THE USE OF BESS FOR THE INTEGRATION OF WIND ENERGY

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Abstract – In this paper we investigate the use of Battery Energy Storage System (BESS) for the integration of wind energy. We study two applications: energy time-shifting and capacity firming. Scheduling routines based on various approaches are programmed to work out the optimal schedule for the charging and discharging of the BESS for these applications. The approaches we studied are based on heuristics, deterministic, stochastic and robust optimization. The results and the performance of these approaches are reported and analyzed in this paper.

Keywords: BESS, energy storage, integration of wind energy, deterministic optimization, stochastic optimization.

1 INTRODUCTION

The recent increase in wind energy in power system production is a result of global effort in the reduction of CO_2 emission. While we can profit from having more green energy, such intermittent and fluctuating energy source, wind, is posing a lot of technical challenges to the transmission or distribution network operators. Even with the improvement of weather forecast technologies, the forecast errors can still be sufficient enough to cause operational challenges.

Energy storage is a technology which can help alleviate the fluctuation and intermittency of wind farms. In this article, the authors focus on Battery Energy Storage System (BESS) with different battery technologies such as Li-ion, NaS, Lead Acid, etc. which can exhibit different technical and economical characteristics such as minimum discharging time, cycle efficiency, maximum number of complete charge-discharge cycles and cost/kW or cost/kWh. For example, Li-ion batteries can be discharged very rapidly, i.e. in minutes without damaging the cells; while NaS is only suitable for slow discharge applications, i.e. up to hours, and have a relatively high maximum number of charge-discharge cycles, which implies a longer lifetime.

We look into two applications: capacity firming and energy time-shifting for wind. Capacity firming refers to the increase of minimum output of the wind facilities over a certain period by charging the BESS when the original output is high and discharging when it is low. Energy time-shifting is similar, except that the objective is to maximize the gain from energy markets by buying (charging) when the prices are low and selling (discharging) when the prices are high. There is a possibility of combining the two applications when the low-price period coincides with the high wind production period.

Simulation models which represent the different types of batteries have been developed in order to investigate the technical and financial profits one can theoretically achieve with the BESS. Technical profits can be measured through the amount of firmed capacity for the wind facilities while financial ones can be measured through the monetary gains from selling energy and capacity to the various energy markets. The results of this paper are obtained using realistic market and wind data from Europe while taking into account the local energy policies and market rules.

Five approaches have been implemented for finding an optimal daily schedule of the BESS:

- deterministic optimization with predicted prices
- heuristics with predicted prices
- robust optimization with uncertain prices for the worst case price scenario
- optimization with uncertain prices for the best case price scenario
- stochastic optimization with stochastic prices

The optimization routines employ MILP (Mixed Integer Linear Programming) while robust optimization uses also YALMIP [1][2], a MATLAB based modelling language for rapid development of optimization based algorithms. Besides the best case scenario optimization which requires the CPLEX MIQP (QP = Quadratic Programming) solver, we use the SCIP solver [3]-[5] to solve all the other optimization problems in this paper. These different approaches, their simulation results, as well as their performances will be presented.

2 BESS

Utility-scale energy storage exists since decades in the form of hydro pumped storage. The advantages of this technology are that such storage can respond relatively fast and reliably for power systems' needs. However, the installation sites are limited by the geological conditions. Utility-scale CAES (Compressed Air Energy Storage) is becoming topical. However, special requirements on the installation site apply because of the need of sealed underground air pockets or caverns to store the compressed air.

Advanced battery systems are not restricted to geology like hydro pumped storage and have higher energy density than CAES. With the advance of battery technologies, their life cycle has also improved. Another advantage of BESS is that it can provide fast response for power systems' needs such as frequency regulation or other ancillary services. Batteries using lead acid or Li-ion technologies are suitable for such applications. Indeed in some markets in the USA have modified their market rules to allow for the participation of energy storage in the regulation markets [6].

For applications which only require slow charging/discharging, e.g. capacity firming for wind, NaS (Sodium-Sulphur) or NaNiCl (Sodium-Nickelchloride) batteries are suitable. Sodium-based batteries operate in a high temperate environment (300C°). Their advantages are high energy and power density, high efficiency and long life cycle. They are at the moment less costly than Li-ion batteries [7]. Figure 1 shows an overview of the performance of various storage technologies based on the installations as of end 2008 [8].

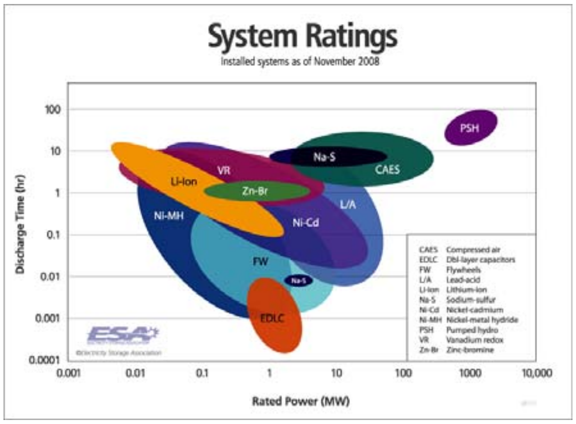


Figure 1 Performance of Energy Storage Technologies: Discharge Time Vs Rated Power (Source: Electricity Storage Association)

3 APPLICATIONS OF BESS

3.1 Energy Storage for the Integration of Wind

One of the challenges of integration renewable energy such as wind is the intermittency. The security of supply improves little when adding new wind farm than adding a traditional dispatchable plant [9]. Wind energy exhibits in all time scale, i.e. wind can stop blowing in seconds and the total wind output from a year to the next can be very different.

With batteries such as Li-ion which can perform fast charging and discharging, both short-term and longer term fluctuations can be alleviated. In this paper we only focus on longer-term applications, i.e. with a time scale of hours. Therefore the batteries which are suitable technically and economically are NaS or NaNiCl. It is foreseen that the price of Li-ion batteries will drop significantly in the next few years due to the popularity of EV (Electric Vehicles). When that happens, Li-ion will become an interesting option because of its ability of fast charging/discharging. The applications which are considered in this paper are wind energy time-shifting and capacity firming.

3.2 Wind Energy Time-Shifting/Trading

Wind energy time-shifting/trading is an application to optimize the gain from selling energy markets by storing the energy when the prices are low and releasing the energy when the prices are high. This is especially interesting for daily cycles with wind generation because in many situations there is often excess generation during night time while the prices are low (since the demand is low). If the difference between the high and low prices is enough to offset the charging cycle losses then it makes sense to use the energy storage. The concept is illustrated in Figure 2. The diagram shows the optimal charging/discharging of the BESS in a daily cycle for two consequent days with the objective of maximizing the gain from selling energy to an energy market in Europe.

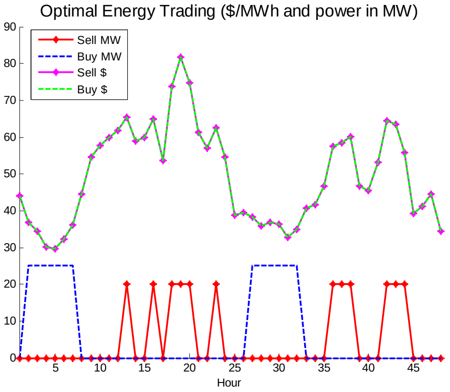


Figure 2 Illustration of Energy Time-Shifting using BESS

In this paper we assume that wind generation can now participate in the energy markets. It should be noted that nowadays wind energy does not participate in energy markets and that wind generation owners are given feed-in tariffs instead. Sometimes it is the system operator who has to take the wind energy as it comes and gets reimbursed with the market prices set by other generation facilities in the system, i.e. it is a price-taker. However, with the increasing amount of wind energy in the system such practice has proven to be a big technical and financial liability to some system operators, e.g. when market prices become negative. Because of this and other reasons it is possible that regulation can change in the future to allow wind facilities to participate in energy markets.

3.3 Wind Capacity Firming

Wind Capacity Firming refers to the increased available capacity of the wind facilitates over a certain period of time. In this paper the duration we assume is one day. In reality most of the capacity markets worldwide require generation companies to commit the firmed capacity over a longer duration, e.g. 1 year. However, with the uncertainties coming from wind energy production it is not possible for wind capacity to participate over such a long period. For day-ahead markets (for capacity), the prediction error of wind output is confined and the use of energy storage can help increasing the available capacity over the next day. Figure 1 shows an illustration of this effect based on real data from a German wind farm.

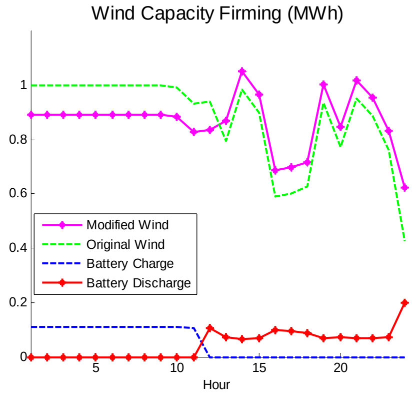


Figure 3 Illustration of Wind Capacity Firming using BESS

4 PROBLEM FORMULATION

4.1 Energy Time-Shifting/Trading

Two algorithms are used to work out the optimal schedule of the BESS operation: MILP and heuristics. The formulation of the MILP problem is described as follows.

The objective function is given by:

$$\min F\left(X \cdot C\right) \qquad (1)$$

where F is the cost function and X comprises the following continuous and binary control variables:

$$X_{sell}^{cont} = [x_{sell1}^{cont}, x_{sell2,...,}^{cont} x_{selli,...,}^{cont} x_{sell24}^{cont}]$$

$$X_{buy}^{cont} = [x_{buy1}^{cont}, x_{buy2,...,}^{cont} x_{buyi,...,}^{cont} x_{buy24}^{cont}]$$

$$X_{sell}^{bin} = [x_{sell1}^{bin}, x_{sell2,...,}^{bin} x_{selli,...,}^{bin} x_{sell24}^{bin}]$$

$$X_{buy}^{bin} = [x_{buy1}^{bin}, x_{buy2,...,}^{bin} x_{buyi,...,}^{bin} x_{buy24}^{bin}] \qquad (2)$$

where $i = 1, 2, ..., 24$ represent the different hours of the day and C is the price curve comprising the hourly prices of the day.

The equations which govern the relationships between the variables are as follow:

$$\sum_{i=1}^{24} x_{selli}^{cont} - \mu \sum_{i=1}^{24} x_{buyi}^{cont} = 0 \qquad (3)$$

$$x_{selli}^{cont} \leq -\mu \cdot x_{buyi}^{bin} + \mu cap_{hourly}$$

$$x_{buyi}^{cont} \leq -x_{selli}^{bin} + cap_{hourly} \qquad (4)$$

$$\forall i = 1, 2, ..., 24$$

Equation 3 represents the conservation of energy in the daily cycle taking into account the charging/discharging cycle efficiency, μ, of the battery. It also makes sure that the SoC (State of Charge) of the battery returns to the initial state at the end of the day, which is assumed to be zero, i.e. an empty battery is given at the beginning of each day. In this article, the losses are taken into account by the fact that one has to buy more than what one can sell afterwards. For example, if the efficiency is 80%, one would have to buy 1 unit in order to be able to sell 0.8 unit afterwards.

Equation 4 ensures that battery cannot both charge and discharge in the same hour with the help of the binary variables for the decision to sell (discharge) or to buy (charge). At the same time, it also ensures that the energy one can sell or buy does not exceed the hourly capacity of the BESS, cap_{hourly}, which can be a restriction imposed by the converter or the battery itself.

In order to ensure that the BESS does not operate more than one complete charging cycle per day, the following constraint is enforced:

$$\sum_{i=1}^{24} x_{buyi}^{cont} \leq cap_{total} \qquad (5)$$

where cap_{total} is the total energy storage capacity of the BESS. It is a non-compulsory operational constraint which is imposed after observation of the results and its rationale will be explained in the next section.

Finally and obviously, the following has to be respected:

$$\begin{aligned} & x_{selli}^{cont} \geq 0 \\ & x_{buyi}^{cont} \geq 0 \\ & x_{selli}^{bin} = [0,1] \\ & x_{buyi}^{bin} = [0,1] \qquad \forall i = 1, 2, ..., 24 \end{aligned} \qquad (6)$$

The second algorithm is based on heuristics and it attempts to find the optimal schedule by locating the high and low prices of the day and matching them to form the best moments for selling/buying. The general procedure is described as follows:

1. Find one of the maxima (1st one)
2. Search the minimum with lower index than the index of the actual maximum
3. First pair of selling/buying is scheduled

4 Take the next maximum

5a. Search the minimum with lower index than the index of the actual maximum OR

5b. Find the minimum with higher index but lower index than one of the actual scheduled maxima with constrains that the corresponding scheduled minimum has a lower index than the actual maximum and the same amount of energy can be obtained (bought) from this minimum.

6. If total scheduled energy = maximum capacity, stop; else back to step 4.

4.2 Wind Capacity Firming

Similarly, LP and heuristics are used to work out the optimal schedule for this application. The formulation of the LP problem is described as follows. It should be noted that no integer variables are needed to solve this problem.

The objective function is given by:

$$\max cap_{firmed} \qquad (7)$$

where cap_{firmed} represents the firmed capacity of the wind farm for the day and it is also the minimum capacity in power unit (MW/kW) for all the 24 hours in the day. This is formulated as follows:

$$cap_{firmed} + x_i^{charge} \le b_i^o \qquad \forall i = 1,2,...,12$$

$$cap_{firmed} - x_j^{discharge} \le b_j^o \qquad \forall j = 13,14,...,24$$

$$\ldots.. \qquad (8)$$

where x_i^{charge} is the amount of energy charged while $x_j^{disharge}$ is the amount of energy discharged in the hour i or j. $b^o{}_i$ and $b^o{}_j$ are the original power output from the wind facilities. To simplify the formulation it is assumed that the battery should only charge during the first 12 hours and should only discharge during the last 12 hours of the day. This is a realistic assumption since wind usually blows stronger during night time, especially for off-shore wind farms. One would need to introduce binary variables when the charging/discharging periods are not predefined. Similar constraints such as those given in equations 3, 5 and 6 are included.

The algorithm based on heuristics follows the same charging and discharging periods and searches the suitable charging hours with the highest wind output in the first 12 hours and those for discharging with the lowest wind output in the other half of the day. The schedule is only accepted if the resulting firmed capacity of the day is higher than that of the original wind output without storage after losses from the charging cycle have been taken into account.

4.3 Best and Worst Case Scenarios

Robust optimization is used to work out the optimal schedule in case of the worst scenario in terms of prices. Mathematically the objective function of the optimization problem stated in equations (1)-(6) can then be expressed as:

$$\min_x \max_d F\left[X \cdot (\tilde{C} \pm d)\right] \qquad (9)$$

where $\tilde{C}$ and d represent the predicted cost curve and the uncertainties of the cost curve respectively. They can be derived using real historical energy prices. YALMIP can translate this originally MIQP problem into a MILP equivalent which is then solved by the SCIP solver.

For the best case scenario, the purpose is to work out the optimal schedule in case of the best price scenario. The objective function is expressed as:

$$\min_{x,d} F\left[X \cdot (\tilde{C} \pm d)\right] \qquad (10)$$

This problem cannot be easily translated into a mixed-integer linear programming formulation and so is solved using a MIQP solver. It should be noted that considering the best case scenario, i.e. optimizing under the most optimistic assumptions, is not a standard approach. However, the authors believe that it could be interesting as a counterpart of the more typical worst case scenario in robust optimization.

4.4 Data Processing and Analysis

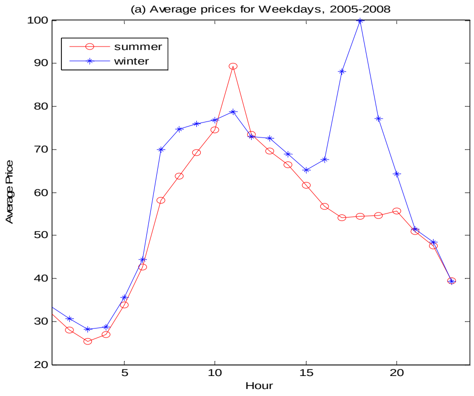
The average price curves used for the heuristics and optimization have been derived in the way described in this section. Inspecting the price data for the years 2005-2008 shows that the daily electricity prices are essentially different for weekdays and weekends, and also Saturdays and Sundays essentially differ (Figure 4a and Figure 4b). Moreover, in late autumn, winter, and early spring, where energy is consumed to heat up buildings, there is a different price pattern (namely showing a clear second price peak in the evening hours) than in the rest of the year. These six daily curves shown in Figure 4a and Figure 4b constitute the basis of the average price curves we used.

Taking the difference of the price data from the years 2005-2008 to the respective average daily curves and inspecting this error, we found that there are systematic deviations of the actual prices from the average daily curves, depending on the season. At daytime (8h-21h), the deviation roughly behaves like one complete sine wave over the year, with two differently behaving periods of time, namely the summer vacation time and around New Year (Figure 4c). We used a corresponding nonlinear regression to approximate this, modeling the abnormalities as Gaussians. At night-time (Figure 4d), the pattern is more complex, and the deviations are less in magnitude. We trained an artificial neural network with one hidden layer consisting of five hyperbolic neurons to approximate this data.

Altogether, our average price curve is computed as follows:

$$\begin{aligned} price = {} & average(hour, weekday/sat/sun, heating\ yes/no) \\ & + \Delta(day\ of\ year, day/night) \end{aligned} \qquad (11)$$

The same procedure was also applied to the data from the years 2005-2009, yielding slightly different approximations.



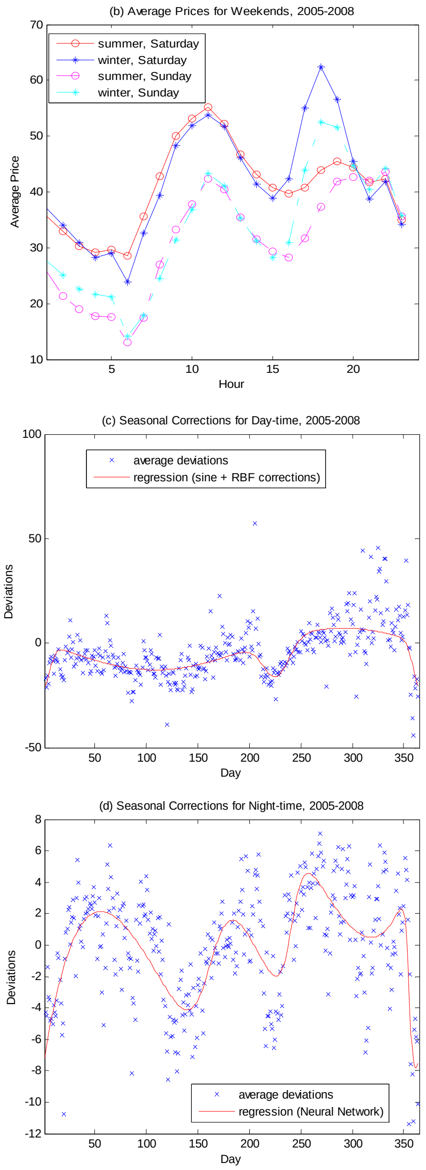


Figure 4 (a,b,c,d) Data Analysis for the Artificial Price Curve

For the Monte-Carlo stochastic optimization, the stochastic scenarios are generated assuming a log-normal mean reversion process:

$$S(t)=F(t)\cdot\exp\Big[\ \sum_{j=1}^{m}-\frac{1}{2}\int_0^t\sigma_j^2e^{-2\alpha(t-u)}du \qquad (12)$$
$$+\ \int_0^t\sigma_je^{-\alpha(t-u)}dZ_j(u)\ \Big]$$

where *S(t)* is a diffusion process with m independent factor sources and relaxation time constant *1/α*. *F(t)* is the trend and $\{Z_j(u)\}$ are m independent Brownian motions. For derivation and details refer to literature [10][11]. The process is adapted to provide scenarios in discrete time with sampling period of 1 hour.

5 RESULTS AND ANALYSES

5.1 Energy Trading Application

Simulations were conducted using the aforementioned formulations and derived input data. In order to benchmark the performance of the various approaches the ideal case is solved which involves using the real prices of 2009 for deterministic optimization. A BESS with 1.5MWh energy capacity and 0.2MW power capacity with 80% charging/discharging round-trip cycle efficiency is employed. The ideal optimal schedule (for 2 consecutive days) and the daily benefits obtained are plotted in Figure 5 and Figure 6.

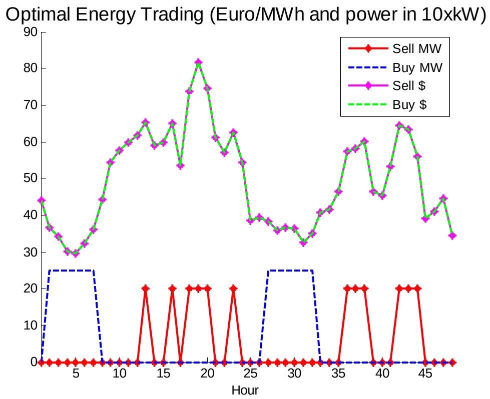


Figure 5 Ideal Optimal Schedule

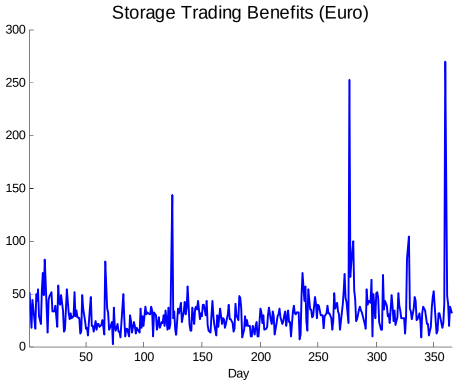


Figure 6 Ideal Trading Benefits

In reality, one cannot have perfect knowledge of the prices in the future. Therefore, one would need to rely on predictions. Moreover, different approaches can be applied to find an optimal schedule to decide when one should buy/sell energy. Once the schedules are found they are applied with the real (after-the-fact) prices to work out their corresponding benefits. The approaches we investigate in the paper are:

a) DO-PP: Deterministic Optimization with Predicted Prices (Section 4.4)
b) H-PP: Heuristics with Predicted Prices (Section 4.4)
c) RO-UP: Robust Optimization with Uncertain Prices for worst case price scenario (Least beneficial price curve based on average predicted prices from Section 4.4 ± σ)

d) O-UP: Optimization with Uncertain Prices for best case price scenario (Most beneficial price curve based on average predicted prices from Section 4.4 ± σ)

e) SO-MC: Stochastic Optimization with Monte-Carlo simulations using stochastic prices (stochastic scenarios described in last part of Section 4.4)

The more varying numerical outcomes are from scenarios c, d and e and they are shown in Figure 7 to Figure 12, even though the underlying are not necessarily the most performing as described later on in this section. Note that they are only the theoretical outcomes as if the prices were exactly the same as the inputs used. Note that in Figure 9 the selling and buying prices are different, which are the theoretical extremes which can result in the best price scenario, it does not mean that in reality there can be different prices for selling and buying. In our case it means that at each time point the optimization problem will choose the price from one of these two values for buying or selling which can result in the best gain from the market.

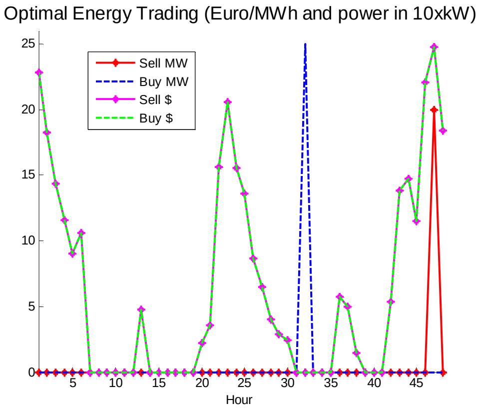


Figure 7 Theoretical Optimal Schedule for Worst Case Scenario

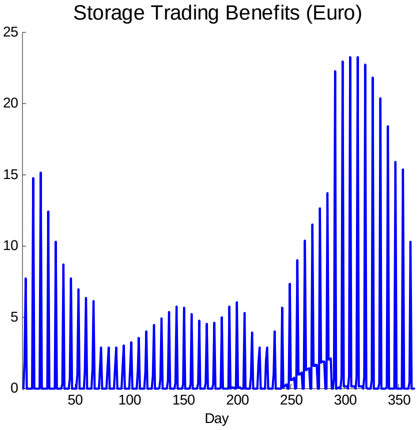


Figure 8 Theoretical Trading Benefits for Worst Case Scenario

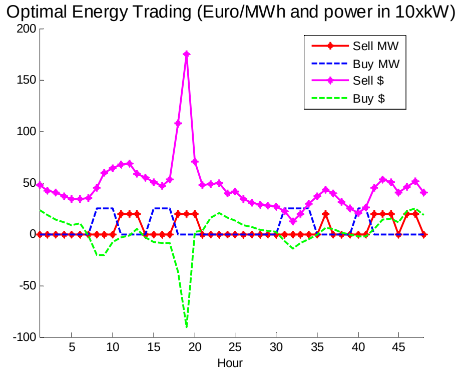


Figure 9 Theoretical Optimal Schedule for Best Case Scenario

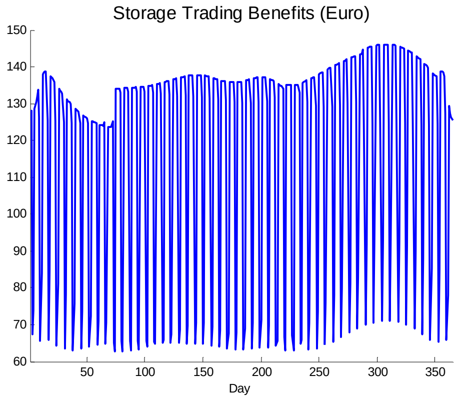


Figure 10 Theoretical Trading Benefits for Best Case Scenario

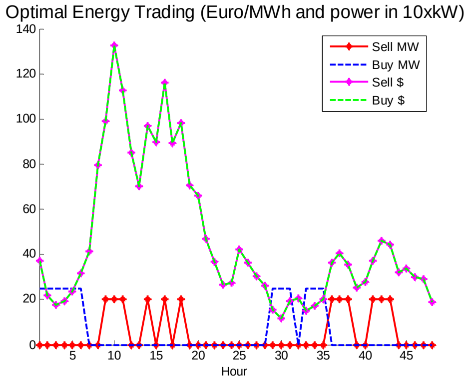


Figure 11 Theoretical Optimal Schedule from Stochastic Optimization

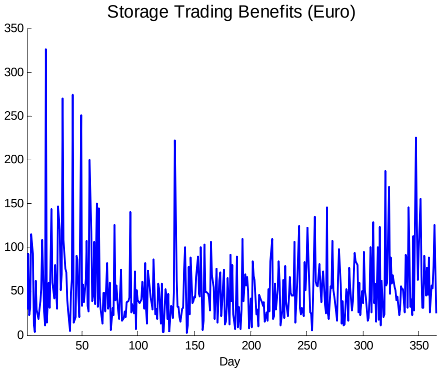


Figure 12 Theoretical Trading Benefits from Stochastic Optimization

As described previously, these "optimal" schedules are applied to 2009 prices for performance comparison. The results are listed in the following table.

Approach	2009 Total Benefits (2009 Prices)	2009 Total Benefits (With corresponding Input Prices)
Ideal	1.1663e+004	1.1663e+004
(a) DO-PP	8.9742e+003	1.2422e+004
(b) H-PP	8.9817e+003	9.0079e+003
(c) RO-UP	1.1941e+003	548
(d) O-UP	6.0628e+003	4.2545e+004
(e) SO-MC	7.4031e+003	2.0090e+004

Table 1 Results from Different Approaches

The values show that the heuristic approach performs as well as the MILP approach since they give the same values for the ideal case. Indeed, when applied to the real prices for 2009, the heuristics (b) work even slightly better than the deterministic optimization (a). It is also noted that the stochastic scenarios (e) produced based on an assumed log-normal mean reversion process can result in high gains in the theoretical case, because the stochastics can introduce contrasting prices in a day.

In section 4.1 it is mentioned that an additional constraint stated in equation (5) is necessary in order to limit the number of charging cycles to less than or equal to one. In fact this is not imposed by the equipment but something we found out after we analyzed our results in the first round without such constraint. It was found that the schedules found were not as satisfactory as those with the constraint when they were tested against the real 2009 prices.

5.2 *Wind Capacity Firming Application*

The results of the capacity firming application are reported in this section. The same BESS is used: 1.5MWh energy capacity and 0.2MW power capacity with 80% efficiency. Because of the lack of historical data on the wind power output so no data analysis was conducted to create the predicted wind power similar to what we did in the previous section on prices. Therefore we will only focus on the results using the real wind outputs and analyze the performance of the two different scheduling approaches: deterministic optimization (LP) and heuristics. As mentioned in section 4.2, the heuristics is based on very simple logic to locate the hours of the highest wind output in the first half of the day for storage charging and locate those of the lowest wind output in the second half of the day for complete storage discharging in the second half. The restriction is that if the modified wind curve does not provide a higher minimum output in the day (e.g. because the wind output is low in the first 12 hours and higher in the next 12 hours), the storage is not used in this day and remains idol. In fact the use of the batteries can induce wear so unnecessary charging and discharging should be avoided. The results from both methods are listed in the following table:

Approach	No. of Days Additional Firmed Capacity > 0	Yearly Revenues from Selling Daily Firmed Capacity (USD)
Deterministic Optimization (6-12 hours charging/discharging)	182	8.2326e+003
Heuristics (6 hours charging/discharging)	154	7.0081e+003

Table 2 Capacity Firming Results from Different Approaches

The value used to calculate the daily capacity firming revenue is from one of the US markets (since no daily capacity market in Europe is known) and it is 0.312 USD/kW-day.

It is noted that the results from the LP are better. It is because the constraint on the duration of charging or discharging is relaxed in the LP problem: between 6 and 12 hours; while this is fixed for 6 hours in the heuristics to simplify the logic. To see the firming effect of the solution from LP one can refer to Figure 3. The daily firmed capacity determined by heuristics is shown in Figure 13 . It is noted there are many days in which the firmed capacity is less than the maximum capacity allowed by the BESS, because of the unfavorable wind output.

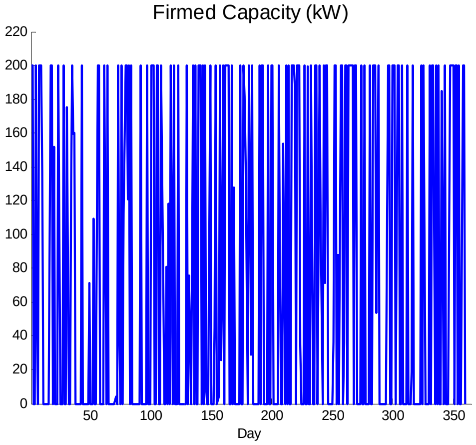


Figure 13 Daily Firmed Capacity Determined By Heuristics

6 CONCLUSIONS

In this article we look into two applications of BESS which can assist the integration of wind energy. The first application is energy shifting/trading whose primary objective is to maximize the gain from energy markets. By shifting the energy which the system does not require (in case of forced spillage or low system prices) to another time of the day when energy is in a higher demand (signaled by high system prices), one can better use the intermittent wind energy and can even avoid extreme situations in which energy prices become negative, which have happened in the past in some European countries. Even though wind energy does not participate in energy markets nowadays and is usually reimbursed through feed-in tariffs or similar mechanisms, it is believed that this situation can change in the future with higher amount of renewable energy and CO_2 taxes.

We employed various techniques to work out optimal schedules of the BESS in order to get the best gain and they include heuristics, deterministic, robust and stochastic optimization. Various data analysis techniques were used to provide the price input data and uncertainties which are fed into these algorithms to work out the optimal schedules. It was found that the schedules from heuristics and deterministic optimization using a well defined price curve (as our prediction) can give good benefits when applied to the real prices from 2009. The stochastic process approach might give better results when the sample size is increased beyond one year.

The second application is wind capacity firming in which we try to maximize the minimum power output from the wind facilities for a day. The capacity markets nowadays required longer term commitment but regulations might change to allow wind energy to provide firmed capacity to the power systems. For this application we did not have enough historical data on wind output to conduct similar studies which we did for the first application. Instead, we compared simply the results from the heuristics and deterministic optimization.

Further studies should include analyses of additional historical wind output data. Also, multi-objective optimization might be an interesting approach to investigate the possibilities of an optimal aggregation of these two applications. This is especially promising when wind blows while the system does not need this energy since the two applications will complement each other well in this condition.

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