bound. Due to this diminishing marginal return on the storage size, any further investment in storage capacity might not be profitable enough. This also leads us to conclude that the ETP policy presented in this paper (used to sell or store wind energy based on the threshold price calculations shown in Section III) will yield near optimal results (approximately within 90% of optimal revenue) even when we have a reasonably limited storage capacity. We also observe from Fig. 6 that the storage level reaches higher values when we have imperfect statistics. Table III shows that when the statistics are not accurate, the revenues from ETP are somewhat less. Nevertheless, the revenue obtained by ETP policy is still between 85−90% of the upper bound.

TABLE I
REVENUES IN \$/MW OF SYSTEM CAPACITIES FOR DIFFERENT CAPACITY OF ENERGY STORAGE FOR CASE 1 ($d = 1$MW, $\eta = 1$).

Storage Capacity (MWhr)	Using ETP method	Upper Bound using LP	ETP revenue as % of upper bound
0	\$13,723	\$13,723	100%
5	\$16,058	\$18,916	84.9%
10	\$17,253	\$19,395	89.0%
15	\$17,875	\$19,635	91.0%
20	\$17,890	\$19,755	90.6%
25	\$18,091	\$19,810	91.3%
30	\$18,535	\$19,854	93.4%
35	\$18,856	\$19,889	94.8%
40	\$19,053	\$19,913	95.7%
45	\$19,163	\$19,927	96.2%
unlimited	\$19,255	\$19,931	96.6%

TABLE II
REVENUES IN \$/MW OF SYSTEM CAPACITIES FOR DIFFERENT CAPACITY OF ENERGY STORAGE FOR CASE 2 ($d = 1$MW, $\eta = 0.9$).

Storage Capacity (MWhr)	Using ETP method	Upper Bound using LP	ETP revenue as % of upper bound
0	\$13,723	\$13,723	100%
5	\$15,241	\$18,149	84.0%
10	\$16,611	\$18,609	89.3%
15	\$16,956	\$18,840	90.0%
20	\$17,055	\$18,952	90.0%
25	\$17,104	\$19,008	90.0%
30	\$17,556	\$19,052	92.1%
35	\$17,867	\$19,086	93.6%
40	\$17,970	\$19,111	94.0%
45	\$18,068	\$19,125	94.5%
unlimited	\$18,087	\$19,130	94.5%

V. CONCLUSION

We present and analyze a simple policy for windfarms with on-site storage to determine when to buy and sell energy to the market. The policy sells power (subject to availability of energy through wind generation or in storage) whenever the price exceeds a certain fixed threshold. The proposed energy-balancing threshold price (ETP) policy attempts to sell energy at the highest prices, subject to attaining a balance between the energy inflow and outflow from the system in the long run. A practically appealing feature of our policy is that it can be determined only based on the long term statistics (steady state distributions) of the wind power generation rates and electricity prices, and does not require complex modeling or prediction of how these random processes evolve. Comparison with a idealized prescient policy shows that the revenue obtained by our policy is about 90% of maximum attainable revenue (computed using knowledge of future prices and wind power generation rates) with limited storage capacity of 10−15 times the power rating of the windfarm.

TABLE III
REVENUES IN \$/MW OF SYSTEM CAPACITIES FOR DIFFERENT CAPACITY OF ENERGY STORAGE FOR CASE 3 (USING IMPERFECT STATISTICS, $d = 1$MW, $\eta = 1$).

Storage Capacity (MWhr)	Using ETP method	Upper Bound using LP	ETP revenue as % of upper bound
0	\$13,723	\$13,723	100%
5	\$16,322	\$18,916	86.3%
10	\$17,072	\$19,395	88.0%
15	\$16,968	\$19,635	86.4%
20	\$17,008	\$19,755	86.1%
25	\$17,060	\$19,810	86.1%
30	\$16,927	\$19,854	85.3%
35	\$16,778	\$19,889	84.4%
40	\$16,633	\$19,913	83.5%
45	\$16,321	\$19,927	81.9%
unlimited	\$16,311	\$19,931	81.8%

TABLE IV
THRESHOLD PRICES AND MAXIMUM STORAGE LEVELS.

Case	Threshold Price R_β (\$/MWhr)	Maximum Storage Level (MWhr)
Case 1 ETP	\$80	47.35
Case 1 LP	NA	50.06
Case 2 ETP	\$80	46.39
Case 2 LP	NA	50.13
Case 3 ETP	\$82	63.25

From a theoretical perspective, several related questions remain open for future investigation. We believe that the proposed ETP policy can be shown to be optimal (in terms of the long-term revenue generated) under the Markovian assumptions on the wind power generation and future price processes as stated earlier in the paper. This belief is based on our analysis of a similar energy-balancing threshold policy for a different yet related rechargeable sensor activation model in our prior work [10]. In [10], we showed that a similar energy-balancing threshold policy approaches the optimal performance (for the system considered in that paper), as the energy storage capacity grows unlimited. While we believe that the same line of analysis can be used to obtain a similar result for the model in the current paper, this remains to be formally shown. Note that the calculation of the threshold price only depends on the long-term distributions of the wind power generation and electricity price processes. The optimality of the ETP policy for large energy storage capacities may therefore hold for a broader class of power generation and price processes (beyond Markovian), possibly over all processes whose long-term distributions converge. Similarly, whether the independence between the power generation and price processes (which may not strictly hold in practice) is needed to provide the optimality of ETP also remains to be investigated. These are some questions that could be explored in future work.

From a practical perspective, it may be worth exploring whether the performance difference (about 10% for reasonable storage capacities) between the ETP policy and the optimal prescient policy can be bridged further, utilizing information on the current system state (say the amount of energy in the storage) or limited predictability of the power generation and price processes. Validating the performance results over a larger class of data sets also remains to be done. We plan to explore and report our results on some of the above mentioned issues in a full version of this work.

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