

Incentives for Optimal Integration of Fluctuating Power Generation

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Abstract - The present paper investigates how a storage unit, coupled with a wind farm could influence the economic operation of the power system. For this reason two optimization algorithms are implemented, where the storage capacity is assigned certain costs and is able to vary in size. The objective of the first optimization is to identify the optimal power infeed as well as the necessary battery capacity in order to maximize the profits of the wind farm. The objective of the second optimization is to identify the necessary battery capacity, which in relationship with the wind power infeed will minimize the total costs of the system. The wind farm is assumed to provide “cheap” energy to the network and has no knowledge of the effects its power infeed has on the Locational Marginal Prices (LMPs) it receives. It has been found that for small wind farms, which cannot influence the LMPs with their infeed, the maximum profit policy coincided with the power infeed policy for the minimization of the costs. On the contrary, the wind farm could not identify the optimal policy which would maximize its profits, when its size is big enough to influence the LMPs. Incentives are identified so that the wind farm can receive a price signal which will be of benefit for both the wind farm and the system.

Keywords - incentives, storage, wind farm, large wind penetration

1 Introduction

During the last one or two decades a fast and successful development of renewable energy sources was observed. The European Commission set the target of 20% EU energy consumption to come from renewable resources until 2020 [1], while projects such as Desertec [2] suggest the connection of a significant amount of off-shore wind farms and concentrated solar photovoltaics in Europe, Africa and Middle East. The power of renewable energy sources is intermittent, i.e. is not continuously available and not necessarily at times most needed. The integration of storage is an effective solution in order to offer the necessary control power and also account for the uncertainties in the forecasted energy generation. At the same time, due to market developments, electricity storage can take advantage of on- and off-peak electricity prices by storing energy when prices are low and discharging when prices are high.

Previous works have dealt frequently with the energy storage sizing problem, when coupled with fluctuating generation. An optimal sizing method for provision of control power is proposed in [3]. A multiple time-scale model predictive control framework dealing with battery storage, determining its capacity for energy arbitrage and

identifying an optimal control strategy for generation dispatch and frequency regulation is presented in [4]. A variety of optimization techniques have been proposed for the optimal economic operation of the energy storage. In [5], the authors deal with the optimal storage sizing for minimizing the total system costs while in [6] the impact of storage in social welfare is examined. In [7] and [8] the authors investigate the impact of storage with large wind penetration in the system and propose a technique for optimal battery placement respectively. Several papers deal with the optimal sizing and control of energy storage in order to maximize the profits of the renewable power producer, assuming either prices from spot markets or from system operators [9], [10].

The present paper focusses on the effect that the size of the renewable power plant has (e.g. a wind farm) – when operating in conjunction with an energy storage – on the prices it receives from the system. As indicated in [11], large wind penetration has an effect on the market prices. This paper examines the optimal size and control of energy storage from a system’s point of view (i.e. minimize costs) and from a power producer’s point of view (i.e. maximize profits) and compares the results. It investigates if the two different control strategies differ or coincide, for different renewable power plant sizes. If they differ, then incentives are identified, which the system operator can offer to the renewable power producer in order to install and optimally operate energy storage units such that a minimization of the total system costs can be achieved.

2 System Setup

In order to illustrate the proposed method, the example of an off-shore wind farm which is connected to the grid through an HVDC cable will be used (see Fig. 1). The grid is assumed to be a 10-bus network, as described in [12], with a minor modification. Instead of having a generator on bus 7, the wind farm is assumed to be connected at bus 10. Large production units are installed in the top left area. The generator on bus 3 is representing aggregated production of nuclear units. Generator 5 is an aggregation of conventional thermal units. On bus 2 hydro power installations are assumed, while thermal generator 8 in the lower right part of the network has high production costs. Large loads are located at buses 3, 7, 8, and 10, forming two main load areas: one close to the production in the top left part of the network and one in the lower part close to the expensive generator 8. The peak demand of the system is 12 p.u. (throughout the whole paper we assume 1 p.u. = 1’000 MW). Due to the load and generator locations, dur-

ing high demand periods, line 2-10 is usually congested while lines 2-3 and 2-9 sustain loadings above 70%.

The focus of this paper is on the wind farm size, connected at node 10, and on the storage capacity, and how storage could influence the wind farm and the grid operation. We assumed a battery as an energy storage, but the developed algorithms can be applied for any types of storage.

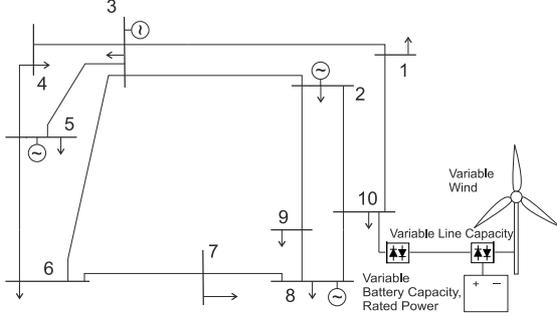


Figure 1: Illustration of the system under study.

The wind farm operator can decide how much of the produced power will be offered to the grid and how much will be stored in the battery. For example, in case the price is low, the wind farm will prefer to store a part of the produced power in the battery and inject it later, when the price will be higher. The optimization algorithm decides on the following four parameters: the optimal power infeed from the wind farm over a given time horizon, the optimal battery capacity, the optimal rated power of the battery and the optimal capacity of the HVDC cable.

Accordingly, optimization algorithms for two different problems are designed and solved. The objective of the first problem is the maximization of the wind farm profits, when the wind farm acts as an independent power producer. The second problem had as an objective to minimize the total costs of the system, assuming that the system operator can fully control the wind power infeed and the battery.

In both problem setups, it is assumed that every power producer sends a cost function to the Independent System Operator (ISO). The ISO has a complete model of the transmission system and can carry out an Optimal Power Flow (OPF) calculation. Through the OPF, the Locational Marginal Prices (LMPs or nodal prices) are determined, which can be used in the following manner: generators are paid the nodal price for energy; loads must pay the nodal price for energy. The LMPs are derived from the Lagrange multipliers of the optimization's equality constraints [13]. In this paper, an OPF based on the DC approximations has been used (DC-OPF).

3 Maximizing the Profits of the Wind Farm

The wind farm in this problem is assumed to act as an independent power producer. Given a wind time series¹, the wind farm tries to identify which amounts of power, $P_{\text{inf},k}$, over a time horizon $k = [1 \dots N]$, would result in

¹Historical wind data from Germany, in 2008, are given as input.

²There might exist cases where the two algorithms iterate to infinity between two different $P_{\text{inf},k}$ policies. In such an occasion the $P_{\text{inf},k}$ policy that results to higher profits for the wind farm is selected.

such LMPs, so that the product $\mathbf{LMP}^T \cdot \mathbf{P}_{\text{inf}}$ becomes maximum. In order to achieve this, an iterative procedure takes place, as shown in Fig. 2.

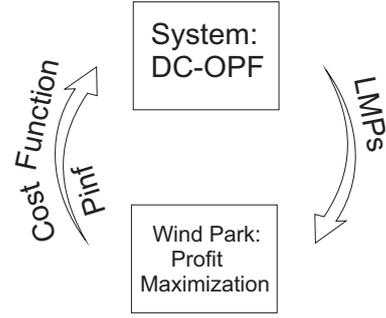


Figure 2: Illustration of the wind farm profit maximization algorithm.

The wind farm takes advantage of the battery storage, in order to inject the optimal P_{inf} . This flexibility, however, is not offered for free. In the optimization, costs are assumed for the battery and the HVDC line to be installed. The algorithm takes into account these costs and decides what is the minimum capacity of the battery (and thermal line limit) that would result in the highest profits. In order to emulate current legislative frameworks, where wind farms have a priority in the dispatch, and considering the future CO₂ taxes of conventional generators, a relatively low operating cost of the wind farm is assumed, equal to the costs of the “cheap” conventional generators in the grid. However, if the wind farm decides for a large storage capacity, the cost function will inevitably result into higher costs per MWh, and the wind farm may not be fully dispatched.

The description of the algorithm follows. Assuming a time horizon N and arbitrary Locational Marginal Prices for this horizon, the profit maximization algorithm determines the optimum amount of power, $P_{\text{inf},k}$, that the wind farm must offer to the power system in each time step k . At the same time, it defines the capacity and power rating of the battery, the capacity of the HVDC cable and calculates a cost function. The cost function, $C_{\text{WF,tot}}$, depends on the selected battery capacity and rated power as well as the selected line capacity and is expressed in Eur/MWh (see Eq. 1). Then the algorithm passes the values $P_{\text{inf},k}$ and the corresponding cost function to a multi-period DC-OPF. The OPF assumes the values $P_{\text{inf},k}$ as the maximum power limit of the wind farm (see Eq. 7). After the OPF calculation, the resulting Locational Marginal Prices at node 10, where the wind farm is connected, LMP_k , are passed back to the wind farm profit maximization algorithm. A new profit maximization is solved and the new $P_{\text{inf},k}$ and cost function are calculated. The algorithm converges when the profit of the wind farm remains unchanged for a number of consecutive iterations².

$$C_{\text{WF,tot}}(\cdot) = \left(C_{\text{WF,op}} + \frac{C_{\text{Bat,Q}} + C_{\text{Bat,P}} + C_{\text{Line}}}{\sum_{k=1}^N P_{\text{inf},k}} \right) \cdot P_{\text{WF},k}^{\text{OPF}} \quad (1)$$

where

$C_{WF,op}$: operating costs of the wind farm [Eur/MWh]

$C_{Bat,Q}, C_{Bat,P}$: costs of battery capacity and rated power,
referred to the time horizon N [Eur]

C_{Line} : costs of line capacity, referred to the time
horizon N [Eur]

$P_{WF,k}^{OPF}$: the wind farm *hourly* power dispatch
determined from the OPF
[MW for 1 hour \equiv MWh]

In the following, the multi-period DC-OPF is presented:

$$\min \sum_{k=1}^N \left(\sum_{j=1}^{N_{gen}} C_{jk}(P_{jk}) + C_{WF,tot}(P_{WF,k}^{OPF}) \right) \quad (2)$$

subject to, $\forall k = [1, N]$:

$$\mathbf{B} \cdot \theta_k = \mathbf{P}_k - \mathbf{D}_k \quad (3)$$

$$\theta_{ref} = 0 \quad (4)$$

$$\left| \frac{1}{x_{mn}} (\theta_{mk} - \theta_{nk}) \right| \leq F_{mn}^{max} \quad (5)$$

$$0 \leq P_{jk} \leq P_j^{max} \quad (6)$$

$$0 \leq P_{WF,k}^{OPF} \leq P_{inf,k} \quad (7)$$

The demand \mathbf{D} is assumed inelastic and it fluctuates over time; F_{mn}^{max} is the power limit of the transmission line connecting node m with node n . If the determined battery capacity is not too large, the wind farm is usually one of the ‘‘cheapest’’ power producers. Therefore, it often holds $P_{WF,k}^{OPF} = P_{inf,k}$. For all presented algorithms, the time interval between step k and $k+1$ is selected equal to 1 hour. As a result, all the values expressing power (e.g. $P_{inf,k}$, $P_{WF,k}^{OPF}$, P_{jk} , etc.) coincide with the respective values for energy, expressed in MWh. Thus, no distinct notation is used for the MWh values required in the cost function.

The profit maximization part of the algorithm is formulated as follows:

$$\begin{aligned} & \max \sum_{k=1}^N (\text{LMP}_k \cdot P_{inf,k} - C_{WF,op} \cdot P_{WF,k}) - \\ & - C_{Bat,Q} \cdot Q_{Bat,max} - C_{Bat,P} \cdot P_{Bat,max} - C_{Line} \cdot P_{Line} \end{aligned} \quad (8)$$

subject to, $\forall k = [1, N]$:

$$Q_{Bat,max} \geq 0 \quad (9)$$

$$P_{Bat,max} \geq 0 \quad (10)$$

$$P_{Line} \geq 0 \quad (11)$$

$$0 \leq P_{WF,k} \leq P_{Wind,k} \quad (12)$$

$$P_{inf,k} \leq P_{Line} \quad (13)$$

$$P_{WF,k} - P_{inf,k} = P_{Bat,in,k} - P_{Bat,out,k} \quad (14)$$

$$0 \leq P_{Bat,in,k} \leq P_{Bat,max} \quad (15)$$

$$0 \leq P_{Bat,out,k} \leq P_{Bat,max} \quad (16)$$

$$|P_{Bat,in,k} - P_{Bat,out,k}| \leq P_{Bat,max} \quad (17)$$

$$\mathbf{P}_{Bat,in}^T \cdot \mathbf{P}_{Bat,out} \leq \text{Tol} \quad (18)$$

$$Q_{k+1} = \eta_{Standby} Q_k + \Delta t \cdot (\eta_{in} P_{Bat,in,k} - \eta_{out} P_{Bat,out,k}) \quad (19)$$

$$0 \leq \eta_{Standby} Q_k + \Delta t (\eta_{in} P_{Bat,in,k} - \eta_{out} P_{Bat,out,k}) \leq Q_{Bat,max} \quad (20)$$

Eq. 8 represents the wind farm profits, taking into account the revenues $\text{LMP}_k \cdot P_{inf,k}$ minus the operating costs $C_{WF,op} \cdot P_{WF,k}$, as well as the battery and line costs. $P_{WF,k}$ is the generated power from the wind farm, while $P_{inf,k}$ is the power that is actually injected at node 10, in conjunction with the battery operation (see Eq. 14). According to Eq. 12, the wind farm is allowed to produce any amount of power ($P_{WF,k}$) below the available wind energy $P_{Wind,k}$. The incorporation of the battery efficiency in the constraints turns the optimization into a non-linear problem. Two power flows are assumed: $P_{Bat,in,k}$, when the battery is charged and $P_{Bat,out,k}$, when the battery is discharged. In order to guarantee that when $P_{Bat,in,k} \neq 0$, then $P_{Bat,out,k} \approx 0$ and vice-versa, Eq. 18 is included in the constraints, with $\text{Tol}=0.005$ (not zero due to numerical problems of the solver; $P_{Bat,in,k}$ and $P_{Bat,out,k}$ are expressed in p.u. values). The energy content of the battery in the next time step is defined by Eq. 19, taking into account the standby and the conversion losses. Eq. 20 ensures that the energy content of the battery does not exceed the limit $Q_{bat,max}$. Regarding the efficiencies, in our case it holds that $\eta_{out} = 1/\eta_{in}$.

4 Cost Minimization of the Whole System

The second optimization problem minimizes the total cost of the power system, including the wind farm and the battery installation costs. In the following sections, we will refer to this optimization also as ‘overall optimization’. Given a load profile and a wind infeed, the system operator tries to optimally use the battery storage, so that the stored energy can replace the use of high-cost generators in times of high consumption. In effect, the problem is formulated as the minimization of the objective function (21) subject to all the constraints defined in the profit maximization problem:

$$\begin{aligned} & \min \sum_{k=1}^N \left(\sum_{j=1}^{N_{gen}} C_{jk}(P_{jk}) + C_{WF,op} \cdot P_{WF,k} \right) + \\ & C_{Bat,Q} \cdot Q_{Bat,max} + C_{Bat,P} \cdot P_{Bat,max} + C_{Line} \cdot P_{Line} \end{aligned} \quad (21)$$

subject to $\forall k = [1, N]$:

Constraints (3) – (6)

Constraints (9) – (20)

The algorithms are implemented in MATLAB[®] R2008b. The `fmincon` solver from the Optimization Toolbox has been used.

5 General System Behaviour

5.1 Storage Placement

In a first step the wind farm was connected on different nodes and it was studied how the LMP variation influences the wind farm's profits. It was observed that the size of the battery storage is strongly dependent on the volatility of the prices. If the LMPs were constantly in a high or in a low level, then the installation of a battery storage would not be economical neither for the wind farm nor for the system at most of the times. However, if during a time period (e.g. a day), the highest price differs significantly from the lowest, a battery storage can help the wind farm increase its profits. In our 10-bus system, we observed that the LMPs had the greatest volatility on node 10. In the following, the wind farm and the battery storage are assumed to be connected at node 10.

5.2 Size of the wind farm

Carrying on with the analysis, we studied the influence of the wind farm size on the LMPs. Assuming that the wind farm is connected at node 10, we injected different amounts of power for different system loadings. The results are illustrated in Fig. 3.

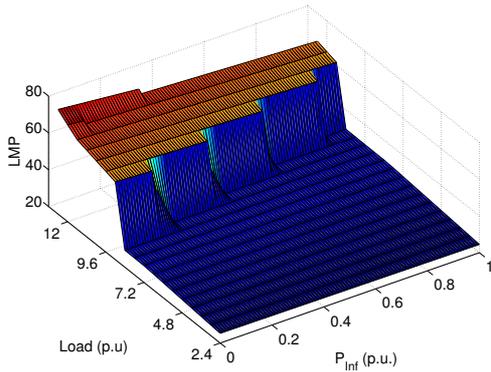


Figure 3: LMP variation at node 10 with respect to the system loading and the power infeed (P_{inf}) from the wind farm.

It can be observed that the loading of the system has the most significant impact on the LMP. When the total consumption is up to 80% of the maximum (9.6 p.u.), then the LMP is low. However, above 80% loading, congestions occur and more expensive generators have to be dispatched; therefore, the LMP rises. In the P_{inf} axis, the effect of the wind power infeed is illustrated. Note that when the total consumption is too low, or too high, the wind farm infeed has almost no influence on the LMPs. However, during a loading of about 8.5 p.u. to 11 p.u., the wind farm is shown to be able to influence the LMPs. In other words, if the size of the wind farm is significant, it might be able to find a strategy which will influence the LMPs in a way that it can further maximize its profits.

6 Case Studies

Two cases are presented in this section. One where the wind farm size is 0.12 p.u. (i.e. maximum wind infeed = 0.12 p.u.) and one with a size of 0.72 p.u. The assumed

wind curves are exactly the same, with the difference that the data for the big wind farm are scaled by a factor of 6. Fig. 4 and Fig. 7 present the average hourly values of the two wind profiles.

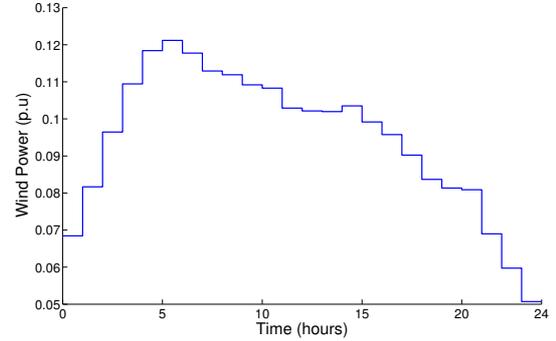


Figure 4: Wind infeed for a day. Wind farm maximum infeed = 0.12 p.u.

For our case studies, we assumed a realistic load curve, representing a winter day in Switzerland. The data were extracted from [14], where we have converted the real data into per unit values (maximum loading = 100%) and adapted to the maximum loading for our system. The load profile is displayed in Fig. 5.

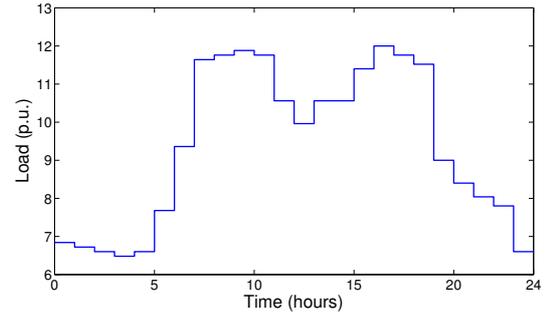


Figure 5: Assumed load profile during a day.

6.1 Small Wind Farm

Both algorithms were solved and the results were compared for the small wind farm. As illustrated in Fig. 6, the two algorithms converge to the same solution. This implies that the optimal policy for the wind farm, leading to maximizing its profits, is also the optimal power infeed that the system requires in order to minimize its generation costs. In general, both the wind farm and the system have common interests. Since the wind farm infeed is considered "cheap", the system tries to use the wind farm when the consumption rises in order to minimize the costs. Therefore, the wind farm is allowed to charge its batteries and feeds only a limited amount of power to the system until 6:00 am. When the consumption increases, it offers all its available power, both the currently produced as well as from the battery. At 19:00 p.m. it has no more stored power to offer and, therefore, after 19:00 p.m. the power infeed profile of the wind farm, as shown in Fig. 6, follows the wind profile. Similar is the situation from the wind farm's point of view. When the consumption increases, the LMP at node 10 rises as well. As a result, the wind farm tries to store as much energy as possible at the be-

ginning of the day in order to inject it later. As long as the consumption lies above 9 p.u., the LMP at Node 10 will remain high for relatively small wind infeed. Both algorithms identify the optimal battery capacity equal to 0.360 p.u with a rated power of 0.068 p.u., while the HVDC line should have a maximum loading of 0.125 p.u. The net profit of the wind farm as well as the total conventional generator costs are presented in Table 1. As a general remark for this case, it seems that for small wind farms, their interests coincide with the interests of the ISO to minimize the total generation costs. As a result, no incentives are necessary in such a case (see Sect. 7).

	WF Profit	Gen.Costs
Profit Maximization	99'256	6'050'368
Overall Optimization	99'256	6'050'368

Table 1: Wind farm net profit and generator costs for the two optimization algorithms [Euros/day].

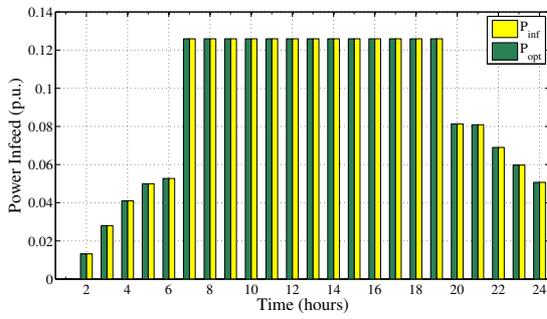


Figure 6: Comparison of the wind farm power infeed from the cost minimization P_{opt} and the profit maximization algorithm P_{inf} . Wind farm maximum infeed = 0.12 p.u.

This first case study can be seen as a verification of the well-known price taker assumption in perfectly competitive markets, where it is claimed that market participants which are small compared to the overall market size cannot influence prices, and thus, act as price takers. An additional conclusion can be drawn from a market efficiency perspective. When market participants act as price takers the objectives of individual profit maximization and overall cost minimization lead to the same market outcome.

6.2 Large Wind Farm

For this case, the available wind infeed was assumed to be six times as large, as shown in Fig. 7.

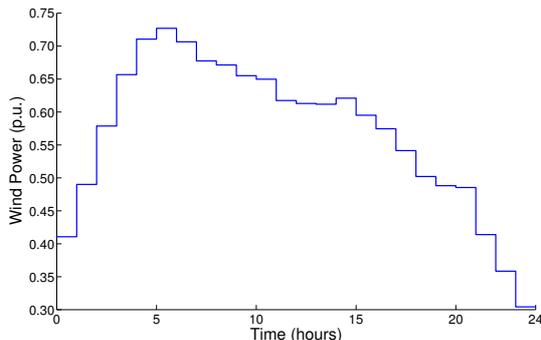


Figure 7: Wind infeed for a day. Wind farm maximum infeed = 0.72 p.u.

With the increased wind farm capacity, the Profit Maximization algorithm does not converge to a single solution. As illustrated in Fig. 8, after a few steps the algorithm iterates between two solutions.

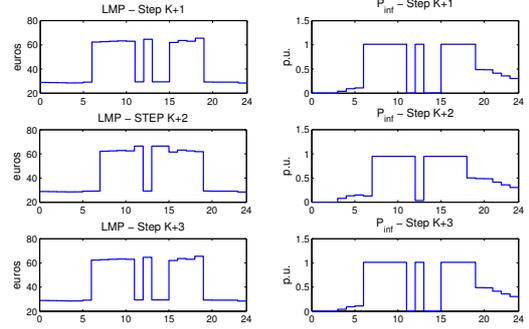


Figure 8: Iterations of the profit maximization algorithm. 1st left: LMPs as input to the profit maximization (step K+1); 1st right: P_{inf} resulting from the LMPs (ProfitMax); 2nd left: LMPs resulting from the P_{inf} at step K+1 (DC-OPF), and so on.

Note, that the size of the wind farm is now significant enough to influence the LMPs at node 10. However, the wind farm has no knowledge of the effect its power infeed has on the LMPs. This leads to the following case: the profit maximization algorithm receives a set of LMPs at Step K+1 as shown in Fig. 8 and optimizes its power infeed according to these LMPs (see P_{inf} –Step K+1); this P_{inf} , however leads to a new set of LMPs (see LMP–Step K+2); optimizing again for this LMP set, at step K+2, a new P_{inf} is determined; when this is given to the DC-OPF at step K+3, it results in the same set of LMPs as in step K+1. A stopping criterion has been implemented for such cases, where after a certain number of iterations, the algorithm stops and selects the solution that offers the highest profits during the last 10 iterations, i.e. the product $LMP_{i+1}^T \cdot \mathbf{P}_{WF,i}^{OPF}$ has the highest value (in most cases the wind farm is one of the “cheapest” producers, so it usually holds $\mathbf{P}_{WF,i}^{OPF} = \mathbf{P}_{inf,i}$).

The P_{inf} , resulting in the maximum profit for the wind farm is shown in Fig. 9. This is compared with the power infeed P_{opt} , which is the power infeed at Node 10, determined from the overall optimization algorithm. Overall optimization determines a battery capacity of 0.781 p.u. with a rated power of 0.127 p.u., while the HVDC line can reach a maximum loading of 0.679 p.u. On the other hand, the profit maximization fails to identify the optimal battery and line capacity, resulting in a value of 2.954 p.u. and 0.617 p.u. for battery capacity and rated power respectively, while the line should be able to sustain loadings up to 1.012 p.u. Of course, such high values increase significantly the costs and have an effect on the profits. As Table 2 indicates, the resulting wind farm profit from the profit maximization algorithm results in a smaller value than the overall optimization. This occurs, because the wind farm maximizes its profit depending on the given LMPs, which it assumes as constant for any P_{inf} policy it selects. Not being in a position to identify the effect its power infeed has on the LMPs results in a lower net profit for the wind farm and higher generator costs for the system. A proper price signal in this case would benefit not

only the system but also the wind farm.

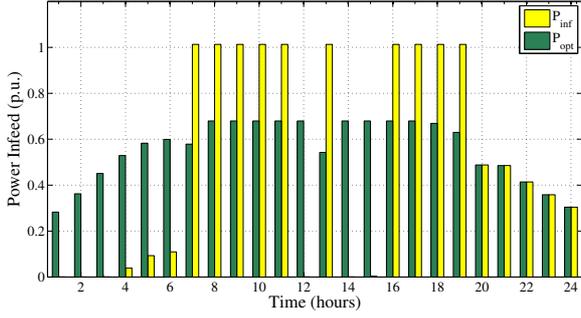


Figure 9: Comparison of the wind farm power infeed from the cost minimization and the profit maximization algorithm. Wind farm maximum infeed = 0.72 p.u.

7 Incentives

The above simulations show that a market participant which does not take prices as given - and subsequently acts as price setter - distorts market efficiency, i.e. the market outcome is not cost-efficient in comparison with the previously described case study where the wind farm acted as price taker. In order to overcome this market inefficiency, in this section an "artificial" set of locational marginal prices is proposed to "guide" the system into an equilibrium that is again cost-efficient from an overall system perspective.

An algorithm was developed for the identification of the proper price signals, as illustrated in Fig. 10. A set of LMPs were given to the wind farm and the resulting P_{inf} was evaluated. If it differed significantly from the system's optimal power infeed P_{opt} , determined through the overall optimization, a slightly modified set of LMPs were given: if $P_{inf,k,i} > P_{opt,k}$ then $LMP_{k,i+1} < LMP_{k,i}$; and vice-versa (where k is the timepoint within the horizon N and i is the iteration step). A stopping criterion was also included, selecting the LMPs that minimized the difference $P_{inf,k,i} - P_{opt,k}$, if the maximum number of iterations was exceeded. The LMPs resulting from this algorithm will be called hereafter 'desired LMPs'.

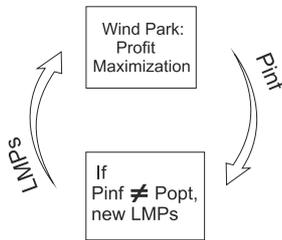


Figure 10: Algorithm for determining the LMPs which result in the optimal power infeed of the wind farm.

A modified version of the profit maximization algorithm is now solved, as shown in Fig. 11. Instead of the LMPs from the DC-OPF to be given as input, an artificial LMP signal is generated, being always equal to the 'desired LMP'. In this way, the wind farm would in effect act as a price taker.

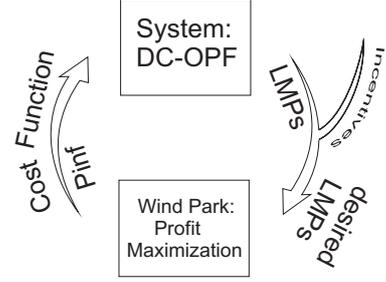


Figure 11: Algorithm for providing the wind farm maximization algorithm with the correct price signals.

Fig. 12 compares the different LMP values. The red bars present the LMPs resulting through the profit maximization (see Section 6.2), while the 'desired LMPs' are illustrated in grey. Taking a closer look at the red bars, it can be observed that they coincide with the step LMP-K+2 of Fig. 8. As already explained, however, the LMPs according to which the profit maximization determined the optimal infeed are those of the step LMP-K+1. Comparing step LMP-K+1 with the 'desired LMPs' some useful remarks can be made. We notice that at time 12.00, 14.00 and 15.00, 'desired LMPs' are significantly higher. Thus, the wind farm receives a signal that it is more preferable to feed-in power instead of charging the batteries. The opposite happens at time 13.00.

Based on the 'desired LMPs', the wind farm determines a new power infeed, $P_{inf}^{incent.}$ which is presented in Fig. 13. Because of this power infeed, the actual LMPs appearing on Node 10 are the black bars of Fig. 12. However, the wind farm never notices these prices, as it always receives the 'desired LMPs' at its input. The incentives to be given are the differences between the grey and the black bars, i.e. the 'desired LMPs' and the LMPs at the output of the DC-OPF.

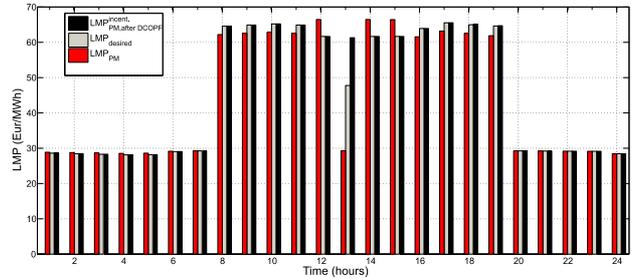


Figure 12: Comparison of the LMPs determined through the profit maximization (red), the 'desired LMPs' (grey) and the actual LMPs on node 10 due to the wind farm injection (black).

The $P_{inf}^{incent.}$ determined through the artificial price signals is compared with the optimal power infeed P_{opt} in Fig. 13. As it can be observed, the new $P_{inf}^{incent.}$ after the incentives matches more closely with the P_{opt} curve. Similar to the overall optimization results (see Section 6.2) are also the determined battery capacity and rated power, with values equal to 0.685 p.u. and 0.111 p.u., as well as the line capacity having a value of 0.677 p.u. In Table 2, the costs for the three different optimizations are shown. As long as the wind farm cannot identify the effect its power injection has on the LMPs, the overall optimization performs better than the other two algorithms. However, by supplying the wind farm with some artificial price signals, this performance can almost be matched, as the

profit maximization with the incentives results in slightly less profit for the wind farm and slightly increased costs for the generators. In other words, between the two profit maximizations, the wind farm would obtain higher profits, if it relies on the artificial price signals. Equally interesting is the fact that the incentives have a negative sign. This is also demonstrated in Fig. 12, where the grey bars are always less or equal to the black bars. This means that the ISO pays the wind farm owner less for his offered energy than if the wind farm was paid the actual LMP (i.e. black bars of Fig. 12). Here, it should be noted that if the wind farm optimized its infeed according to the actual LMPs, in the end the determined power infeed would result in less profits for the wind farm, due to the problems presented in Fig. 8.

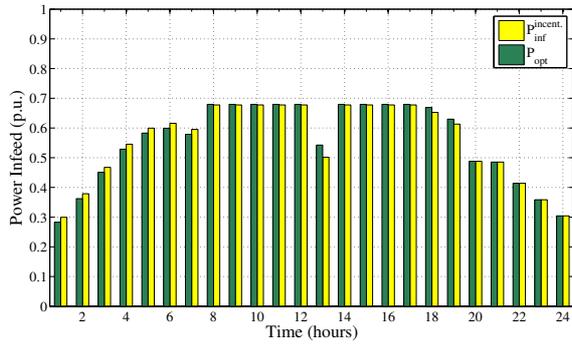
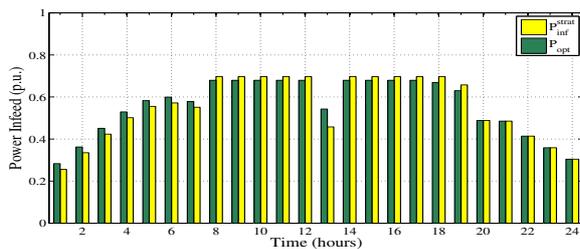


Figure 13: Comparison of the wind farm power infeed from the overall optimization (P_{opt}) and the infeed when the wind farm receives the artificial LMPs ($P_{inf}^{incent.}$ with incentives).

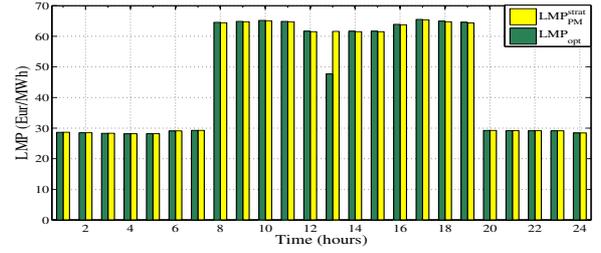
	WF Profit	Gen.Costs
Profit Maximization	430'536	5'655'784
Prof. Max. with Incentives	516'419	5'591'842
Overall Optimization	516'485	5'591'231
Cost of Incentives	-7022	

Table 2: Wind farm net profit and generator costs for the three different optimizations [Euros/day].

Concluding this section, we investigate a last case, where we assume that the wind farm has full knowledge of its influence on the LMPs. The power infeed from the wind farm and the corresponding LMPs are presented in Fig. 14. The wind farm profit and system costs are shown in Table 3. Observe that in such a case the wind farm can increase its profits more than with the incentives; the system costs also increase.



(a) Comparison with the power infeed from the overall optimization



(b) Comparison with the LMPs from the overall optimization

Figure 14: Wind farm power infeed (P_{inf}^{strat}) and the corresponding LMPs, when the wind farm knows how to influence the LMPs.

	WF Profit	Gen.Costs
Profit Maximization	521'802	5'592'486

Table 3: Wind farm net profit and generator costs when the wind farm has knowledge of its power infeed effect on the LMPs [Euros/day].

8 Conclusions

The present paper investigated how a storage unit, coupled with a wind farm, could influence the economic operation of the power system. For this reason two optimization algorithms are implemented, where the storage capacity is assigned certain costs and is able to vary in size. Both optimizations try to determine an optimal power infeed and identify the optimal battery size. The objective of the first optimization was to maximize the profits of the wind farm. The second optimization focussed on minimizing the total costs of the system. The wind farm is assumed to provide “cheap” energy to the network and has no knowledge of the effects its power infeed has on the Locational Marginal Prices (LMPs) it receives. Results suggest the following:

- As long as the wind production is considered “cheap”, the interests of the wind farm coincide with the interests of the system. When the size of the wind farm is small enough not to influence the LMPs, both algorithms converge to the same solution. As a result, the system operator does not need to give any incentives to the wind farm in order to comply with the optimal power infeed for minimizing the total costs.
- As long as wind farms have no knowledge of their impact on the LMPs, large-scale wind farms cannot identify the optimal policy which leads to their profit maximization. Incentives in the form of artificial price signals are necessary in this case, in order to lead the wind farm to increased profits but also minimize the system costs.
- The incentives do not necessarily have to result into extra costs for the system operator. In the presented case, the artificial price signals result into the wind farm increasing substantially its profits, but, nevertheless, being paid less than if it received the actual LMPs as payment.

Furthermore, it was found that, as it would have been expected, a storage device is not economical both for the

wind farm and for the system when connected to a node with low volatility of the Locational Marginal Prices.

In the last section, a case where the wind farm is assumed to have full knowledge of its effect on the LMPs was presented. It is shown that if the wind farm had this information, it could increase its own profits and induce at the same time an increase of the system costs.

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