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Calculating the profits of an economic MPC applied to CSP plants with thermal storage system

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ABSTRACT

Electricity producers participating in a day-ahead energy market aim to maximize profits derived from electricity sales. The daily generation schedule has to be offered in advance, usually the previous day before a certain moment in time. The development of an economically-optimal generation schedule is the core of the generation scheduling problem. To solve this problem, renewable energy plant owners need, besides energy prices forecast, weather prediction. Among renewable energy sources, concentrated solar power (CSP) plants with thermal energy storage (TES) may find it easier to participate in electricity markets due to their semi-dispatchable generation. In any case, the limited accuracy of forecasting solar resource brings about the risk of penalties that may be imposed to CSP plants for deviation from the submitted schedule. This paper proposes a model-based predictive control (MPC) approach with an economic objective function to tackle the scheduling problem in CSP plants with TES. By this approach, the most recent forecast and the current status of plant can be used by the proposed economic MPC approach to reschedule the generation conveniently at regular time intervals. On the other hand, a more feasible generation schedule for the next day is performed at the appropriate time thanks to the use of short-term forecast. The proposed approach is applied, in a simulation context, to a 50 MW parabolic trough collector-based CSP plant with TES under the assumptions of perfect price forecasts and participation in the Spanish day-ahead energy market. A case study based on a half-year period to test several meteorological conditions is performed. In this study, an economic analysis is carried out using actual values of energy price, penalty cost, solar resource data and its day-ahead forecast. Results show an economic improvement in comparison with a traditional day-ahead scheduling strategy, especially in periods with a bad weather forecast. To overcome the lack of short-term weather forecast data for this study, a synthetic short-term predictor, whose accuracy level can be tuned by means of a parameter, is used. Sweeping this accuracy level between the situation with no forecast improvement and perfect short-term forecast, the MPC strategy reaches an improvement in total profits during the six months period between 13.9% and 33.3% of the maximum room for improvement. This maximum ideal improvement is defined as the difference in profits between the MPC strategy with perfect forecasts and the day-ahead scheduling strategy.

1. Introduction

Concentrating solar power (CSP) is a promising technology that has drawn much attention in countries such as Spain and the USA, where subsidy policies have promoted its development. The most commercially-attractive (Purohit et al., 2013) and widely installed CSP technology (Zhang et al., 2013) is found in plants based on parabolic trough collector (PTC), which use synthetic or organic oil as the heat transfer fluid (HTF). CSP has arisen interest, primarily because of the semi-dispatchable nature of CSP plants with thermal energy storage (TES) and/or backup systems based on fossil-fuels. The benefits yielded by these systems are as follows: (1) a cutback in real-time net power variability in the event of poor solar energy, (2) an extension of the whole production period, and (3) a possible rearrangement of production towards high-price periods. More specifically, the advantages of CSP with TES have been proven on an experimental basis in Dinter and Gonzalez (2014), achieving an operability similar to that of mainstream fossil-fired power plants. Additionally, an evaluation of the

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Nomenclature

Power variables refer to average values in the step Time indices, time steps and numbers of steps

- i, j, k — time indices for the current time, the MPC model and the synthetic short-term predictor
- $\Delta t_w, \Delta t_o$ — time steps for control update and the MPC model
- N, N_{TI}, N_{STF} — numbers of steps in the MPC sliding window, the TI interval and the ST forecast

Parameters

- Δw — length of the MPC sliding window
- $t_{schedule\_del}$ — deadline hour in day D for the delivery of the generation schedule for the day D + 1
- $t_{schedule\_end}$ — end time of the committed generation schedule
- ω — accuracy parameter of the synthetic short-term predictor
- ϕ — constant estimation for the penalty costs per MW h of deviation
- $\bar{\phi}$ — mean value for the penalty costs per MW h during the studied time period
- γ — relative importance of the penalty term in the economic MPC
- K — constant in the terminal value term of the MPC objective function
- η — efficiency factor for the conversion of stored energy to net electric energy
- p_{vlow} — value much lower than the minimum electricity price in the studied period

Variables

- $t(i)$ — current time
- $x_c(t(i))$ — current continuous state of the CSP plant
- $x_d(t(i))$ — current discrete state of the CSP plant
- $p(j/i)$ — electricity price forecast made at time $t(i)$
- $P_{SFmax}(j/i)$ — predictions for the maximum thermal power available from the SF
- $P_{SFmax\_DA}(k/i)$ — day-ahead forecasted maximum thermal power available from the SF
- $P_{SFmax\_STF}(k/i)$ — short-term forecasted maximum thermal power available from the SF
- $P_{SFmax\_actual}(k/i)$ — actual maximum thermal power available from the SF
- $P_{eref}(j/i)$ — committed generation schedule still to be met (gross value)
- $P_{erefnet}(j/i)$ — committed generation schedule still to be met (net value)
- $P_e(j/i)$ — turbine-generated gross electric power
- $P_{enet}(j/i)$ — turbine-generated net electric power
- $P_{e\_SP}(1/i)$ — setpoint for electricity generation calculated by the MPC (gross value)
- $E(j/i)$ — TES energy level at the beginning of the step j
- $u(j/i)$ — general decision variables in the MPC approach
- $\phi(j/i)$ — estimation of the penalty cost per kWh of deviation
- $f_{cost}(.)$ — undefined function for generation costs
- $s(.)$ — undefined function for the terminal value term of the MPC objective function

Acronyms

- CSP — concentrated solar power
- DAS — day-ahead scheduling
- DNI — direct normal irradiance
- HTF — heat transfer fluid
- MILP — mixed-integer linear programming
- MIP — mixed-integer programming
- MPC — model-based predictive control
- NSI — next schedule interval
- PTC — parabolic trough collector
- SF — solar field
- TES — thermal energy storage
- TI — tracking interval

economic performance of CSP plants using TES can be found in Madaeni et al. (2012) demonstrating that it could be a reliable option. Nowadays, the most commercially mature technology for TES is an indirect two-tank molten salt storage system (Kuravi et al., 2013).

As mentioned above, CSP systems become semi-dispatchable power sources thanks to TES (it cannot be total dispatchable due to the limited amount of stored energy). This aspect encourages CSP plants to participate in electricity markets due to, among other things, being able to rearrange production from lower to higher price periods. Therefore, it is interesting to approach the optimal generation scheduling problem (also called *self-scheduling*). In deregulated markets, the purpose of electricity producers is to maximize profits from the sale of energy. Furthermore, power plant owners also have to offer a daily schedule in electricity markets ahead of time. As a consequence, forecast for the price of the electricity and the weather must be considered in the optimization problem.

The paper (Sioshansi and Denholm, 2010) was one of the first works on the optimal operation of a CSP plant, and it analyses the profits obtained by a CSP plant using TES in electricity markets in several different areas of the USA. The optimization problem was overcome with two models: the widely-used SAM tool (SAM, 2017), which provides the thermal power produced in solar fields (SF), and a model for optimization based on mixed-integer linear programming (MILP). More examples of the use of the MILP approach can be found in Usaola (2012), Kost et al. (2013), Vasallo and Bravo (2016b). Pousinho et al. (2014, 2016) study scheduling for energy and spinning reserve of wind/CSP plants again from an MILP approach. Different approaches to MILP can be found in Lizarraga-Garcia et al. (2013), Powell et al. (2014) where Nonlinear Programming is used, and in Wittmann et al. (2011) and Channon and Eames (2014), where Dynamic Programming is used.

One of the disadvantages of CSP plants is the predictability of its electricity production since it is limited by the accuracy of forecasting direct normal irradiance (DNI). As a result, operations carried out in electricity markets run the risk of being penalized for deviating from the generation schedule. Such penalties depend to a large extent on the actual deviation, so the accuracy of DNI forecasts is no doubt a relevant aspect (Law et al., 2014). There are papers that analyze the financial value of CSP plants based on DNI forecasts, namely (Kraas et al., 2013; Law et al., 2016a). Robust and stochastic approaches are also used to solve optimal scheduling problems due to the uncertainty of CSP production forecasts and the difficulty of forecasting market prices accurately (Domínguez et al., 2012; Pousinho et al., 2015; He et al., 2016). These papers analyze optimal operation in an MILP framework and suggest offering strategies to electricity markets.

According to the literature review, we find that the most widely-used method for modeling optimal scheduling problems in CSP plants is MILP. MILP is generally a powerful mechanism used for optimal scheduling problems in power systems (Simoglou et al., 2012). MILP is useful for these problems given that it is capable of formulating unit, startup, shutdown and ramp-rate constraints, as well as piecewise linear functions. In addition, some efficient MILP solvers nowadays find global optimal solutions in short computation times.

As mentioned above, CSP plants operating in electricity markets run the risk of being penalized for deviating from the scheduled generation as a result of inaccurate DNI forecasts. To reduce this risk, the authors of this paper suggested using a model-based predictive control (MPC) approach for generation scheduling in CSP plants based on a mixed-integer programming (MIP) model (Vasallo and Bravo, 2016a). MPC is a control strategy amply used in the industry and in academia alike. The power systems community has recently become interested in MPC due to its ability to deal with forecasts and complex constraints. Applications to scheduling and control problems arising in power systems can be seen in the literature (Petrollese et al., 2016; Sokoler et al., 2016). MPC exercises control based on a sliding-window strategy where a cost function is optimized over a moving time-horizon. It, therefore, allows for real-time optimization. Thus, information on the status of the plant and the most recent forecast becomes useful to regularly improve its operation. Categorically speaking, the purpose of the MPC approach contained in Vasallo and Bravo (2016a) is twofold: (1) the appropriate, regular tracking of the generation schedule that the plant has committed until that moment, (2) the development, at the appropriate time, of the optimal generation schedule for the following day. The information on how to track the generation schedule committed by CSP plants allows for a better estimation of their status at the beginning of the following day, permitting the development of a more achievable generation schedule. It is worth noting that the proposed MPC approach is applied only to the generation scheduling and not to the control problem, as the later issue is supposed to be efficiently resolved. This approximation is common in works about CSP scheduling found in literature (see previous references).

This paper has been inspired by the following question: what is the impact on profits of using a MPC approach for generation scheduling in CSP plants? In this regard, an economic version of the general MPC approach presented in Vasallo and Bravo (2016a) is proposed and tested. It is based on the fact that the cost function used to track the committed generation schedule is defined such that pricing and penalty information is added, unlike the application example in Vasallo and Bravo (2016a) where the even distribution of the generation error was the objective for the tracking. This way, penalties could be partially balanced by increasing revenues thanks to the use of economic information. Since all terms of the cost function now have an economic nature, this MPC approach belongs to the class of MPC strategies called *economic MPC* in literature (Dieulot et al., 2015; Touretzky and Baldea, 2014).

The proposed approach is applied, in a simulation context, to a 50 MW PTC-based CSP plant with molten-salt-based TES under the assumptions of perfect price forecast and participation in the Spanish day-ahead energy market. Unlike the work in Vasallo and Bravo (2016a), an economic analysis is performed, taking into account a half-year period to test several weather scenarios. Actual values for energy price, penalty cost, solar resource data and its day-ahead forecast are used. Moreover, several configurations of the MPC approach are studied. An economic improvement over the traditional day-ahead scheduling is shown in results. A related approach has been presented in Law et al. (2016b) but it is applied to the Australian electricity market, i.e., with different electricity market regulations.

A general description of the economic MPC approach is given in Section 2. The case study is described in Section 3, where Sections 3.1 and 3.2 depict the models used and Section 3.3 describes the characteristics of certain input data. Section 4 draws the results and discussion. Finally, conclusions are put forward in Section 5.

2. Description of the economic MPC approach

The economic MPC approach proposed in this paper is a specific version of the general approach presented in Vasallo and Bravo (2016a). The new cost function includes the pricing and penalty information. Therefore, all the terms of the cost function are economic, and the proposed MPC approach can be classified as an economic MPC. This section includes a complete description of the economic MPC approach to provide a better understanding of the rest of the paper (the variables and parameters defined are cited in the following sections). Readers are referred to (Vasallo and Bravo, 2016a) for more details.

The proposed approach assumes the participation in a day-ahead energy market and the producer's price-taking property (i.e. its production schedules do not influence market prices). As mentioned in Section 1, the dual purpose of the proposed MPC approach is: (1) the appropriate, regular tracking of the generation schedule that has been committed and (2) the development of the optimal generation schedule for the next trading day at the appropriate time. It is worth noting that the two purposes of the MPC approach are based on the following statements: (1) information on the status of the plant and the most recent forecast (e.g. short-term DNI forecast or perfect knowledge of electricity prices) would be useful to regularly improve the operation of the plant; and (2) the status of the plant at the beginning of the following day is better estimated thanks to the latter statement, and, consequently, a more feasible generation schedule can be developed.

The two objectives of the MPC approach require its sliding window to be divided into two intervals (see Fig. 1): the tracking interval (TI) and the next schedule interval (NSI). The generation schedule must then be updated to track the schedule that has been committed to within the TI interval, while the NSI interval is used to maximize future profits and generate the schedule for the following day at the appropriate time. Several variables and parameters related to the sliding window are defined next:

- $t(i) = i\Delta t_w$, where $i = 0, 1, \ldots$are the time instants when MPC control output is generated. The beginning time of the sliding window when in position i is set to instant $t(i)$. Case $i = 0$ refers to instant 0.0 h of the current day D. Δt_w is the time step for control update.
- $t_{schedule\_del}$ is defined as the deadline hour in day D for the delivery of the generation schedule for the following day D + 1. This deadline hour depends on each country's market.
- $t_{schedule\_end}$ is the end time of the committed generation schedule. If the current time has not reached the time $t_{schedule\_del}$, $t_{schedule\_end}$ shall usually be 24.0 h of day D. On the contrary, $t_{schedule\_end}$ shall be 24.0 h of day D + 1 because the generation schedule for this day has already been delivered.
- Δw is the length of the constant sliding window.

According to the above definitions, the endpoints of the TI and NSI intervals are shown in Fig. 1. It is also worth noting that the sliding window length is constant, but the lengths of both intervals are time-variant.

When $t(i) = t_{schedule\_del}$, the generation schedule solved by the MPC control for the NSI interval until 24.0 h of day D + 1 can be regarded as the generation schedule for this day. As the typical optimal scheduling problem has an optimization horizon based on the following one or two trading days (Wittmann et al., 2011) and an assumed constant sliding window length, the value of this

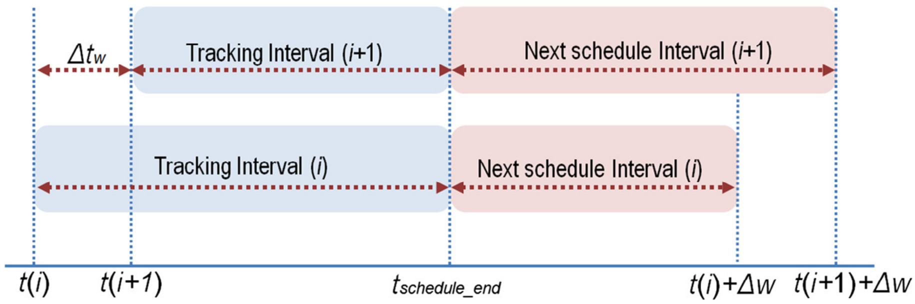


Fig. 1. Sliding window of the economic MPC.

length (Δw) can be between $24 - t_{schedule\_del}$+24 h (one-day strategy) and $24 - t_{schedule\_del}$+48 h (two-day strategy).

Fig. 2 shows the block diagram of the MPC approach. MPC control receives the following information at each sliding window position i:

1. Current continuous state of the CSP plant ($x_c(t(i))$), e.g., the TES energy level and thermal state in the SF.
2. Current discrete state of the plant ($x_d(t(i))$), e.g., active operating phases in the SF, TES or turbine.
3. Electricity price forecast made at time $t(i)$ ($p(j/i)$, for $j = 1, \ldots, N$), where j indicates each step in the MPC model, $N = \Delta w/\Delta t_o$ is the number of steps in the sliding window, and Δt_o is the time step of the MPC model expressed in hours.
4. Predictions of the average value of the maximum thermal power available from the SF ($P_{SFmax}(j/i)$, for $j = 1, \ldots, N$) made at time $t(i)$. The qualifying term 'maximum' is introduced to indicate that a partial defocus in the SF can result in a decrease in the available thermal power. A CSP plant model, DNI and other meteorological variables forecasts and initial conditions for $x_c(t(i))$ and $x_d(t(i))$ are used to generate these predictions.
5. Committed generation schedule still to be met ($P_{eref}(j/i)$, for $j = 1, \ldots, N_{TI}$), expressed in average gross electric power, where $N_{TI} = (t_{schedule\_end} - t(i))/\Delta t_o$ is the number of steps in the TI interval.

The outputs indicated below are generated as a result of the optimization at the sliding window position i:

1. Decision variables at time $t(i)$ ($u(j/i)$, for $j = 1, \ldots, N$). Only the decision variables $u(1/i)$ are applied to the plant as common in MPC approaches.
2. Average values of turbine-generated gross electric power calculated at time $t(i)$ ($P_e(j/i)$, for $j = 1, \ldots, N$). When $t(i) = t_{schedule\_del}$, values inside the NSI interval until 24.0 h of the next day are given as the new generation schedule for this day ($P_{eref}(j/i) = P_e(j/i)$, for $j = N_{TI} + 1, \ldots, N'_{TI}$, where $N'_{TI} = N_{TI} + 24/\Delta t_o$ is the new number of steps in the TI interval).

The objective function to minimize is expressed by Eq. (1)

$$J(i) = -\Delta t_o \sum_{j=1}^{N_{TI}} [p(j/i)P_{enet}(j/i) - \phi(j/i)(P_{erefnet}(j/i) - P_{enet}(j/i)) - f_{cost}(\cdot)] - \Delta t_o \sum_{j=N_{TI}+1}^{N} (p(j/i)P_{enet}(j/i) - f_{cost}(\cdot)) - s(E(N+1/i)) \quad (1)$$

where $\phi(j/i)$ is an estimation of the penalty cost per kW h of deviation at hour j, $P_{enet}(j/i)$ is the turbine-generated net electric power, $P_{erefnet}(j/i)$ is the committed net electric power, $f_{cost}(.)$ represents generation costs, and $s(E(N+1/i))$ is a terminal value term applied to the final TES energy level. It is worth noting that function $-J(i)$ represents the profits along the sliding window. In this paper, it is assumed that the electricity production does not exceed the committed schedule and therefore, the term $\phi(j/i)$ refers to *falling* penalty.

According to the general proposal seen in Vasallo and Bravo (2016a), the MPC optimization model is an MIP model which includes technical and physical constraints and the dynamic model of the plant. Given that a generation scheduling problem is being addressed and that control is assumed to be efficiently resolved, fast dynamics must be removed. The MPC optimization model (hereinafter referred to as the MIP-MPC model) is proposed to

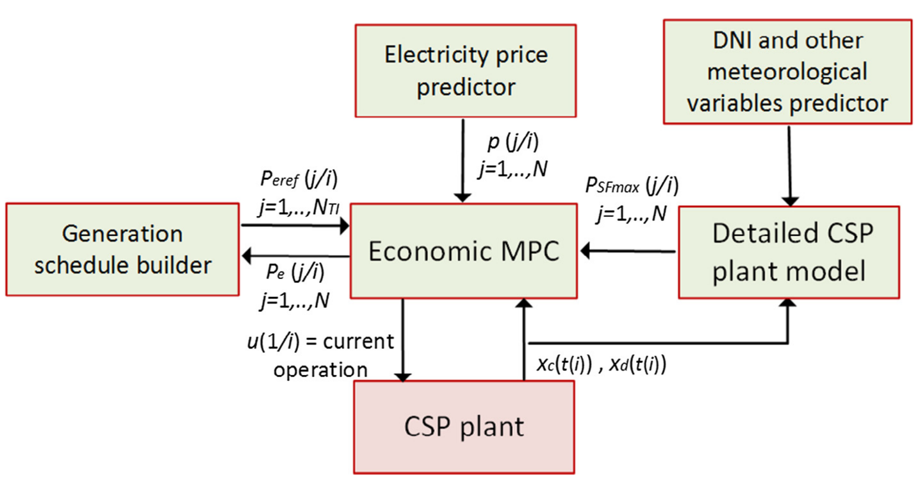


Fig. 2. Block diagram of the economic MPC.

adjust to the features of the CSP plant model (much more detailed) as much as possible yet preserving enough simplicity to avoid increasing the computational burden in a prohibitive way. Futhermore, the time step in the MIP-MPC model should be higher than that in the detailed CSP plant model to avoid high computation times.

3. Description of the case study

The economic MPC approach proposed by this paper is applied, in a simulation context, to a 50 MW PTC-based CSP plant with molten-salt-based TES. The CSP plant is based on the model presented in García et al. (2011) and also used in Vasallo and Bravo (2016a), which describes the plant *Andasol* 2 in Granada, Spain. Some characteristics of this model (adapted to this case study) are shown in Table 1.

The simulation scenario developed for this case study has the following features:

1. A sufficient time period is considered (from 01/01/2013 to 30/06/2013) with the purpose of testing several meteorological conditions.
2. The Spanish day-ahead energy market and the producer's price-taking property are considered. Price forecasts are assumed to be perfect and obtained from data of the Iberian market operator (OMIE, 2017). No premium per MW h is considered. Penalty costs per MW h are also obtained from OMIE. In order to keep things simple, generation costs are not taken into consideration.
3. The generation schedule and MIP-MPC model resolutions are hourly. The frequency of the rescheduling is also hourly. Therefore, $\Delta t_o = \Delta t_w = 1.0$ h (see Fig. 1). Parameter $t_{schedule\_del}$ is set to 10.0 h (Spanish market in 2013). Parameter Δw is set to 48 h to reach a compromise between computation time of the MIP-MPC model and the possibility of conserving energy for its sale after the end of the following day. Therefore, the length of the NSI interval at 10.0 h is 34 h, and the scheduling problem for the following day is based on the next 1 + 5/12 days (i.e., an intermediate scheme between the one-day and two-day strategies).
4. The detailed CSP plant model from Vasallo and Bravo (2016a) is used to generate predictions $P_{SFmax}(j/i)$ (see Fig. 2). DNI and ambient temperature are the only meteorological variables considered, and ambient temperature forecasts are assumed to be perfect and created from TMY2 data (TMY, 2017).
5. The CSP plant is represented by a one-hour-resolution model to avoid very high simulation times, as is common in literature, e.g. (Kraas et al., 2013; Law et al., 2016a). Specifically, a MIP model derived from the MIP-MPC model itself is employed and, therefore, performance differences between the optimization model and the plant are only due to DNI forecast errors. This model is referred to in this work as the MIP-plant model.
6. In order to address a realistic scenario, authors have used day-ahead global solar radiation forecasts, obtained from the Integrated Forecast System model (IFS) of the European Centre for Medium-range Weather Forecasts (ECMWF) and a set of solar radiation measures provided from a photovoltaic solar plant. These data sets are used to obtain forecasted and measured DNI profiles by means of statistical processing. This processing aims to develop a measured DNI profile coherent with the studied location and a realistic forecasted DNI profile (similar forecasting metrics to those found in (Marquez and Coimbra, 2011)). Finally, both sets are converted to maximum thermal power available from the SF by simulation with the detailed CSP plant model (see point 4).
7. Short-term DNI forecasts are also taken into account in this study. Several methods can be consulted in Law et al. (2014). A parameterized model is used to emulate the short-term predictor and to overcome the lack of short-term DNI forecast data for this study. One of its parameters, ω, is a value between 0 and 1, and represents the accuracy of the forecasts (from ideally perfect short-term DNI forecast to day-ahead DNI forecast, respectively). This range allows analyzing the influence of short-term DNI forecasts. Moreover, the developed predictor model works directly with the variable $P_{SFmax}(j/i)$ to avoid conversion from DNI values.

Table 1
Characteristics of the CSP plant.

Turbine capacity (gross)	52.5 MW-e
Solar field capacity	250 MW-t
Thermal capacity of the powerblock in solar-only mode	140 MW-t
Thermal capacity of the powerblock in TES-only mode	119 MW-t
Solar multiple	1.8
TES capacity (TES-only mode)	8 h
Turbine efficiency (full load)	38%
Fossil backup	only to prevent HTF freezing

The economic MPC strategy proposed in this paper is tested against the traditional day-ahead scheduling strategy (DAS strategy). This strategy is characterized by the following features:

1. The schedule for day D + 1 is generated at $t_{schedule\_del}$ of day D. At this moment, initial conditions for day D + 1 are estimated using the current status of the plant, the day-ahead forecast and the schedule still to be met.
2. Its time horizon is 34 h, i.e., the length of the NSI interval at $t_{schedule\_del}$ in the MPC approach. This election is made for a fair comparison between strategies.
3. The generation schedule is tracked without any rescheduling. Then, the hourly generation is the maximum that can be reached according to the committed value.

The optimization model used to generate the schedule in the DAS strategy is also derived from the MIP-MPC model. This optimization model is referred to as the MIP-DAS model in this paper. Tables 2 and 3 summarizes all information about the scheduling strategies and the models used.

Section 3.1 describes the synthetic short-term predictor. MIP-MPC, MIP-DAS and MIP-plant models are explained in Section 3.2. Section 3.3 describes the characteristics of the following input data: solar resource, its day-ahead forecast, electricity prices and the penalty costs per MW h of deviation. Finally, the results and discussion are shown in Section 4.

3.1. Synthetic short-term predictor

A synthetic short-term predictor is used to analyze the influence of short-term DNI forecasts. It is assumed that short-term forecasts are never worse than day-ahead forecasts. Eq. (2) describes the predictor:

$$P_{SFmax\_STF}(k/i) = P_{SFmax\_actual}(k/i) + r(k)\omega(P_{SFmax\_DA}(k/i) - P_{SFmax\_actual}(k/i)) \quad (2)$$

for $k = 1$ to $N_{STF} + 1$; where N_{STF} is the horizon (hours) of the short-term forecast; $r(k)$ is a linear function of index $k, r(1) = 1, r(N_{STF} + 1) = 1/(\omega + \epsilon), \epsilon$ is a very small amount to avoid division by zero; $P_{SFmax\_STF}(k/i), P_{SFmax\_actual}(k/i)$ and $P_{SFmax\_DA}(k/i)$ are

Table 2
Information about the scheduling strategies used.

Model	Strategy	Rescheduling	Short-term forecast	Feedback of the status of the plant
MIP-MPC	MPC	Hourly	Hourly	Hourly
MIP-DAS	DAS	No	No	Daily

Table 3
Information about the models used.

Model	Function
MIP-MPC	MPC strategy
MIP-DAS	DAS strategy
MIP-plant	To represent the plant
detailed model	To convert DNI to $P_{SFmax}(j)$

the short-term forecasted, actual and day-ahead forecasted maximum thermal powers available from SF; and ω is a parameter between 0 and 1, which represents the accuracy of the short-term forecast (from ideally perfect short-term DNI forecast to day-ahead DNI forecast, respectively). It is also worth noting that ω is the percentage of day-ahead forecast error to be added to the actual value to generate the short-term forecast of the first hour. This percentage grows linearly over time (with a non-null value of ω) and reaches 100% when $k = N_{STF} + 1$ (i.e., out of the horizon of the short-term forecast). Typical values for N_{STF} are 5 or 6 h (Law et al., 2014, 2016a). The objective of the synthetic predictor is to enable the approximate analysis of short-term DNI forecasts influence, overcoming the lack of such data for this case study. Therefore, it is not the focus of this paper to develop a more realistic short-term predictor. With the variation of parameter ω, the two extreme cases (ideally perfect short-term DNI forecast and lack of short-term forecast) and other intermediate cases are simulated. In this regard, the variable $P_{SFmax\_STF}(k/i)$ could represent the mathematical expectation of the short-term forecast.

3.2. MIP models

This subsection describes briefly the three one-hour-resolution MIP models. The MIP-DAS and MIP-plant models are derived from the MIP-MPC model. The formulation of the three MIP models for this case study was carried out without any non-linear element, except for binary variables. Thus, they are MILP models.

At this stage, it is important to clarify the following: The plant operator and control systems of the plant under study are supposed to take decisions based on two goals albeit with different priorities (Vasallo and Bravo, 2016a). The high-priority goal is to minimize the generation error. Once this objective is met, the low-priority goal can be applied, which consists of minimizing the defocused thermal power in the SF (thus maximizing the TES energy level). Therefore, the plant under study only has one independent decision variable in relation to power sharing, e.g., the setpoint for electricity generation. Then, the MPC action $u(1/i) = P_{e\_SP}(1/i)$. Equation $P_{e\_SP}(1/i) = P_e(1/i)$ is used to obtain the setpoint, where $P_e(1/i)$ is a value generated by the MPC control.

3.2.1. MIP-MPC model

Most MIP-MPC model constraints are derived from a linear one-hour-resolution simplification of the detailed CSP plant model (excluding the SF). The set of equations and inequalities comprising the MIP-MPC model and the values for its parameters are described in Vasallo and Bravo (2016a). Moreover, the synthetic predictor is added in order to generate the short-term predictions of $P_{SFmax}(j/i)$. The objective function to minimize is expressed in Eq. (3), which is a specific case of the objective function in Section 2.

$$J(i) = -\Delta t_o \sum_{j=1}^{N_{TI}} [p(j/i)P_{enet}(j/i) - \phi(j/i)(P_{erefnet}(j/i) - P_{enet}(j/i))] - \Delta t_o \sum_{j=N_{TI}+1}^{N} (p(j/i)P_{enet}(j/i)) - KE(N+1/i) \quad (3)$$

In this objective function, generation costs are not taken into consideration and $KE(N+1/i)$ is the terminal value term formed by a value proportional to the final TES energy level, with constant K defined by equation $K = \eta p_{vlow}$, where η is an efficiency factor for the conversion of stored energy to net electric energy, and p_{vlow} is a value much lower than the minimum electricity price in the simulation period. This way, the terminal value term of the objective function makes the defocused thermal energy be as low as possible once the maximum economic profits (without terminal value term) have been obtained.

In the Spanish market, deviation from the scheduled generation produces penalty costs if it requires the intervention of the transmission system operator. These penalties are associated with the costs incurred to stabilize the system, and do not follow any pregiven function. Therefore, these costs are difficult to estimate. An average value for $\phi(j/i)$ is assumed in Section 3.3. An analysis is conducted on the performance of the MPC strategy when this average value varies in Section 4.

3.2.2. MIP-DAS model

The MIP-DAS model is an optimization model which generates the generation schedule for day D + 1 when $t(i) = t_{schedule\_del}$ at day D in case of the DAS strategy. The MIP-DAS model is derived from the MIP-MPC model in the following manner: the TI interval is removed and the NSI interval begins the hour 0 of day D + 1. Initial values for the moment before hour 0 of day D + 1 are estimated at $t_{schedule\_del}$ of day D using the current status of the plant, the day-ahead forecast and the schedule still to be met.

3.2.3. MIP-plant model

The MIP-plant model is a one-hour-resolution model used to represent the plant in the several-month-long simulation, and it prevents high simulation times. It is composed of two consecutive optimization models derived from the MIP-MPC model. The two goals with different priorities that guide the decisions of the plant operator and control systems (see the beginning of Section 3.2) explain this scheme. The MIP-plant model incorporates the constraints included in the MIP-MPC model but, unlike the latter, its time horizon is a one-hour step in order to represent the plant in the evolution of the simulation.

3.3. Input data description

The characteristics of the solar resource, its day-ahead forecast, electricity prices and the penalty costs per MW h of deviation for the studied time period are described in this subsection. Fig. 3 shows the hourly average values of the maximum thermal power available from the SF, $P_{SFmax\_actual}(j)$, which have been obtained using solar radiation data and the detailed CSP plant model. As can be seen in the figure, as the days advance, the $P_{SFmax\_actual}(j)$ profile increases in intensity and length. Furthermore, approximately

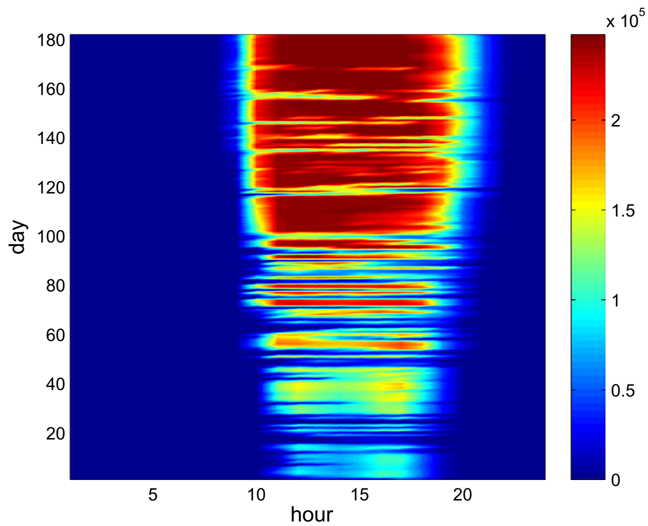


Fig. 3. Hourly average values for maximum thermal power available from the SF (kW).

the first one hundred days present a high meteorological variability, while the stability increases in the last eighty days.

An important variable that can influence the performance of scheduling strategies is, obviously, the day-ahead forecast error of the maximum thermal power available from the SF. In general, the forecast error increases with the meteorology variability, that is, winter days present higher prediction errors than clear summer days. In order to characterize the day-ahead forecast error on a monthly basis, some metrics are shown in Table 4. It is worth noting that only daylight hours are used to obtain the metrics, as the prediction error is absent during night hours. The mean of the maximum thermal power available from SF is denoted by $\overline{P}_{SFmax\_actual}$. The Relative Root Mean Squared Error and the Relative Mean Bias Error are denoted by *rRMSE* and *rMBE* respectively, (see Kraas et al., 2013 for expressions of these metrics). Some observations may be useful. The mean of the maximum thermal power available from the SF increases by 237% from January to June. The relative error is higher in winter months. In fact, March has been particularly bad in the studied period. Finally, the monthly bias error can vary widely.

Fig. 4 shows the difference between daily maximum thermal energy available from the SF and its day-ahead forecast. Red[1] is used if the predicted value is higher and black if it is lower. The width of the line is proportional to the forecast error. The figure shows days with little error and days with a very high forecast error. Roughly, the relative prediction error is higher in the first one hundred days and decreases in the last eighty days. Fig. 5 shows three example days for day-ahead forecast of P_{SFmax_actual}: May 26, 27 and 28. The three days present examples of underestimated, overestimated and accurate forecasts, respectively.

The electricity prices are shown in Fig. 6. Prices reach higher values during the first two months of the year (winter). Smaller values are found in the second two months of the year (moderate temperatures of the spring).

Fig. 7 shows an hourly boxplot of the penalty costs per MW h of deviation from the scheduled generation (falling penalties in this case study). Fig. 8 shows the autocorrelation of the penalty costs time series. There is no significant 24-h autocorrelation, so, it is no easy task to use autoregressive models to predict the penalty

[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

Table 4
Metrics of day-ahead forecast error for maximum thermal power from the SF.

Month	$\overline{P}_{SFmax\_actual}$ (MW)	*rRMSE* (%)	*rMBE* (%)
1	52.6	51.6	17.5
2	82.5	45.4	3.8
3	87.6	70.0	8.4
4	152.4	40.8	–5.3
5	164.4	28.2	10.6
6	177.5	13.4	–7.8

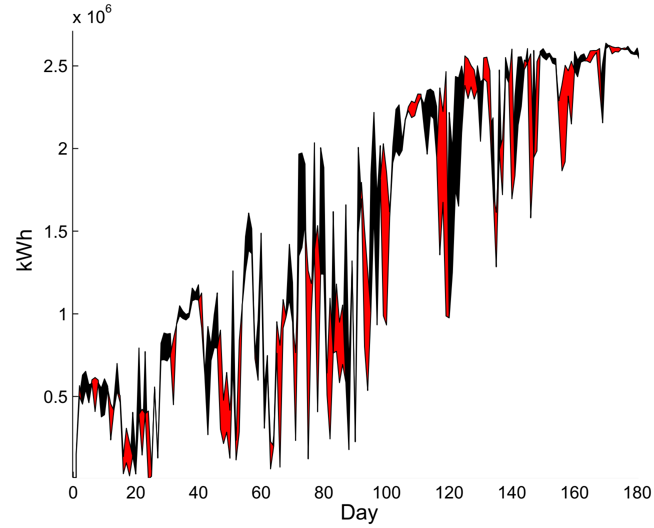


Fig. 4. Daily maximum thermal energy available from the SF and its day-ahead forecast.

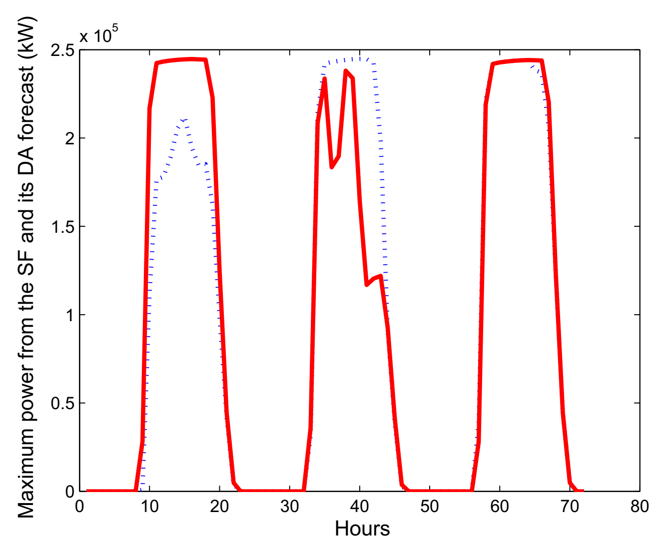


Fig. 5. Three example days for day-ahead forecast. Actual value: solid, red line; forecasted value: dotted, blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

costs per MW h of deviation. For this reason, the proposed economic MPC approach uses an estimation $\phi(j,i)$ for this value. This estimation $\phi(j,i) = \phi = \gamma\bar{\phi}$, where $\bar{\phi} = 7.69$ Euros/MW h is the mean value for the penalty costs per MW h during the simulation period and $\gamma \geqslant 0$ is a parameter to be defined by the user. It is worth noting that γ defines the relative importance of the penaliza-

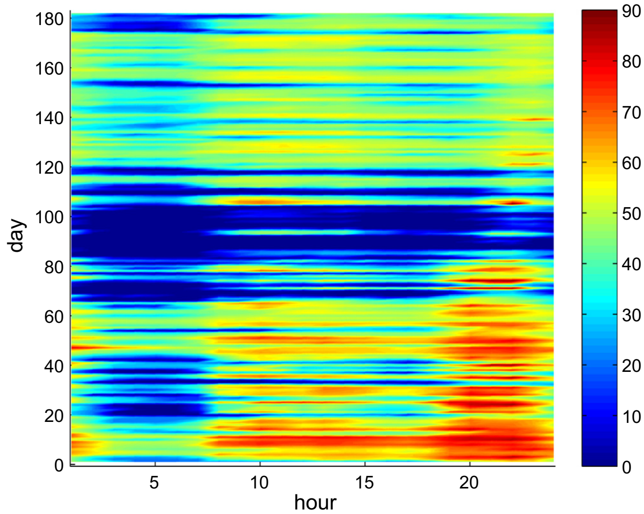


Fig. 6. Electricty prices (Euros/MW h).

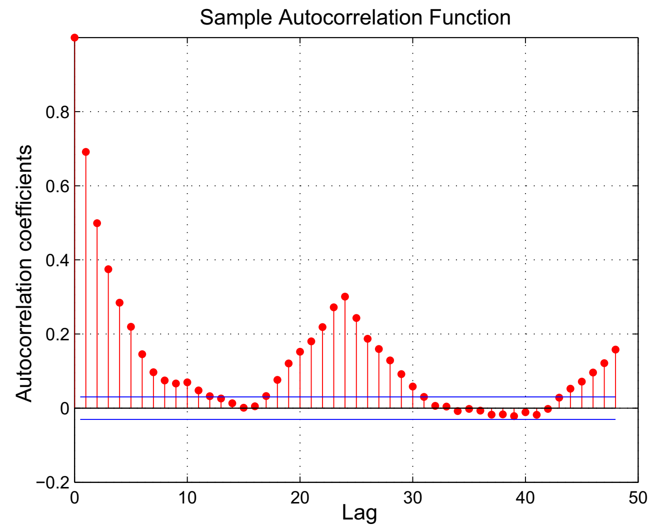


Fig. 8. Autocorrelation of penalty costs per MW h.

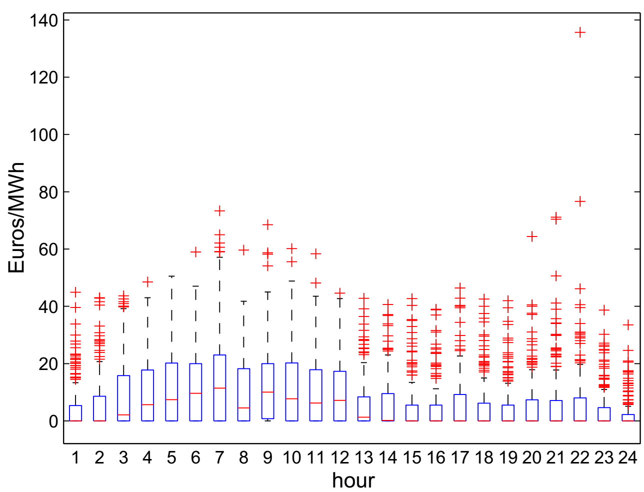


Fig. 7. Hourly boxplot for penalty costs per MW h of deviation. In each box, the central mark is the median; the edges of the box are the 25th and 75th percentiles. The whiskers extending to the most extreme datapoints (black bars) are not considered to be outliers. The outliers are plotted individually (red marks). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

tion term in the economic MPC approach. Since $\bar{\phi}$ is an unknown value a priori, several simulations with different values of γ have been conducted in this paper. This allows studying the economic impact of constant γ and analyzing the importance of an accurate estimation of $\bar{\phi}$.

4. Results and discussion

Simulation results are shown and discussed in this section. It is important to stress that there are many factors that affect the economic results of scheduling strategies, e.g., electricity market regulations, the local climate of the plant site, forecast quality, plant design, simplification hypothesis and models used (Law et al., 2016a). Therefore, the conclusions drawn from this case study could be different in other scenarios. Several configurations of the MPC strategy are compared to the reference strategy, that is, the day-ahead scheduling strategy. The configuration of the MPC strategy is set by two parameters. In this regard, $MPC_{\omega}(\gamma)$ denotes a configuration where the penalty cost per MW h is $\gamma\bar{\phi}$ (see Section 3.3) and the accuracy of the synthetic short-term predictor is ω (see Section 3.1). It is worth noting that while parameter γ is a tuning parameter of the MPC strategy, parameter ω characterizes the accuracy of the synthetic short-term predictor considered. $\gamma = 0.1, 0.5, 1, 2, 2.5, 3$ and $\omega = 0, 0.001, 0.5, 1$ values are used, so, 24 simulations have been carried out to study the different scenarios. Moreover, the horizon of the synthetic short-term predictor, N_{STF}, is set to 5 h in all scenarios, and the initial conditions for the simulation are turbine shut-down and zero TES energy level. Next, the following analysis are described: (1) economic comparison between MPC and DAS strategies varying γ and ω; (2) calculation of the percentage of improvement in profits of the MPC strategy with respect to the DAS strategy on a monthly basis; (3) study of the influence of the horizon of the short-term predictor on the profits; (4) economic comparison between MPC and DAS strategies considering the maximum room for improvement; and (5) energy analysis of both strategies. Finally, the conclusions drawn from the results are exposed.

4.1. Economic comparison between MPC and DAS strategies varying γ and ω

Total results in the six-month period are studied in this subsection. Figs. 9–11 show, respectively, the gross revenues, the penalty costs and the final profits obtained by several configurations of the MPC strategy and by the DAS strategy. Revenues decrease as the value of parameter ω increases, that is, as the short-term prediction worsens (see Fig. 9). Moreover, as the value of parameter γ increases, the obtained gross revenues decrease. This is coherent because an increase of the penalty cost makes the scheduler sacrifice revenues in order to meet the committed schedule. The higher revenues of the MPC strategy over the DAS strategy are explained by its rescheduling capacity. The penalty costs decrease as parameter γ increases (see Fig. 10). At first, a decrease of costs is convenient. However, as revenues decrease too, it is necessary to study the profits in order to evaluate the results. The higher penalty costs of the MPC strategy over the DAS strategy are justified in Section 4.5.

In relation to total profits (see Fig. 11), three conclusions are worth mentioning. Firstly, it should be underlined that the results obtained by the MPC scheduler outperform the profits obtained by

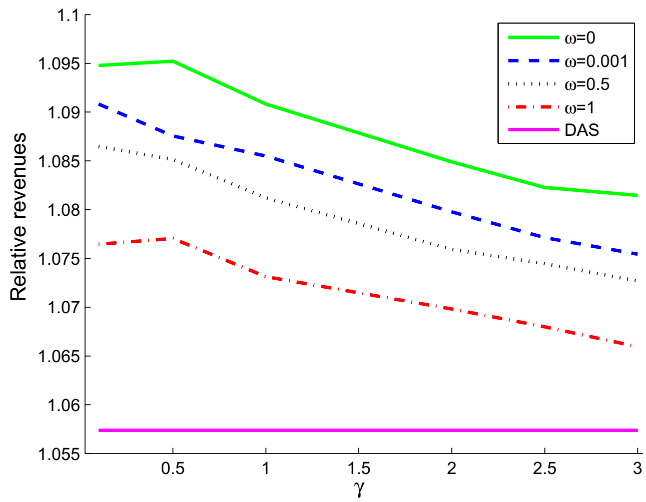


Fig. 9. Revenues obtained during the six-month period by the DAS strategy and by the MPC strategy for different values of penalty parameter (γ) and of parameter of short-term forecast accuracy (ω). The revenues are expressed in relative values with respect to a reference value. This latter value is defined as $\bar{p}N_H P_{enetmax} F_C$, where $\bar{p}$ is the mean energy price during the six-month period, N_H is the number of hours, $P_{enetmax}$ is the plant net capacity (50 MW) and F_C is the plant capacity factor (0.41, *Andasol* 2).

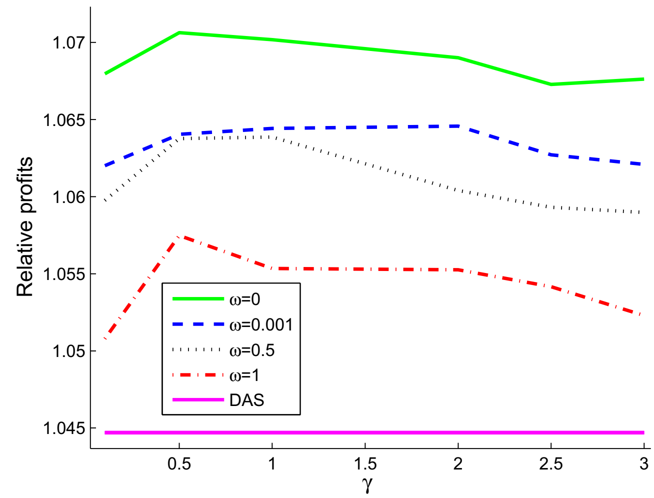


Fig. 11. Profits obtained during the six-month period by the DAS strategy and by the MPC strategy for different values of penalty parameter (γ) and of parameter of short-term forecast accuracy (ω). The profits are expressed in relative values with respect to a reference value (see the caption of Fig. 9).

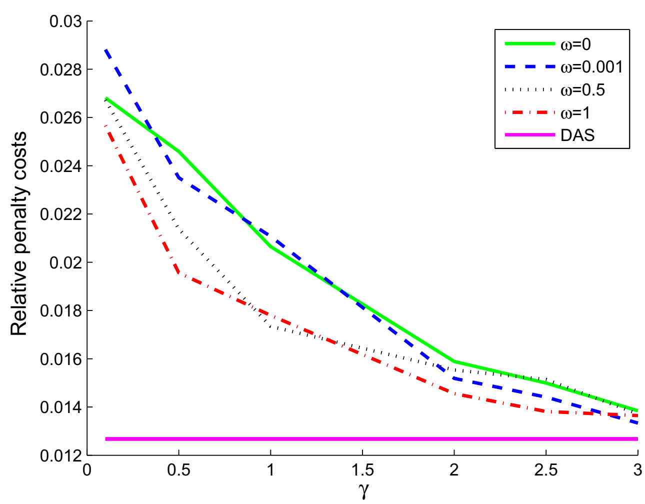


Fig. 10. Penalty costs charged during the six-month period when the DAS strategy and the MPC strategy are applied. The latter is applied for different values of penalty parameter (γ) and of parameter of short-term forecast accuracy (ω). The penalty costs are expressed in relative values with respect to a reference value (see the caption of Fig. 9).

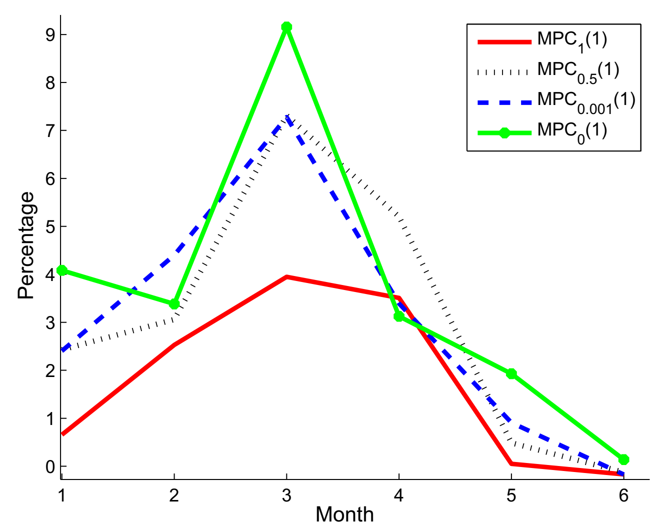


Fig. 12. Percentage of improvement in profits for $MPC_\omega(1)$ strategy with respect to the DAS strategy for each month and for different values of short-term forecast accuracy parameter (ω).

the reference scheduler in all cases. In fact, the MPC strategy without short-term forecast ($\omega = 1$) also overcomes the reference strategy. Secondly, it is also noted that improvements in the parameter ω increase the profits. This point confirms the importance of having a good short-term predictor. Finally, a value for the tuning parameter γ is proposed. It can be observed that when γ is within the interval (0.5–2) total profits are higher and they do not vary significantly. Then, a $\gamma = 1$ value can be a good option, that is, to use the mean $\bar{\phi}$ as an estimation for the penalty cost per MW h of deviation. Moreover, the existence of this interval causes the accuracy of this estimation not to be critical. In this regard, the following values represent the ratio between mean values (during the first six months) for penalty cost per MW h in consecutive years from 2012 to 2015: 2.06, 1.32, 0.85 and 1.09. It can be observed that these values are within the identified interval (except value 2.06 by very little). Therefore, the mean value from the previous year is proposed as an estimation of the penalty cost per MW h for the current year, assuming that the validity of the identified interval is maintained over the years.

4.2. Calculation of the percentage of improvement in profits of the MPC strategy with respect to the DAS strategy on a monthly basis

Fig. 12 shows the percentage of improvement for each month in profits of the $MPC_\omega(1)$ strategy with $\omega = 1, 0.5, 0.001$ and 0 with respect to the reference strategy. As can be seen, the MPC strategy obtains substantial improvements in the first four months, when the meteorological instability is present. In fact, the best result is obtained in March, that is, the month with the worse forecast for the maximum thermal power available from the SF. Therefore, the MPC strategy can compensate bad forecast situations.

4.3. Study of the influence of the horizon of the short-term predictor on the profits

As mentioned above, the horizon of the synthetic short-term predictor, N_{STF}, is set to 5 h. However, it may be interesting to study the evolution of the profits when a higher time horizon is used. Fig. 13 shows the profits obtained using $N_{STF} = 5, 6, 7, 8, 10$ and 12 applying a $MPC_{0.001}(2)$ scheduler. A slight increase in profits can be observed as the value of N_{STF} increases. In fact, the profits for $N_{STF} = 12$ almost reaches the profits of the $MPC_0(2)$ scheduler with $N_{STF} = 5$, that is, using perfect short-term forecast (see Fig. 11). The test was also performed with the $MPC_{0.001}(1)$ strategy and the resulting overall trend of profits was also incremental to the N_{STF} value. Nevertheless, some fluctuations arose. Theses fluctuations are possibly due to the higher penalty risk level with $\gamma = 1$ (see Section 4.5 for clarification of this point).

4.4. Economic comparison between MPC and DAS strategies considering the maximum room for improvement

A final economic analysis of the $MPC_{\omega}(1)$ strategy is carried out in comparison with the reference strategy. To partially overcome the dependence of results with the studied scenario, the maximum ideal profits (using perfect solar resource forecast) for the specifications of this case study are taken into account. Fig. 14 shows total profits in the six-month period of the following strategies: (1) MPC strategy with perfect day-ahead forecast; (2) DAS strategy with perfect day-ahead forecast; (3) $MPC_{\omega}(1)$ strategy with $\omega = 0, 0.001, 0.5$ and 1; and (4) DAS strategy. It is worth noting that perfect day-ahead forecast means perfect short-term forecast in this case study. The profits of these strategies decrease according to the order in which they are cited. With perfect day-ahead forecasts, the MPC strategy outperforms the DAS strategy thanks to the hourly rescheduling, which allows having information about the energy prices for the hours immediately after the end of the time horizon of the DAS strategy. Then, the MPC strategy could reserve energy for future high-price hours and, consequently, accept some deviation at the moment of the decision. Considering the profits of the MPC strategy with the perfect day-ahead forecast as the maximum ideal profits, the percentage difference in profits between MPC and DAS strategies in relation to the maximum ideal gain is 33.3%, 25,7%, 25.0% and 13.9% for $\omega = 0, 0.001, 0.5$ and 1. Since a perfect forecast is an idealized situation, it could be said that profits obtained by the MPC strategy are remarkable.

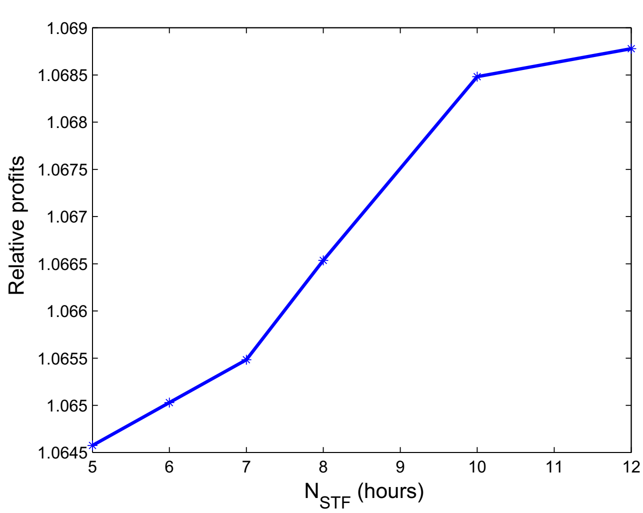


Fig. 13. Profits vs horizon of short-term forecast for strategy $MPC_{0.001}(2)$. Profits are expressed in relative values with respect to a reference value (see the caption of Fig. 9).

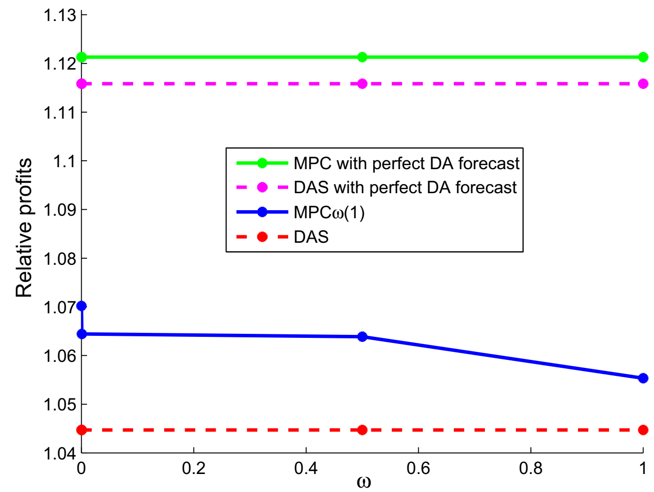


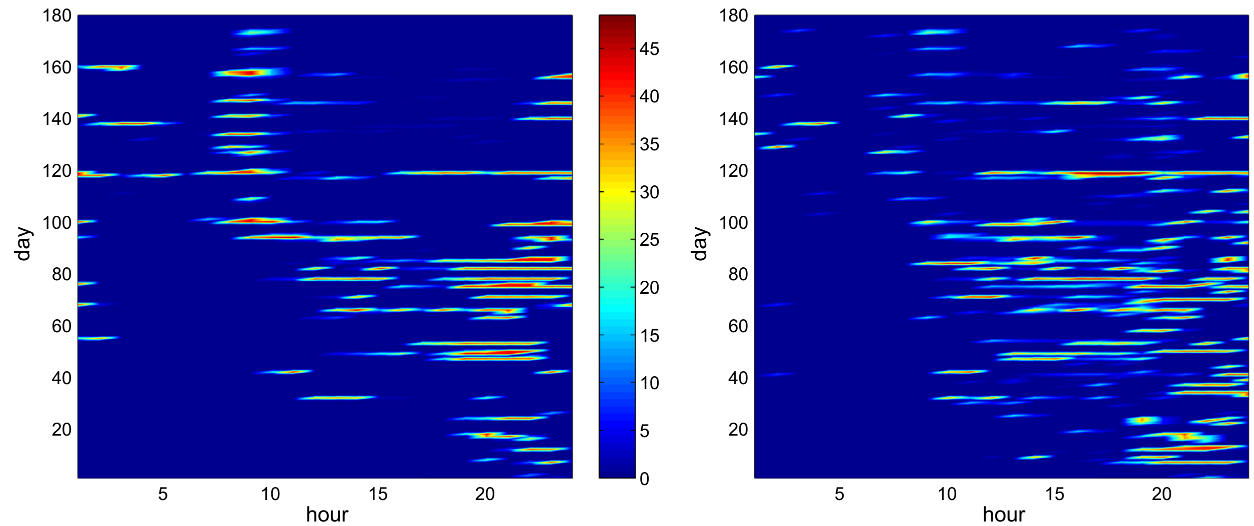
Fig. 14. Comparison between MPC and DAS strategies considering maximum ideal profits. The comparison is based on total values during the six-month period. Different values of short-term forecast accuracy parameter (ω) are used. Penalty parameter (γ) is set to 1. Profits are expressed in relative values with respect to a reference value (see the caption of Fig. 9).

4.5. Energy analysis of both strategies

Next, some energy results of DAS and $MPC_{0.001}(1)$ strategies are shown in Table 5. The amount of thermal energy available from the SF which is not transferred to the turbine and/or TES must be eliminated by means of a partial/total solar collector defocusing. This amount of energy is referred to as defocused energy (see Table 5). We can see that generation is slightly lower with the $MPC_{0.001}(1)$ strategy. Moreover, values for deviation and defocused energy with MPC strategy are also worse. The economic improvement of MPC strategy is shown in parameter *equivalent sale price*. This parameter is defined as the ratio between total profits and total generation. The worse energy results of the MPC strategy are explained by its capability to admit deviation in order to reserve energy to potentially attain higher future revenues, as its higher mean TES energy level confirms. As mentioned above, this capability is based on the hourly slide of the MPC window, which incorporates new information (precise or not). The parameter γ allows reducing this capability and can be used to regulate the risk level. In any case, while total deviation can be higher with the MPC strategy, this approach distributes it by taking advantage of the most favorable hours (see Figs. 6, 15(a) and (b)). The DAS deviations are concentrated around some concrete hours. However, MPC deviations are expanded along the day as a result of the search for high prices (see the example in Fig. 16 for better clarity). Finally, Fig. 17 shows the distribution of electric generation with price intervals for both strategies. The displacement of the generation to higher prices in the MPC strategy compared to the DAS strategy can be observed.

Table 5
Energy results of DAS and $MPC_{0.001}(1)$ strategies during the six-month period.

Hourly mean value	DAS	$MPC_{0.001}(1)$	Inc. ($MPC_{0.001}(1)$ over DAS)
Generation (MW h-e)	18.87	18.84	–0.18%
Deviation (MW h-e)	1.73	2.16	25.18%
Defocused energy (MW h-t)	4.83	4.96	2.75%
TES energy level (%)	33.4	39.6	18.71 %
Equivalent sale price (Euros/MW h-e)	42.13	43	2.07%



(a) Deviation with DAS strategy (MWh-e) (b) Deviation with MPC strategy (MWh-e)

Fig. 15. Deviation (MW h-e).

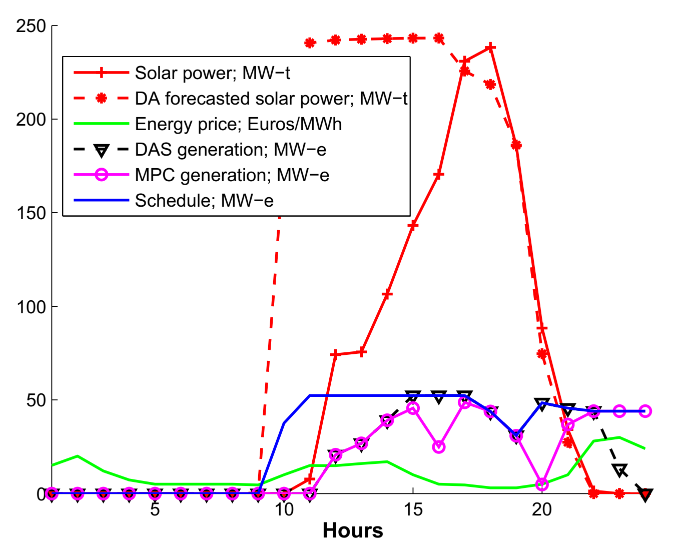


Fig. 16. Example of generation displacement to higher prices in the MPC strategy in comparison to the DAS strategy during a day with overestimated solar resource.

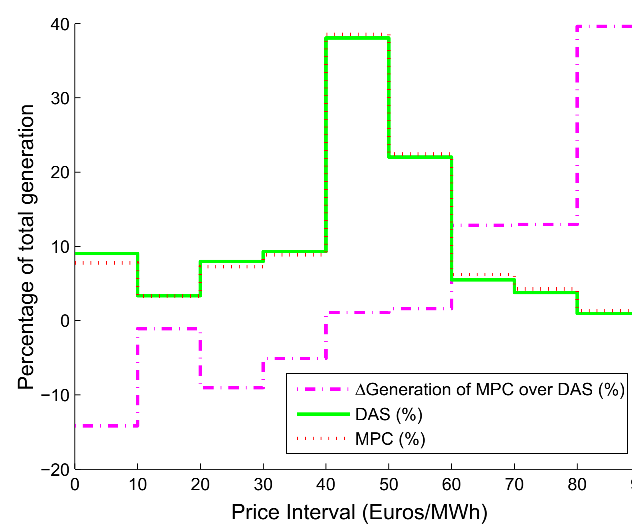


Fig. 17. Distribution of generation with price intervals for DAS and MPC strategies (%).

4.6. Conclusions drawn from the results

In summary, the following conclusions can be drawn after analyzing the results:

1. The MPC strategy obtains higher total profits than the DAS strategy during the period of six months, including the case without short-term forecasts. Moreover, improvements in short-term forecasts increase the profits. These results are expected because of the capabilities of MPC approaches.
2. To estimate the penalty cost per MW h of deviation, its mean value (during the studied period) from the previous year is proposed (see the last paragraph of Section 4.1)
3. The improvement in profits of the MPC strategy in relation to the reference strategy is higher in periods with a bad forecast. For example, the percentage of improvement during March is higher than 7% in cases with short-term forecasts ($\omega < 1$).
4. A higher horizon of the short-term forecast achieves slightly better results (assuming that the behavior of the short-term forecast is described by the developed synthetic predictor).
5. The MPC strategy reaches an improvement in total profits during the six months period between 13.9% and 33.3% of the maximum room for improvement in this case study. This maximum ideal improvement is defined as the difference in profits between the MPC strategy with perfect day-ahead forecasts and the DAS strategy.
6. The γ parameter allows regulating the risk level of the tracking in the MPC strategy. This strategy tends to admit certain deviation in order to store more energy. The stored energy is then used to potentially achieve higher future revenues, although this performance increases the penalties. This behavior leads to, in addition to a higher deviation, a higher mean TES energy level and, consequently, higher defocused energy. A high enough value of γ can reduce this performance, but it could

adversely affect profits. The ideal value of γ compensates the penalties and the worse energy behavior with higher profits.

In the opinion of the authors, the proposed economic MPC could reach better results in the following situations:

1. In the real case of an imperfect forecast of energy price (a perfect price forecast is supposed in this case study), the economic MPC could outperform the DAS strategy more clearly due to the perfect knowledge of the prices of the current day. Notice that the DAS strategy always uses forecasted prices. Nevertheless, the MPC strategy can utilize exact prices of the current day for its tracking function once the prices were cleared on the market the day before.
2. In scenarios with a higher level of penalty costs per MW h of deviation, the economic MPC could also overcome the DAS strategy more clearly because this high level of penalties could be reduced significantly.

Some improvements for the method are indicated next:

1. More complex models to form the penalization term in the optimization function can be evaluated. For example, the estimation of the penalty cost per MW h of deviation could be supposed to be time-varying. This value could be calculated using a weighted mean of a sliding window along previous values.
2. It is interesting to explore other aspects, such as analyzing the effect of the sliding window length on the results, or including robust terms in the optimization problem. The purpose of these robust terms is to achieve a more conservative generation schedule for the next day, thus avoiding hight deviation due to poor DNI forecast.

5. Conclusion

An economic MPC approach is proposed to address the optimal generation scheduling in CSP plants with TES. One of the main obstacles tackled in this type of problems is the penalty cost charged by the electricity market when deviation from the committed generation schedule arises due to the limited accuracy of the solar resource forecast. The proposed approach addresses this pitfall with two actions: (1) the economically advantageous, regular update of the generation schedule to track the committed schedule using the most recent forecast and the current status of the plant and (2) the generation, at the appropriative time, of a more feasible schedule for the following day thanks to the use of a better estimation for the initial conditions based on short-term forecasts. In order to achieve the proposed aims, the objective function of the MPC consists of economic terms, that uses forecasted electricity prices and estimations of penalty costs. The proposed approach is applied, in a simulation context, to a 50 MW parabolic trough collector based CSP plant with TES under the assumptions of a participation in the Spanish day-ahead energy market and perfect price forecasts. A time period of six months is taken into account in this case study to test several meteorological conditions. The proposed approach is then compared with a reference strategy based on a traditional day-ahead scheduling. The comparative analysis covers economic and energy results. A significant economic improvement is observed, especially in periods with bad forecast of solar resource. Several future research lines are indicated: (1) the analysis of scenarios with imperfect forecast of electricity prices or higher level of penalty costs, (2) the development of more complex methods to estimate the penalty cost per MW h of deviation, and (3) the provision of robustness for the proposed approach. It is also important to highlight that the proposed approach can be translated to another renewable energy source with energy storage system.

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