Solar Energy 144 (2017) 502–516

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Optimal scheduling of grid-connected PV plants with energy storage for integration in the electricity market

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ARTICLE INFO

Article history:
Received 24 July 2016
Received in revised form 14 December 2016
Accepted 16 December 2016

Keywords:
Scheduling
Model Predictive Control
Electricity market
Forecasting

ABSTRACT

The integration of solar energy in the electricity market faces some challenges related to the time-varying nature of energy coming from the sun. The use of energy storage emerges as a technological solution to these problems and opens new possibilities for the integration of photovoltaic (PV) plants in the electrical market. This paper addresses the problem of integration of PV plants in the electricity market, providing a solution for an optimal scheduling, which allows the plant to participate in the daily and intraday markets. In order to perform a proper scheduling, a good estimation of energy prices is of paramount importance. The paper proposes also a price forecast algorithm that provides prices in a one-day horizon, based on price historical data and meteorological information. The development of the scheduling strategy is carried out using Model Predictive Control (MPC) and taking into account operational constraints. The MPC techniques allow maximizing the economic benefit of the PV plant manipulating the energy stored and extracted from the batteries. Some results of the application of the price forecasting approach and the scheduling strategy to a simulated PV plant located in Seville (Spain) are presented. The weather data and electricity prices are publicly available, supplied by the Spanish System Operator.

1. Introduction

The electricity market is a complex process where the production system provides a total amount of energy, in each instant, that must supply a varying load from the consumption. Electricity exchanges first take place in the daily (spot) market, where participants (sellers and buyers) have to propose, before gate closure, their quantity-price bids over the following delivery period. Participants are then financially responsible for any deviation from the contract. Certain electricity pools also integrate intraday markets, where it is possible to take corrective actions. The regulation market, which is managed by the system operator, ensures the real-time balance between generation and consumption. For fast load variations and unforeseen problems with production capacity there are reserves at the system operators disposal as reported in Pinson et al. (2007) and Holttinen (2005). The introduction of energy storage opens new possibilities in the electrical market (Beltran et al., 2013; Carrasco et al., 2006 and Chiang et al., 1998).

The different time-scales of the electricity market make a several-layer control algorithm necessary for solving a wide range of problems including the long-term horizon schedule for the daily market, the different sessions of the intraday market, the deviation management market, the regulation service market and the real-time load sharing (more information about the electrical market can be found in European Wind Energy Association (2012)). This paper addresses the daily and intraday problems. Notice that the outputs of the scheduler developed in this paper will be used as setpoints for the low-level controllers existing in the grid-connected PV plant.

Heuristic algorithms applied to the economical dispatch of PV plants are presented by Chakraborty and Simoes (2008) who solve the economical dispatch of a PV plant with batteries. In the paper presented by Ferrari-Trecate et al. (2004) the development of MPC (Model Predictive Control) for hybrid cogeneration power plants is carried out introducing the Mixed Logical Dynamic (MLD) framework. MPC applied to distributed energy resources with battery storage is developed Negenborn et al. (2009). In their studies Vahidi and Greenwell (2007) and Greenwell and Vahidi (2010) applied MPC to control the load sharing in a microgrid with a hybrid storage system composed of a fuel cell and an ultracapacitor, including some degradation issues, but these studies do not include the connection to the grid. In Garcia-Torres and Bordons (2015) a similar optimization problem for a renewable energy microgrid which exchanges energy with the main grid is developed

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http://dx.doi.org/10.1016/j.solener.2016.12.034
0038-092X/

Nomenclature

DM	daily market
IM	intraday market
E_{DM}	daily electricity energy
E_{IM}	intraday electricity energy
B_{es}	energy stored in the battery
B_{ie}	battery input energy
B_{oe}	battery output energy
B_{ini}	initial energy stored in the battery
B_{final}	final energy stored in the battery
η^{+}	battery charge efficiency
η^{-}	battery discharge efficiency
C	battery cost of usage (€/MW h)
SE	solar energy
$\widehat{P}_{DM}$	estimated daily market price
$\widehat{P}_{IM}$	estimated intraday market energy price
$E_{DM_{pc}}$	percentage of daily electricity market
SH	schedule horizon
MPC_{DM}	MPC daily market
MPC_{IMsi}	MPC intraday market session i

and solved with the use of MPC techniques. In Abdeltawab and Mohamed (2015) a market-oriented energy management system is proposed as an MPC for a hybrid power system composed of a wind energy conversion system and a battery energy storage system.

To run the scheduling algorithm it is necessary to know the price of both daily and intraday markets. However, these prices are set after the offers of the participants. To solve this problem, a price forecast algorithm has also been developed.

The main contribution of this paper is twofold:

- The use of a MPC approach with receding time horizon to energy scheduling in a electricity market with several sessions distributed temporary along the day. In this way, the scheduling of all daily sessions are computed but only the next session results are used as part of the plan. The following sessions are recomputed but with real knowledge of the past sessions and better predictions of prices and weather forecast. Also market rules are considered in the proposed algorithm. For example, in order to participate in the intra-days sessions is mandatory to bid in the daily market.
- The approach is applied to a PV plant with battery storage in a simulation context.

The paper is organized as follows: Section 2 presents the controller design, it is composed of general and scheduling control architecture. Section 3 describes the model of the plant which has two parts: the price forecast and the evolution of the state of the battery. Section 4 presents the optimization problem of the daily and intraday market MPC controllers. In Section 5, the scheduling strategy is applied to a simulated plant of 100 MW located in Seville (Spain), using real weather data of April comprising different weather conditions and different historical electricity prices supplied by the Spanish System Operator. A sensitivity analysis which shows the results is also presented in this section. Finally, Section 6 contains the conclusions of the work.

2. Control design

The control structure has two layers, as shown in Fig. 1. This paper addresses the upper layer (scheduling) and the control strategy has been tested on a model of a PV plant with a nominal power of 100 MW where different size of storage have been analyzed.

The controlled plant is a photovoltaic plant with energy storage. However, the configuration parameters allow the algorithm to be easily adapted to any type of renewable energy plant with storage.

The scheduling algorithm has two aims: the first one is proposing the electricity power that will be offered the following day, in order to participate in the daily and intraday markets. The second one is obtaining the reference values for the variables to be controlled by the MPC of the next level. The block diagram of the different levels of the scheduling is detailed in Fig. 2.

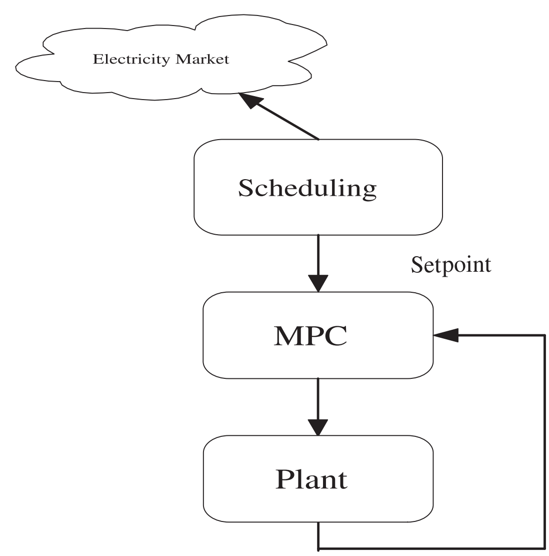


Fig. 1. General control architecture.

The scheduling level consists of 7 cascaded controllers: one for the daily market and one for each of the intraday market sessions. (For the sake of simplicity, only two of them are represented: the daily market controller and the one for the first session of the intraday market).

In order to participate in each of the markets, it is necessary to offer the hourly energy that the plant is able to produce (Time Period in Table 1). The number of outputs for each controller is shown in Table 2.

The market regulation OMIE (Operador del Mercado Ibérico de Energía, Energy Iberian Market Operator) establishes an hourly table that indicates the hour at which bids must be done for the following day (D), (D-1) being the current day (Open Session in Table 1).

Each controller will be executed before those hours and its output indicates the amount of energy offered in any market and session. The bids corresponding to already-executed controllers must be included in the computations of the following controllers. Therefore, each controller has a different prediction horizon (SH in Table 1). The sample time is one hour for all of them. In the case that price and solar energy forecasting did not change, the results for all the controllers that form the scheduling algorithm would produce the same results (limited to the length of their horizons).

The configuration parameters of the scheduling are: the power of the plant, the capacity and the performance of the battery and the percentage of energy assigned to the daily electricity market.

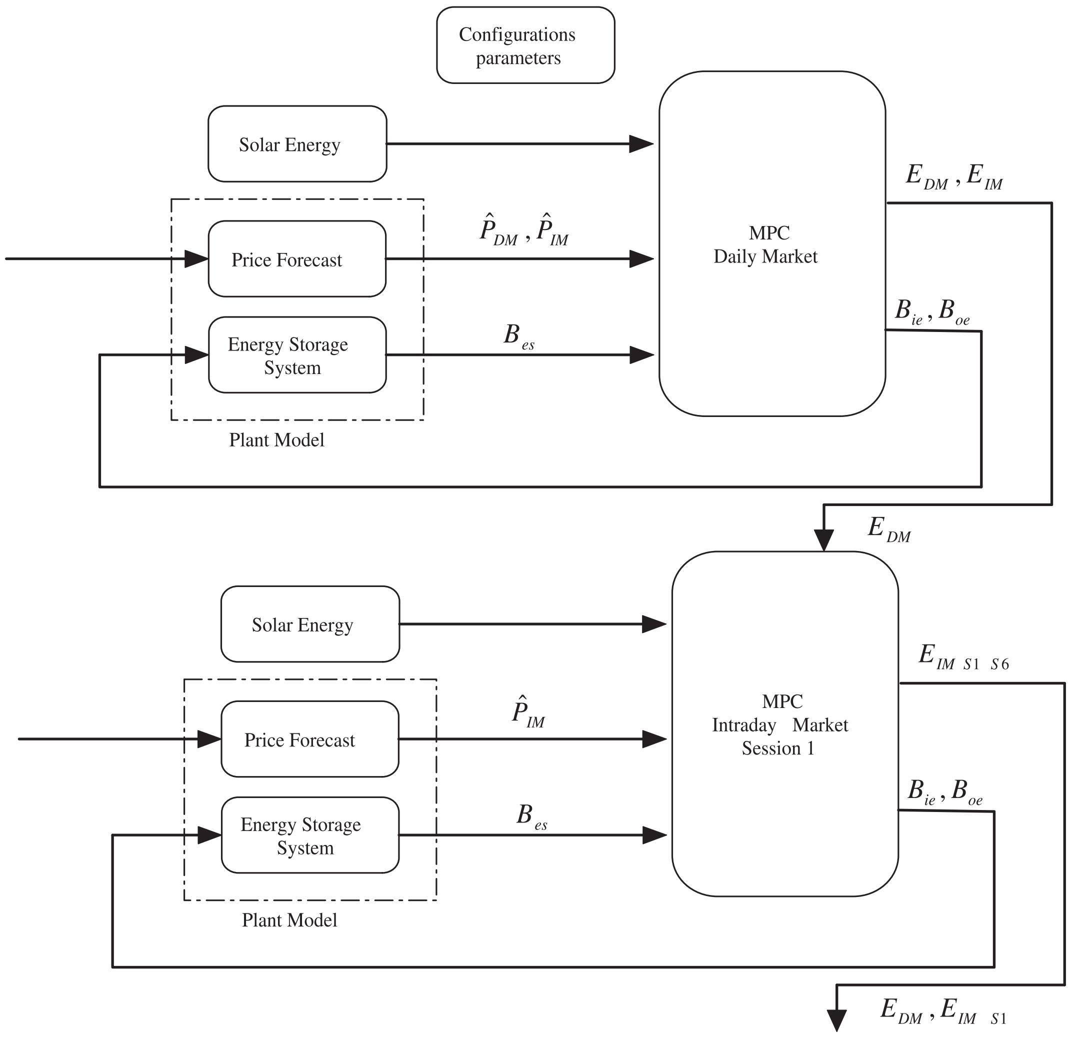


Fig. 2. Scheduling control architecture.

Table 1
Daily market and intraday market session.

	DM	IM S1	IM S2	IM S3	IM S4	IM S5	IM S6
Open session	10:00 (D-1)	17:00 (D-1)	21:00 (D-1)	01:00 (D)	04:00 (D)	08:00 (D)	12:00 (D)
Time period	01:00–24:00	22:00–24:00	1:00–24:00	5:00–24:00	8:00–24:00	12:00–24:00	16:00–24:00
SH	24	27	24	20	17	13	9

Table 2
Time horizon for each controller.

	MPC_{DM}	MPC_{IMs1}	MPC_{IMs2}	MPC_{IMs3}	MPC_{IMs4}	MPC_{IMs5}	MPC_{IMs6}
E_{DM}	24	–	–	–	–	–	–
E_{IMs1}	27	27	–	–	–	–	–
E_{IMs2}	24	24	24	–	–	–	–
E_{IMs3}	20	20	20	20	–	–	–
E_{IMs4}	17	17	17	17	17	–	–
E_{IMs5}	13	13	13	13	13	13	–
E_{IMs6}	9	9	9	9	9	9	9
B_{ie}	24	24	24	20	17	13	9
B_{oe}	24	24	24	20	17	13	9

The scheduling inputs are the following: solar energy (SE), energy stored in the battery at the beginning and end of the day (B_{ini} and B_{final}) and the output of the plant model: estimated prices of the daily ($\widehat{P}_{DM}$) and intraday ($\widehat{P}_{IM}$) markets and the energy stored in the battery (B_{es}).

On the other hand, the outputs of the algorithm are: the electricity to be supplied to the daily (E_{DM}) and intraday (E_{IM}) markets and the input (B_{ie}) and output (B_{oe}) energy of the battery.

3. Model of the plant

The model of the plant has two parts: the price forecast and the evolution of the state of the battery.

3.1. Price forecast

The development of models for the electricity pool markets is a burning issue due to the importance of this sector in the global economy. Several strategies (fuzzy, neural networks, regression...) have been used to predict the price of electricity in different countries (Weron, 2014; Dev and Martin, 2014).

In this case, the aim of the forecasting is providing the prices of the daily and intraday spot markets in a one-day horizon, in order to provide these data to the scheduling program.

The algorithm considers seven kinds of days (Monday to Sunday) and prices are calculated independently for each of the 24 h of the day. The algorithm is run for the daily market and for the six sessions of the intraday market.

3.1.1. Known data

This algorithm uses three kinds of data: historical data (price), wind energy forecast and energy demand forecast. For the three variables, the values of the 182 days previous to the target day are used. Moreover, the wind energy and energy demand forecasts of the target day are also used. All these data are public, and are provided by the operator of the electricity grid. In this work they have been taken from *Red Electrica de España* (ESIOS).

3.1.2. Forecast algorithm

The variation of the prices of electricity depends on many factors. Some of them, like the inflation or the currency exchange, imply a slow variation in the prices. A second group of factors, involving the wind energy, the demand or an isolated event, can make a significant variation between consecutive values. In this paper the price is considered as a signal, which is the summation of low frequency signals, that depend on the first group of factors, and high frequency signals, that depend on the factors of the second group.

The algorithm presented in this paper estimates the overall low frequency 'signal', and studies the correspondence between several factors (wind energy, demand...) and the differences with the real 'signal'. This will create several correlations that will be applied to the predicted value of the target day.

The algorithm is divided in the following steps:

1. First approach (historical data).
2. Wind energy forecast correction.
3. Energy demand forecast correction.
4. Estimated price correction (only for the intraday case).
5. Final corrections.

Steps 1 to 4 use the known data of the target day and all the data of the 179 previous days. These algorithms are applied not only to the target day, but also to the previous three days. The results of these calculations are used in the final corrections.

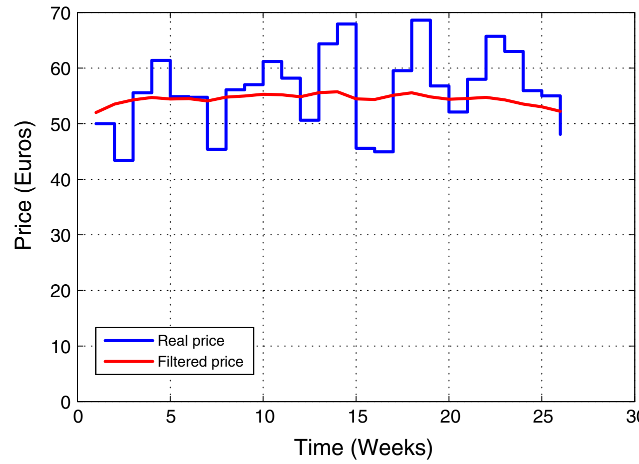


Fig. 3. Historical and filtered data.

3.1.3. First approach: historical data

Analysing the historical data for each hour in each kind of day it is easy to notice that the prices follow a certain trend (Fig. 3). The algorithm estimates this trend and extrapolates its value to the target day. This estimation is done taking the average of two first-order Infinite Impulse Response (IIR) filters (backwards and forwards). The mathematical expression of the filters is shown in Eq. (1).

$$\overline{p}(t) = \alpha \cdot p(t) + (1 - \alpha) \cdot \overline{p}(t - 1) \quad (1)$$

where p is the signal to filter (in this case, the price), $\overline{p}$ is the filtered signal and α is the parameter of the filter.

In Fig. 3 the red[1] line corresponds to the filtered data. With this low-pass filter, the algorithm takes into account the overall effect of all the factors of the first group. These new values are taken as a first approach. The goal of the rest of the algorithm is to estimate the influence of other factors over the error, and so correct this approach.

3.1.4. Wind power generation forecast correction

The wind energy production in Spain represented approximately 21% of the overall electricity production in 2014. However, this source depends highly on the weather conditions, and in the same year the mentioned ratio varied from 0.6 to 64%. The importance of this vector and its continuous oscillation make the wind power generation forecast the most important parameter to be considered to calculate the price forecast. In fact there are several lines of research addressing this particular matter, that is still an open issue (Barthelmie et al., 2008; Cruz et al., 2011; Azofra et al., 2014, 2015).

Nowadays, the impact of solar generation on market prices is negligible but, in case the use of PV plants with storage systems is widespread, solar energy production should be included as another factor to be included in price forecasting.

In this paper, the data of the last 182 days (including the target day) are used to estimate the correlation between the wind power generation and the price error. These data are filtered using the same method as the prices, and the filtered value is subtracted from the real one. With this operation the 'low frequency' variations of the wind energy production, that were considered in the previous point, are removed. Comparing this difference to the error in the prices, a linear correspondence is spotted (Fig. 4). This correlation is estimated with a linear regression. Therefore, the new estimated prices are:

[1] For interpretation of color in Figs. 3 and 11, the reader is referred to the web version of this article.

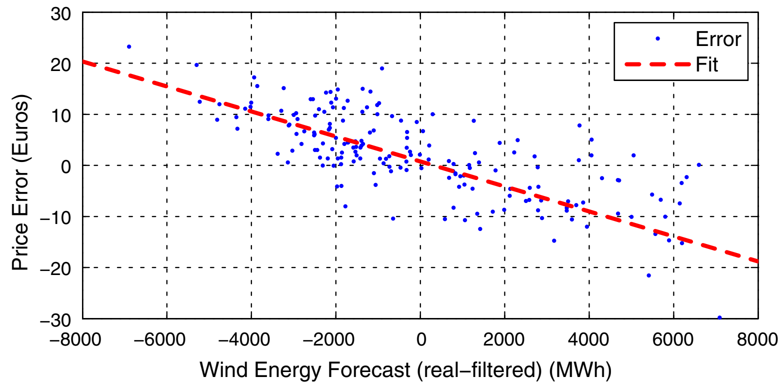


Fig. 4. Price error vs wind energy forecast.

$$p_1 = \overline{p} + a_w(E_w - \overline{E}_w) + b_w \tag{2}$$

where p_1 is the new estimation of the price, $\overline{p}$ is the filtered price, E_w and $\overline{E}_w$ are the real and filtered values of the wind energy and a_w and b_w are the parameters of the linear regression.

3.1.5. Energy demand forecast correction

Following the same steps as above, and plotting the error in the prices versus the difference in the demand (Fig. 5), two behaviors are shown: when the variation in the demand is very low and the rest of the cases. Both behaviors are modeled with a linear regression, and the new error in the price is estimated using fuzzy logic, with two fuzzy sets, as shown in Fig. 5.

3.1.6. Estimated price correction

This step is only used for the intraday market. In this case the price error is corrected depending on the own estimation. As in the first case, a linear correlation can be spotted in the graph. This correlation is modeled by linear regression increasing the accuracy of the prediction.

3.1.7. Final corrections

As explained above, the first four steps use the known data to forecast the price of the electricity. These steps are applied to each hour, and only the data of the same day of the week is considered. However, the prices are also influenced by the values of the previous days. This influence is considered in two new steps:

3.1.7.1. Error in the previous days. The first steps were applied to the last three days, including the target day. As the real prices of the two previous days are known, the real errors of those days can be calculated. This error should be considered to take into account short term issues or weather phenomena. The estimation of the error for the target day is modified with Eq. (3):

$$\widehat{e}_{d,corr} = w_0 \cdot \widehat{e}_d + w_1 \cdot e_{d-1} + w_2 \cdot e_{d-2} \tag{3}$$

where $\widehat{e}$ is the estimated forecast error, e is the real error, d is the target day and w_i are the weights for each day.

3.1.7.2. Error in the last hour of the previous day. This error is the most recent known data, and is used to add an offset to the errors of the target day. The influence of this value decreases along the day, so it is attenuated as shown in Eq. (4).

$$\widehat{e}_{h,corr} = \widehat{e}_h + \left(\frac{24-h}{h}\right) e_{24,d-1} \tag{4}$$

where $\widehat{e}_h$ is the estimated forecast error of the hour h and $e_{24,d-1}$ is the forecast error of the last hour of the previous day. The application of the algorithm to the Spanish market and performance evaluation is presented below in Section 4.1

3.1.8. Validation of the model

To validate the model, the forecasts of the 28 first days of April 2015 were compared to the real value of the prices. The results for the daily market are summarized in Table 3 and Fig. 6, while the results for the intraday markets are shown in Table 4.

The results of the forecast are sent to the scheduling algorithm, which determines whether the energy will be stored or sold depending on the differences of the prices in each hour. Therefore, it is also important that the profiles of the forecasted and the real prices have similar shapes. In Fig. 7 these profiles are represented for the daily market, and a period of one week. The graph shows that even in the cases where the error is higher, the shapes of both curves are still similar.

3.2. Linear state-space model of the plant

The dynamic of the state variable, which is the level of the storage system, considers different efficiencies for battery charge and discharge, and different operative constraints will be considered (see next section). It is given by:

$$B_{es}(i) = B_{es}(i-1) + B_{ie}(i)\eta^+ - B_{oe}(i)\eta^- \tag{5}$$

4. Optimization problem

The aim of the problem is to find the optimal values for the daily and intraday energy markets together, charging and discharging the battery in order to maximize the economic profit.

4.1. Daily market MPC controller

The purpose of the daily market is to handle electricity transactions for the following day through the presentation of electricity sale and purchase bids by market participants. Bids made by these sellers are presented to the market operator and will be included in a matching procedure that will affect the daily programming schedule corresponding to the following day. The market operator matches electricity power purchase and sale bids (received before 10 am on each day).

The time horizon for the daily market is 24 h but it is different for the intraday markets (see Table 5). To achieve this aim, the following cost function is maximized:

$$\max_{E_{DM},E_{IM},B_{ie},B_{oe}} J = \sum_{i=1}^{24} E_{DM}(i)\widehat{P}_{DM}(i) + \sum_{i=1}^{7}\sum_{j=1}^{SH} E_{IM}(i,j)\widehat{P}_{IM}(i,j) - \sum_{i=1}^{24} B_{ie}(i)\eta^+ C - \sum_{i=1}^{24} B_{oe}(i)\eta^- C \tag{6}$$

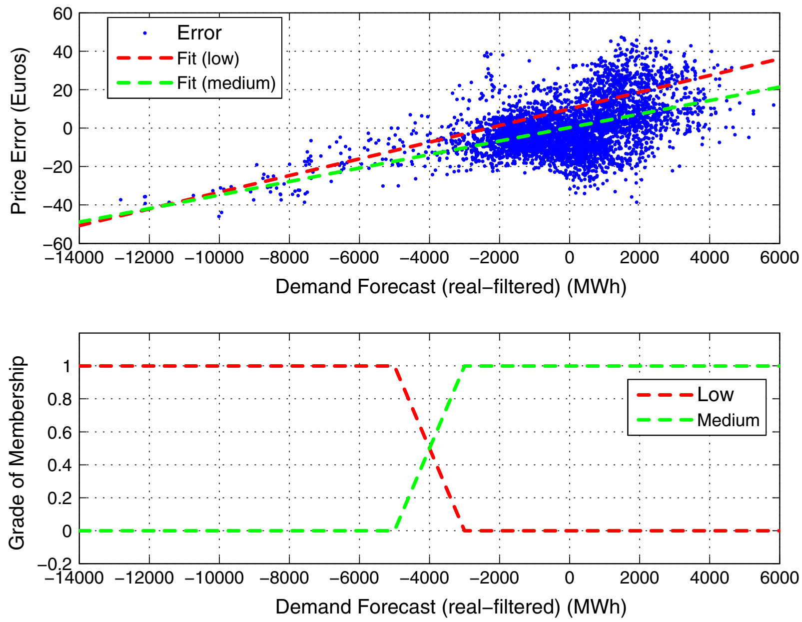


Fig. 5. Price error vs demand forecast.

Table 3
Daily market.

Occurrences	Mean price (euros)	Mean error (euros)	RMS error (euros)
672	44.54	0.42	7.40

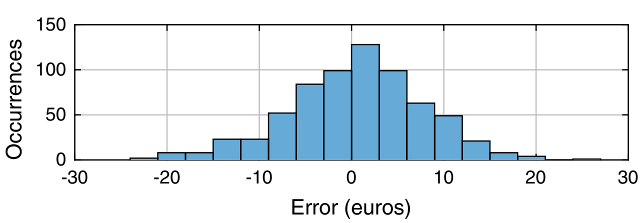


Fig. 6. Price error histogram, 1–28 April (daily market).

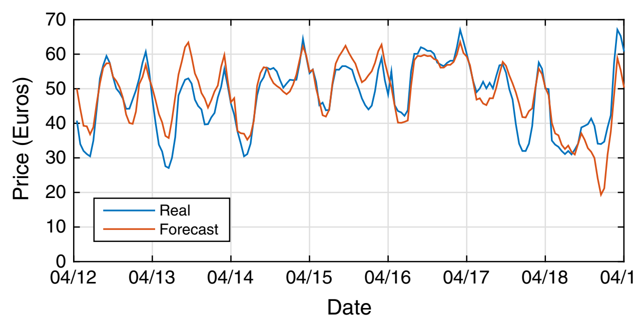


Fig. 7. Real and forecasted prices.

s.t.

$$E_{DM}^{min}(i) \leqslant E_{DM}(i) \leqslant E_{DM}^{max}(i) \quad (7)$$
$$E_{IM}^{min}(i,j) \leqslant E_{IM}(i,j) \leqslant E_{IM}^{max}(i,j) \quad (8)$$
$$B_{ie}^{min}(i) \leqslant B_{ie}(i) \leqslant B_{ie}^{max}(i) \quad (9)$$
$$B_{oe}^{min}(i) \leqslant B_{oe}(i) \leqslant B_{oe}^{max}(i) \quad (10)$$
$$B_{es}^{min}(i) \leqslant B_{es}(i) \leqslant B_{es}^{max}(i) \quad (11)$$
$$B_{ie}(i) \geqslant 0 \quad (12)$$
$$B_{oe}(i) \leqslant 0 \quad (13)$$
$$SE(i) \geqslant E_{DM}(i) + E_{IM}(i,j) + B_{ie}(i) + B_{oe}(i) \quad (14)$$
$$E_{DM}(i) = E_{DM_{pc}}(SE(i) - B_{ie}(i) - B_{oe}(i)) \quad (15)$$

Table 5
Intraday market MPC controllers.

Session	N	SH
1	7	27
2	5	24
3	4	20
4	3	17
5	2	13
6	1	9

The objective of this controller is to compute the energy to be bid in the daily market in order to obtain the highest profit. The prices of the intraday sessions must be included in the cost function, since intraday prices could be bigger than daily ones.

Table 4
Intraday market.

Session	1	2	3	4	5	6	7
Occurrences	672	672	560	476	364	252	84
Mean price (euros)	44.94	45.51	47.25	49.29	48.20	47.09	51.71
Mean error (euros)	0.26	0.40	0.70	0.69	1.17	1.64	2.01
RMS error (euros)	9.16	9.23	8.68	9.40	11.11	10.97	9.20

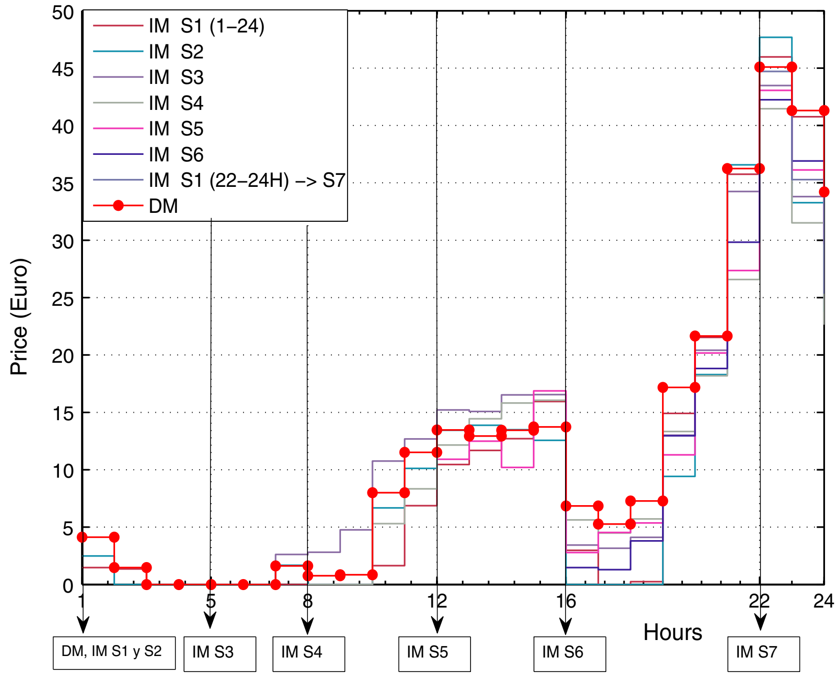


Fig. 8. Days types: clear day and clear day with unexpected clouds. Estimated prices of the daily (red dots) and intraday markets. Date 04/05/2015. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

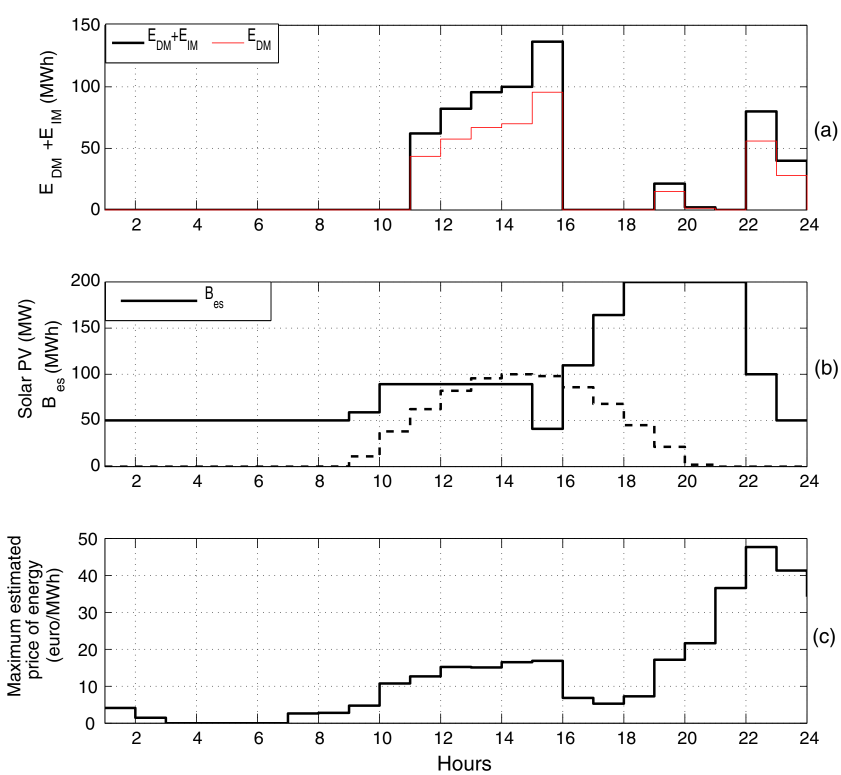
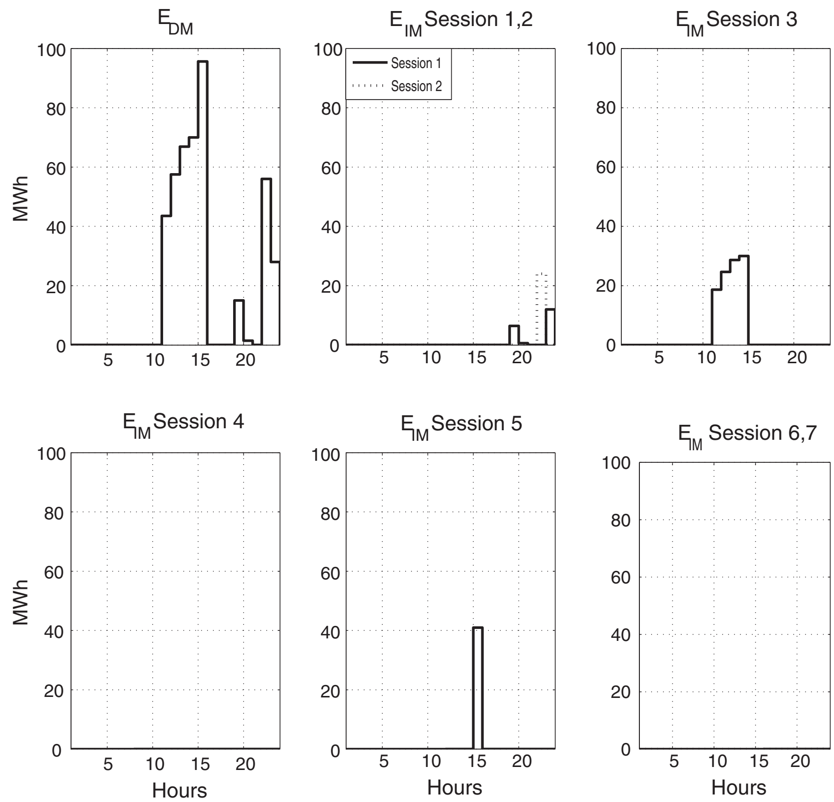


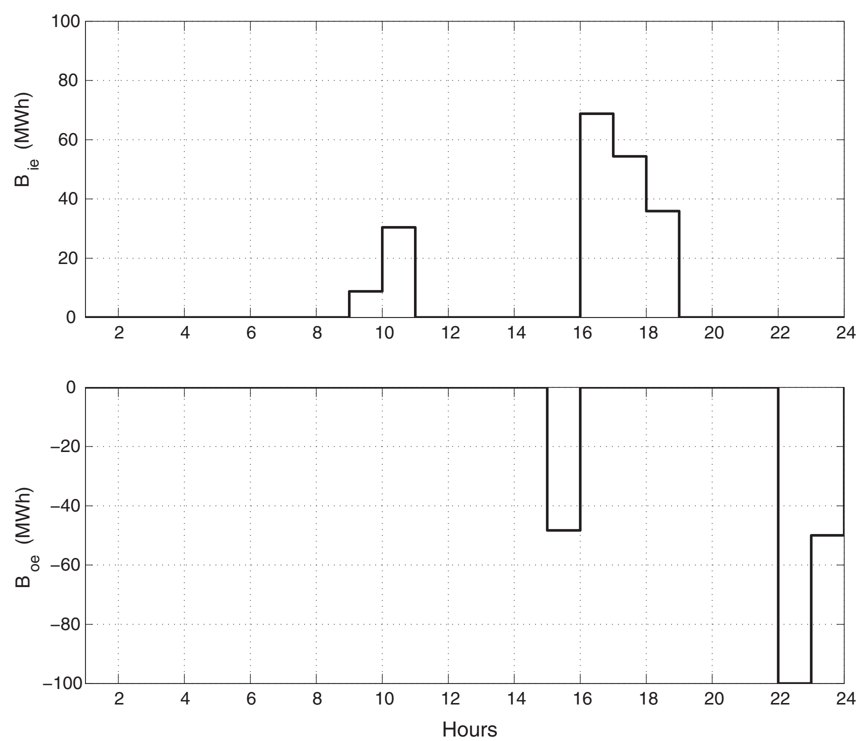
Fig. 9. Day type: clear day. Scheduling results. Date 04/05/2015. (a) Daily and intraday markets energy $E_{DM} + EP_{IM}$. (b) Solar PV Generation and energy stored in the battery B_{es}. (c) Maximum estimated price of energy.

The two first terms in the cost function contain: the daily market energy and intra-daily market energy (E_{DM} and EP_{IM}) multiplied by the respective costs ($\widehat{P}_{DM}$ y $\widehat{P}_{IM}$). And the two last terms penalize charge and discharge of the battery (B_{ie} y B_{oe}) multiplied by their cost.

The first five constraints (Eqs. (7)–(11)) define the maximum and minimum values of the decision variables and the battery capacity. Eqs. (12) and (13) restrict the charging of the battery to positive values and the discharge to negative values. The equations balancing the energy of the plant is modeled by constraint 14.



(a) Daily and intraday electricity energy.



(b) Battery input/output energy

Fig. 10. Day type: clear day. Date 04/05/2015.

Lastly, expression 15 limits the share of the daily energy market to a specific percentage ($E_{DM_{pc}}$).

The controllers have been implemented in MATLAB and to solve the linear programming problem with constraints, the function *linprog* from the optimization toolbox has been used.

The intra-day market consists of six sessions covering different time periods (see Table 1). In the algorithm, each session can be interpreted as a 24 element vector, in which the hourly price rate for hours outside the specific period is set to zero, except for the first session, which would be a 27 element vector as it starts at 22.00 and ends on the next day at 24.00. When implementing the optimization algorithm (Eq. (6)) seven sessions have been taken into consideration, where the seventh session contains the three extra elements of session one. This results in a matrix with seven rows (sessions) and 24 columns (hours).

4.2. Intraday market MPC controllers

The intraday market is a complementary platform for the daily market, where electricity is traded to adjust the quantities traded in the daily market, comprising of a number of daily trading sessions. Each of the intraday market sessions forms a price for the hours which is the object of negotiation in each session with a schedule horizon smaller than in the Daily Market. Market participants may only participate for the hourly periods corresponding to those included in the daily market in which they have participated OMIE.

Now, the six controllers for each intraday session are described.

They differ in the value of the horizon, which is being reduced in each session (see Table 5) and in the length of the output (Table 2). Each one computes energy for its intraday market and the following ones.

$$\max_{E_{IM},B_{ie},B_{oe}} J_{session} = \sum_{i=1}^{N}\sum_{j=1}^{SH} E_{IM}(i,j)\widehat{P}_{IM}(i,j) - \sum_{i=1}^{SH} B_{ie}(i)\eta^{+}C - \sum_{i=1}^{SH} B_{oe}(i)\eta^{-}C \tag{16}$$

s.t.

$$E_{IM}^{min}(i,j) \leqslant E_{IM}(i,j) \leqslant E_{IM}^{max}(i,j) \tag{17}$$
$$B_{ie}^{min}(i) \leqslant B_{ie}(i) \leqslant B_{ie}^{max}(i) \tag{18}$$
$$B_{oe}^{min}(i) \leqslant B_{oe}(i) \leqslant B_{oe}^{max}(i) \tag{19}$$
$$B_{es}^{min}(i) \leqslant B_{es}(i) \leqslant B_{es}^{max}(i) \tag{20}$$
$$B_{ie}(i) \geqslant 0 \tag{21}$$
$$B_{oe}(i) \leqslant 0 \tag{22}$$
$$SE(i) \geqslant E_{DM}(i) + E_{IM}(i,j) + B_{ie}(i) + B_{oe}(i) \tag{23}$$

where session, N and SH take the values shown in Table 5.

5. Results

In this section, the results from running the scheduling algorithm on the 5th and 25th of April 2015 are presented. Two days with different climatology were chosen, the first one was a sunny clear day and the second was a cloudy day. The irradiance data were gathered from latitude 37.40°.

In both cases the following configuration values were chosen: The nominal power of the plant was 100 MW h. The battery capacity was 200 MW h, with an hourly charging/discharging limit of 100 MW h and a battery charge efficiency of $\eta^{+} = \eta^{-} = 0.8$. It is

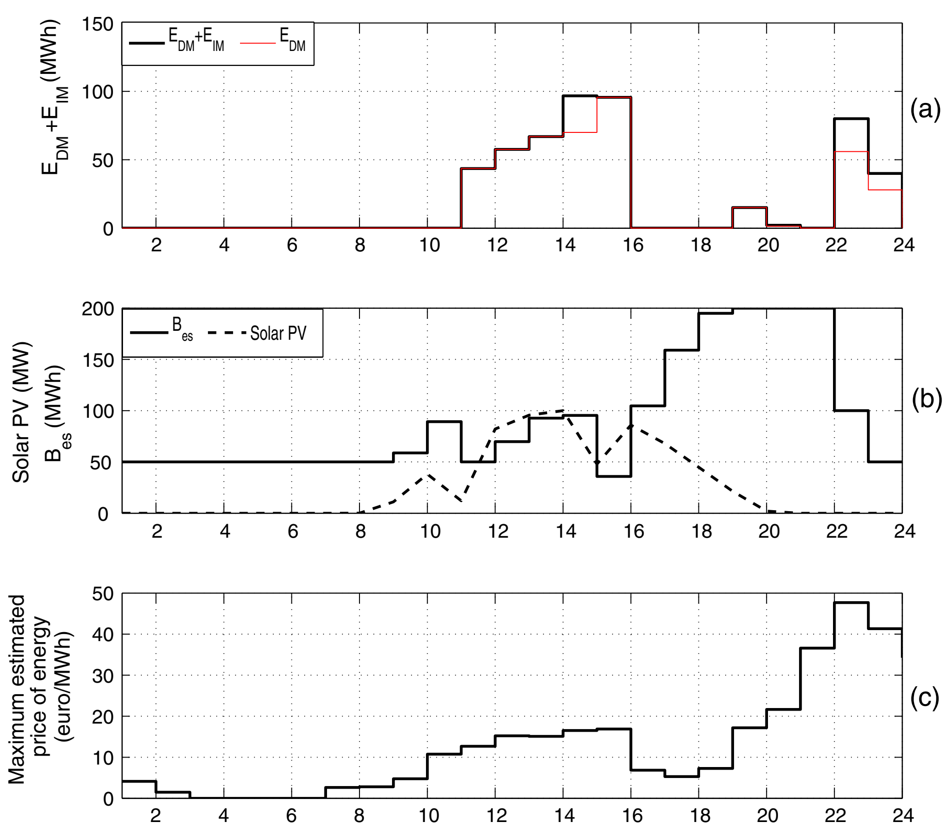
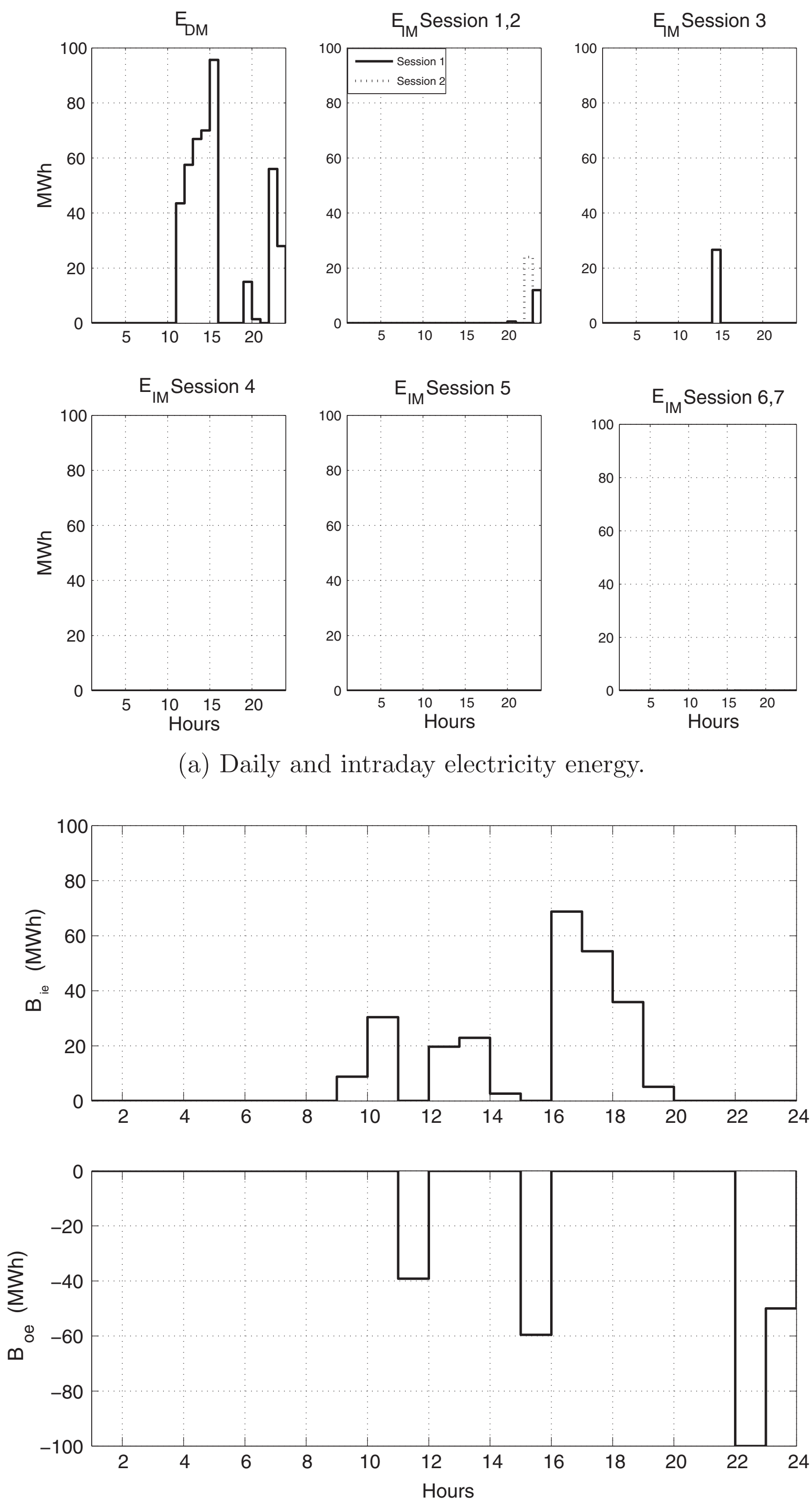


Fig. 11. Day type: clear day with unexpected clouds. Scheduling results: MPC_{IMs1}. Date 04/05/2015. (a) Daily and intraday markets energy $E_{DM} + EP_{IM}$. (b) Solar PV Generation and energy stored in the battery B_{es}. (c) Maximum estimated price of energy.

assumed that the initial state (B_{ini}, the state of the battery before running the scheduling) and final state (B_{final}, the desired state of the battery at the end of day) of the battery is 50 MW h. The minimum energy stored in the battery (B_{es}^{min}) is 25 MW h and that the percentage of the daily market is $E_{DM_{pc}} = 70\%$ of the supplied energy per hour for the following day.

In the simulations it was assumed that the battery is of the manufacturer Eos Energy Storage, and for industrial scale storage systems. These batteries guarantee 10,000 cycles, and their price is 144.43 euros per kW h. The cost of usage (C) of the mentioned batteries was calculated as in Garcia-Torres and Bordons (2015), resulting 7.22 €/MW h.



(a) Daily and intraday electricity energy.

(b) Battery input/output energy

Fig. 12. Day type: clear day with unexpected clouds. MPC_{IMs1}. Date 04/05/2015.

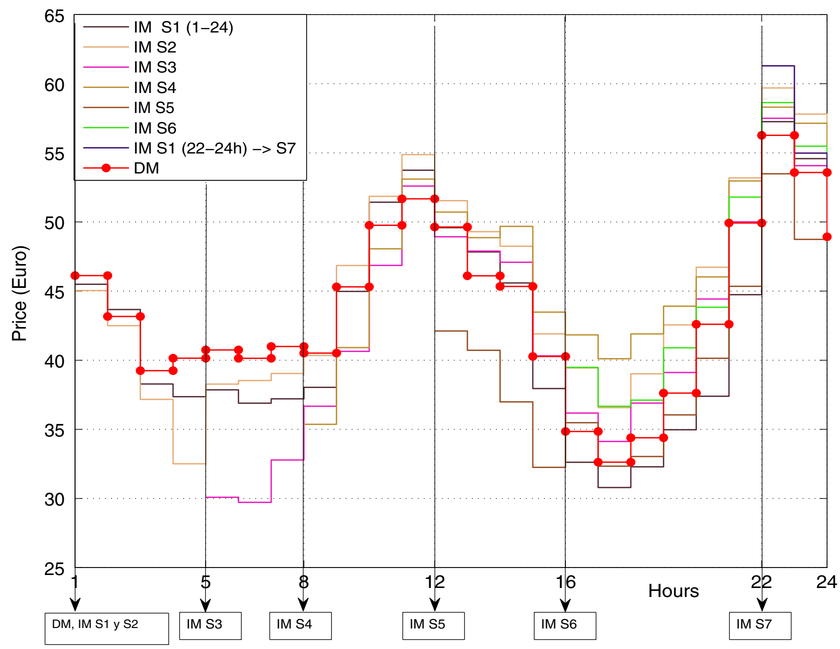


Fig. 13. Day type: cloudy day. Estimated prices of the daily (red dots) and intraday markets. Date 04/25/2015. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

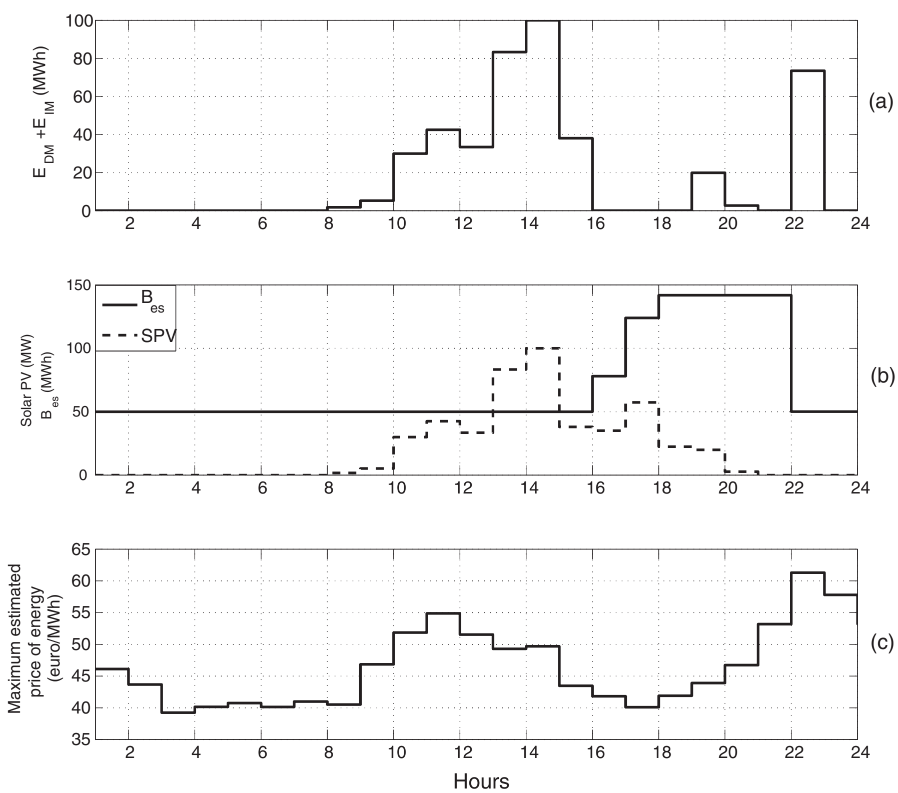


Fig. 14. Day type: cloudy day. Scheduling results. Date 04/25/2015. (a) Daily and intraday markets energy $E_{DM} + EP_{IM}$. (b) Solar PV Generation and energy stored in the battery B_{es}. (c) Maximum estimated price of energy.

5.1. Clear day

In Fig. 8, the estimated prices of the *DM* (red dots) and of the 6 sessions of the *IM* are shown. As it appears on the graph, the values of that day are characterized by a noticeable increase at nightfall, when the solar energy is zero. In these cases the battery plays a very important role and using the optimization management algorithm becomes essential for enhancing economic benefits.

The results of applying the optimization algorithm are shown in Fig. 9. In the first graph the Total Supplied Energy from both the

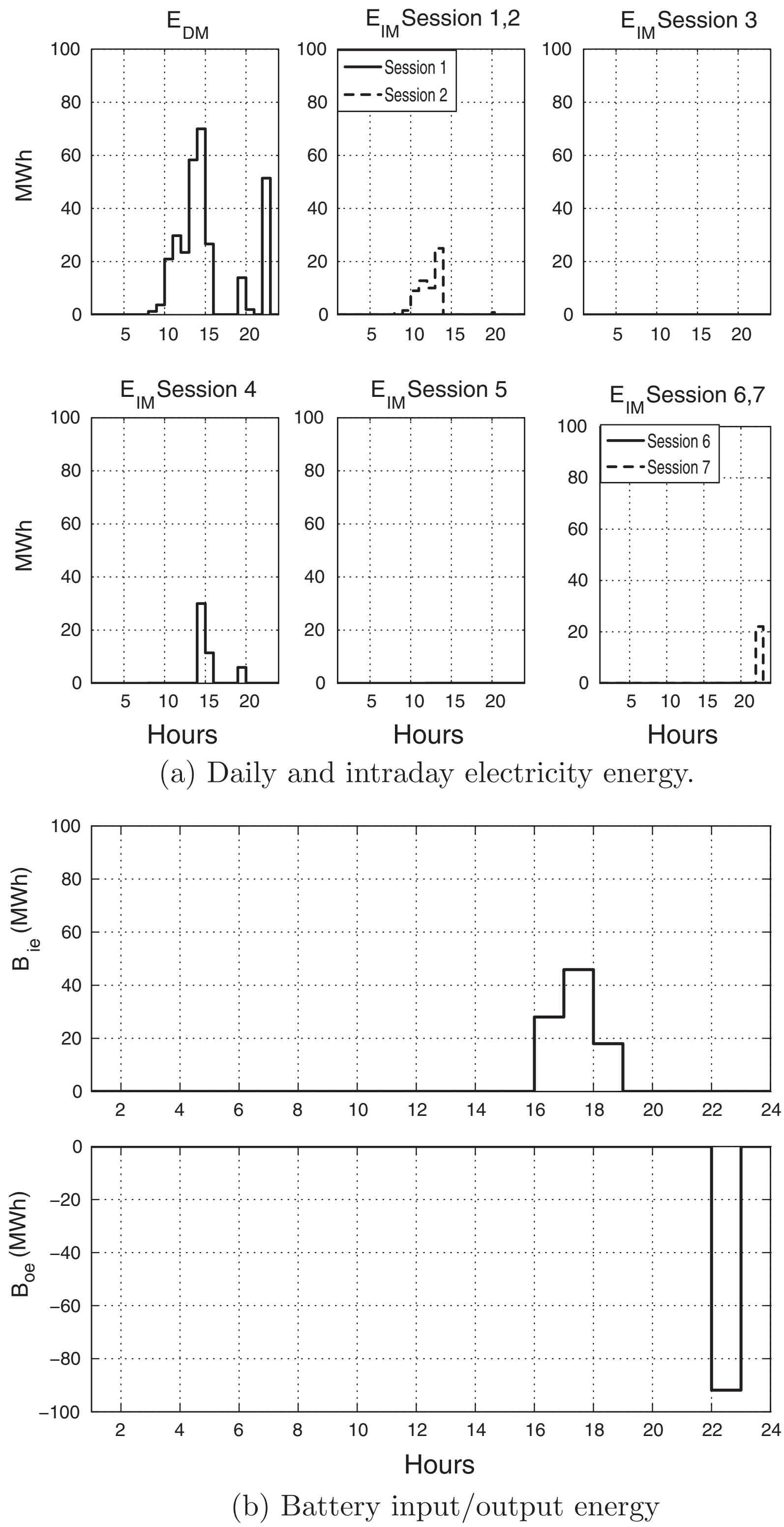
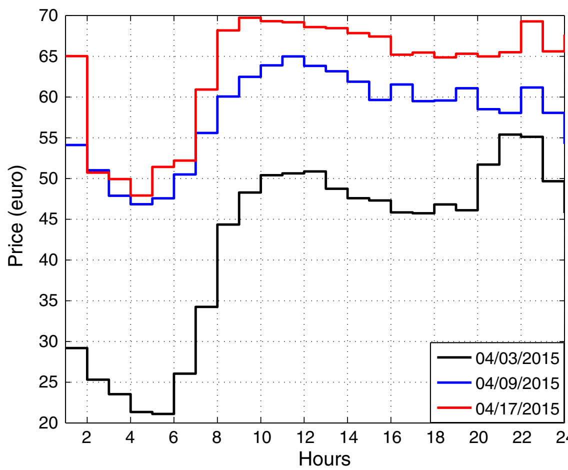


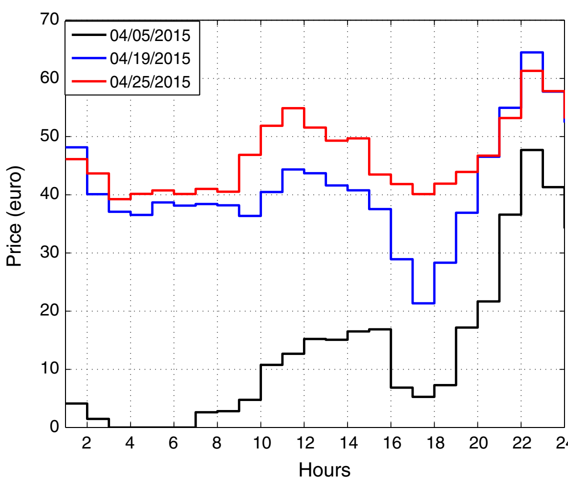
Fig. 15. Day type: cloudy day. Date 04/25/2015.

Table 6
Profit increase obtained from the application of the scheduling algorithm with different battery capacities.

Date	100 MW h	150 MW h	200 MW h	250 MW h	300 MW h
04/05/2015	8.96%	13.14%	15.71%	19.44%	20.38%
04/25/2015	5.05%	6.81%	6.72%	6.43%	6.12%
04/19/2015	8.73%	12.18%	14.7%	16.67%	18.4%
04/17/2015	0%	0%	0%	0%	0%



(a) The algorithm does not use the battery.



(b) The algorithm uses the battery.

Fig. 16. Estimated prices.

DM and the *IM* ($E_{DM} + EP_{IM}$) are represented. The second graph shows the available energy (the summation of the energy produced by the photovoltaic plant and the energy stored in the battery (B_{es})). In the last graph the maximum price at each hour is shown.

It can be observed that the battery is charged in the hours where the prices are the lowest. At 8:00 until 10:00, and from 16:00 until 18:00, reaching its maximum capacity in this final hour.

Correspondingly, the discharge is carried out in the hours of the highest prices, at 15:00 and from 22:00 until 23:00, reaching the value of the desired charge at the end of the day. It should be pointed out that at 15:00 the available energy surpasses the value of 100 MW h, as it is the sum of the solar energy and the stored energy. The algorithm obtains a greater benefit when taking into account the rates throughout the day. In this case, it calculates that at 15:00 it is possible to discharge a necessary amount of battery coinciding with the maximum price during the hours of sunlight.

In Fig. 10 the decision variables of the optimization algorithm have been represented in detail. In the first graph (Fig. 10a) the obtained energy is shown in the daily market and in the 7 sessions of the intra-daily market and in the second graph (Fig. 10b) the charge and discharge of the battery for every hour of the day. All of these values are supplied, as references, to the controller of the following level of the control architecture (*MPC*).

5.2. Clear day with unexpected clouds.

In this section the results of the intraday market controllers are shown. In this case, the starting point is the results of the previous section (clear day), adding a modification in the forecast of the irradiance at 16:00 h of the day D-1. At 10:00H the controller (Eq. (6)) determines the energy offer to the daily market. The next controller to operate is that of session 1 of intraday market (Eq. (16)) at 17:00H. As the forecasted solar energy has changed, the result of this algorithm will be different to the previous one, except in E_{DM}. It is assumed that the forecasted irradiance decreases at 11:00 h and 15:00 h.

In Fig. 11a, the contracted energy in the daily market is shown in red, and it can be observed that it is the same as in Fig. 9. The algorithm, in order to avoid penalties, prioritizes the bid done in previous offers. In this case, as all the contracted energy can be supplied, uses the stored energy in Fig. 12b. and reduces the energy in the intraday market in sessions 1, 3 and 5, as can be seen in graph (a). If there are no more changes in forecasting of prices and irradiance, the other controllers will supply the same results.

5.3. Cloudy day

The estimated prices for the 25th of April are represented in Fig. 13. The maximum and minimum prices are 30 and 60 euros. Two increases are observed, one at 11:00 in the morning and the other at 22:00 at night.

The solution by the scheduling algorithm is shown in graph 14. It can be observed that at the price peak-hours the energy offered is the highest possible, both in terms of solar energy and stored energy.

The battery does not begin charging until the rates decrease, from 16:00 until 18:00. From this time onwards the behavior of the algorithm is very interesting given that at first sight it can be thought that until 20:00 there is still solar energy that should be stored in the battery for discharging afterwards when the prices are higher, around 22:00 and 23:00. However, if the algorithm did that, lower return would be obtained compared to the result shown in the graph. This is due to the loss of energy during the charging and discharging of the battery and the limitation of the desired value at the end of the day.

Finally, the resulting values of the decision variables are presented in detail (Fig. 15). In Fig. 15a, the available energy is given for the daily market as well as for the different sessions of the intra-day market, and in graph 15b the charging and discharging of the battery throughout the day is shown.

5.4. Results of the algorithm as a function of the capacity and battery performance

The result of the scheduling algorithm depends on several factors. One of those is the battery capacity. With the aim of showing its importance a series of experiments was carried out for four days in April with different weather conditions: the two days previously studied (the 5th and the 25th) and two more days, the 17th and the 19th. The first was clear and sunny and the second one cloudy. The days have been chosen with the aim to show the different behaviors of the algorithm.

The values of the configuration parameters are the same as in Section 4.2. For the obtainment of the economic profit, it should be noted that the scheduling algorithm takes the estimated rates into account while the benefits are obtained with the real market rates. The results of the application of the algorithm have been compared to a plant that does not have an energy storage system. They are shown in Table 6, where it can be observed that the obtained benefits are not always proportional to the battery

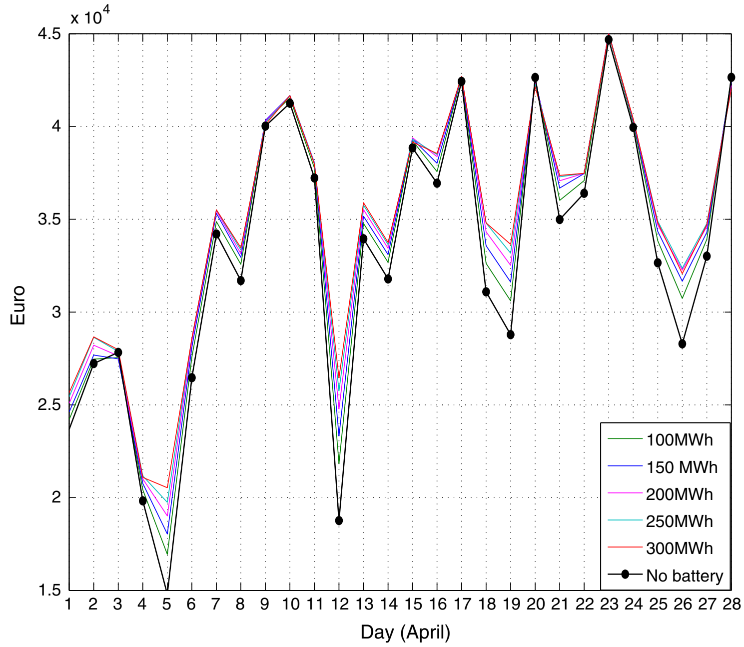


Fig. 17. Profits obtained through the use of the scheduling algorithm with different battery capacities compared to a plant without energy storage. April 2015.

Table 7
Relation between battery efficiency, the amount of time it is used and the profits obtained through the use of the scheduling algorithm.

$\eta^+ = \eta^-$	Battery time (h)	Benefits (%)
0.95	10	22.14%
0.90	9	19.5%
0.85	8	18.38%
0.80	8	15.71%
0.75	7	14.78%

capacity, given that an energy loss exists in the performance of the battery.

For the 5th of April, with a battery of 200 MW h, a 15.71% of economic benefits is obtained, compared to the plant without storage. The best result for this day corresponds to a battery size of 300 MW h. For the 17th of April, benefits are not obtained regarding the battery-less system. That is to say, the algorithm on that day does not make use of the battery because it is more profitable not to use it, due to the energy prices and the values of the battery performances, it calculates that the maximum earning is obtained without using the battery. Generally, if the rates do not have notable increases outside of the solar energy range, the energy loss when using the battery makes it more profitable not to use the battery.

In Fig. 16, the estimated prices from various days are shown; in graph 16a the rates from three different days can be seen (including the 17th of April) where the algorithm does not use the battery, and in Fig. 16b the rates from three days are shown (the previous studies) where benefits are obtained at the end of the day despite the loss of energy due to the usage of the battery. The difference of these two graphs consists in that the first one from 20:00 (when there is no longer any solar radiation) the prices do not vary much regarding the morning increase while in the second graph, the rates at nightfall (22:00) have a notable increase, as it shows the highest value of the day.

This can also be observed in graph 17, where the profits in euros of the first 28 days of April are shown from a system with different capacities of batteries processed by the scheduling algorithm and a floor without storage (the line with black dots).

It is observed that for the majority of the days, the profit obtained from the plant without storage is lower to the one obtained from the plant with different capacity of charge in the battery. In some cases, the economic profits in both situations are similar. However, the system without storage never gets a significatively better result compared with the one with storage. For example, for the 20th the obtained earning without the battery is slightly higher than of the scheduling algorithm. This is because of the error in the rate estimation, considering that the earnings have been calculated with the real market rates and the scheduling uses the estimates.

In the cases where the earnings are equal, the algorithm resolves that it is better not to use the battery, due to the loss of energy that is produced when charging and discharging the battery, and the cost that it supposes. The energy loss is dependent on the performance of the storage system. Therefore, this performance determines the use of the battery. Whenever the battery is used it will be losing energy and the algorithm evaluates automatically for each hour if, despite the fact that it loses energy, it obtains bigger profit. Therefore, in some cases it will be better not to use the storage system.

In Table 7 the number of hours that the battery is used is shown for different battery performance values (assuming $\eta^+ = \eta^-$) and with this the profits from using the scheduling algorithm compared with a plant without energy storage. The experiment is carried out for the fifth of April with a battery of 200 MW h. It shows that the lesser the performance of the battery, meaning how much energy is lost, the lesser it is used, and thereby the smaller the profits.

It would be interesting to compare the scheduling algorithm with an algorithm based on heuristic rules. In order for the comparison to be fair, it must be carried out taking into account all the considerations that the scheduling algorithm has. However it is a complicated task and if it was carried out successfully, the same results as in the scheduling algorithm would be obtained, due to its own nature, being a convex optimization problem, it obtains the optimum value (global maximum) in every interaction.

6. Conclusions

In this paper, a scheduling strategy for the integration of PV plants in the electricity market has been presented. This strategy determines whether the energy will be stored or sold depending on the differences of the hourly prices. This strategy needs a good estimation of the market price of electricity both in the daily and intra-day markets, which is also presented. This algorithm is based on historical data publicly available and is able to estimate prices that fit the real ones with a small error and the adequate profile. The scheduling algorithm has been tested in different situations (different solar generation and market prices), providing good results. A sensitivity analysis regarding changes in battery size has been performed, showing the profit that can be obtained in several situations. The use of this scheduling strategy together with price forecasting facilitates the integration of PV (and other renewable-energy plants) in the electricity market in the same way as done by other kind of generation plants.

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