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Scenario-based model predictive control for energy scheduling in a parabolic trough concentrating solar plant with thermal storage

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ABSTRACT

Optimal energy planning is a key topic in thermal solar trough plants. Obtaining a profitable energy schedule is difficult due to the stochastic nature of solar irradiance and electricity prices. This article focuses on optimal energy planning for thermal solar trough plants, particularly by developing a model predictive control algorithm based on multiple scenarios to deal with uncertainties. The results obtained using the proposed scheme have been tested and compared to other well-known approaches to energy scheduling through a realistic and reliable comparison to evaluate their performances and establish their advantages and weaknesses. Simulations were carried out for a 50 MW parabolic trough concentrating solar plant with a thermal energy storage system, considering different types of days classified according to their solar irradiance, meteorological forecast, and electrical market. Simulation results show that the proposed method outperforms other scheduling methods in dealing with uncertainties by selling energy to the grid at the right times, generating the highest income of about 7.58%.

1. Introduction

The increase in global energy demand, industrial development, and its impact generated by the dependence on fossil fuels has been causing effects on global climate conditions. Eighty percent of total energy consumption is derived from non-renewable sources, as noted [1]. Energy consumption is expected to double in the next few years [2]. Renewable energies, such as solar, wind, geothermal, and hydroelectric, to name a few, have received more attention in recent years because they have emerged as an alternative to face the high impact of carbon footprint on the ecosystem. In particular, since the demand for industrial heat exceeds the demand for electricity worldwide, it will be necessary to decarbonize this sector to significantly reduce carbon emissions [3]. Their benefits in clean, secure, and efficient energy production are well known [4,5].

In this context, solar energy offers relevant benefits and can be considered one of the most attractive renewable resources to generate electricity with perpetual and clean characteristics [4,6]. Solar plants can generate electricity using photovoltaic (PV) cells, directly converting solar irradiance into electrical energy. On the other hand, steam can be produced to drive a turbine and a generator by collecting and concentrating solar power. The main difference between PV plants and thermal Concentrating Solar Power (CSP) plants is that storing a significant amount of electrical energy is much more expensive than storing the equivalent thermal energy in Thermal Energy Storage (TES) systems [7], where excess energy is stored to satisfy the demand at times when there is not enough solar energy.

A wide variety of thermal collectors can convert thermal energy into valuable energy. Some of them are flat plates, compound parabolic, evacuated tubes, parabolic troughs, Fresnel lens, parabolic dishes, and heliostat field collectors [2,8]. This work is focused on parabolic through CSP [9]. However, the idea can be easily extended to other solar plant technologies.

Increasing the performance of solar plants is a challenge. It can be carried out by optimizing the energy supply or reducing investments and operating costs, resulting in increased solar profit [10]. In this sense, several works have addressed different techniques for various combined solar plants with other renewable energy systems [11–13]. A comparison between a classical controller and an optimal control strategy for solar power plants operating in a day-ahead market scheme can be found in [14].

Model Predictive Control (MPC) is a technique widely extended in the industry due to its capability to address disturbances, nonlinearities, delays in processes, constraints on optimization variables, among others; see, e.g., [15,16] and references therein. The main idea

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Nomenclature

Symbols

A_{tank}	Base area of the tanks
c	Prices of selling energy
C_f	Specific heat
Cf_{salts}	Specific heat of the salts
$Cold_{\text{level}}$	Height level of the cold tank
$\cos(\theta)$	Geometric efficiency
C_{th}	Thermal capacity of the solar field
E_{grid}	Delivered energy to the utility power grid
E_{s_+}	Energy extracted from the storage system
E_{s_-}	Energy delivered to the storage system
E_{sol}	Solar field energy
E_{st}	Stored energy
H_l	Coefficient of thermal losses
h_{tank}	Height of the tanks
Hot_{level}	Height level of the hot tank
I	Direct solar irradiance
J	Cost function
K_{opt}	Optical efficiency
N_{p}	Prediction horizon
N_{s}	Number of scenarios
P_{e}	Electrical power
P_{salt}	Power stored or extracted from the tanks
P_{th}	Thermal power
q	Oil flow rate
q_{salts}	Flow of molten salts
S	Total reflective surface
t	Time
$\bar{T}$	Average between outlet and inlet temperatures
T_a	Ambient temperature
T_{cold}	Cold tank temperature
T_{hot}	Hot tank temperature
T_{in}	Inlet temperature of the solar field
T_{out}	Average of the outlet temperature of all the loops of the plant
u	Control variable
Vol_{tank}	Volume of the tanks
x	State vector
α	Thermal losses coefficient in the storage system
α_{cd}	Rate of charge or discharge of energy from the storage system
β	Storage system efficiency
δ_x	Risk of constraint's violation
η_{rank}	Thermo-electric conversion efficiency
ρ_f	Density
ρ_j	Probability of the occurrence of scenario j
ρ_{salts}	Salt density

Acronyms

CSP	Concentrating solar power
MPC	Model predictive control
MS	Multiple-scenarios
PCS	Power conversion system
PF	Perfect forecast
PV	Photovoltaic
TES	Thermal energy storage
UPG	Utility power grid

Superscript

0	Initial instant

following this approach is to compute a sequence of control variables along with a prediction horizon (N_{p}) by solving a finite-horizon optimization problem. Only the first component is applied to the system, whereas the rest is discarded. This problem is repeated at each time interval in a receding horizon fashion [17]. However, the classical MPC does not consider uncertainties in its formulation, and a violation of constraints could occur. Some alternatives have been developed to address this problem. One of them is the Min–Max MPC, which results in an over-conservative control scheme by optimizing the problem related to the worst-case scenario [18]. Several mechanisms have been proposed to robustify the controller and reduce conservatism by modifying the classical MPC formulation. One option is to consider MPC based on multiple scenarios (MS-MPC) obtained from historical data or generated randomly; a unique sequence control input results from solving the optimization problem. MS-MPC controller offers a trade-off between robustness and computational effort [19]. The disturbances are modeled like a branched tree, where non-anticipate constraints are formulated at each bifurcation point, resulting in a tree of control input with a common point at the beginning of the tree. Although this method replicates the main characteristics of disturbances in a tree-shaped structure, the computational burden can be compromised by the number of optimization variables to be solved at each time step [20]. Among several works related to a tree-based MPC formulation in the context of energy systems, [21,22] can be mentioned. An alternative to address uncertainty and improve computational efforts is to express the optimization problem through chance constraints. This method offers a significant improvement related to computational load. However, it is necessary to know the probability distribution functions of the disturbances to rewrite the constraints in terms of their likelihood. A stochastic MPC formulation based on chance constraints can be found in [23,24], and references therein.

The operational benefits of solar trough plants depend mainly on two factors: the irradiance and the prices of the electricity market. Both factors have an uncertain character. From a stochastic point of view, energy scheduling is subject to inherent uncertainties, which play a crucial role. MS-MPC is a well-established technique due to its intuitive idea behind the formulation [18]. This approach computes a unique optimization variable that is valid for all uncertainty scenarios considered. This technique has been applied in different systems [20,25,26] and CSP systems are not the exceptions. Stochastic optimization based on probability distribution functions applied in combined renewable energy systems, such as wind turbines and concentrated solar plants, is shown in [27,28]. In [29], a comparison is made among three different strategies: deterministic, robust, and stochastic based on statistics properties to optimize the scheduling of CSP plants operating in a daily market. Furthermore, a stochastic optimization of a CSP system is presented in [30].

In this work, we propose a scenario-based stochastic formulation to manage the energy of the CSP system from an optimized energy scheduling point of view. It consists of a stochastic MPC based on real historical solar production data and the weather forecast with a prediction horizon of four days. The scheduling considers the thermal energy storage capacity, as well as the turbine capacity, to deliver power to the Utility Power Grid (UPG). In particular, an MS-MPC controller is formulated based on solar production scenarios and the estimation

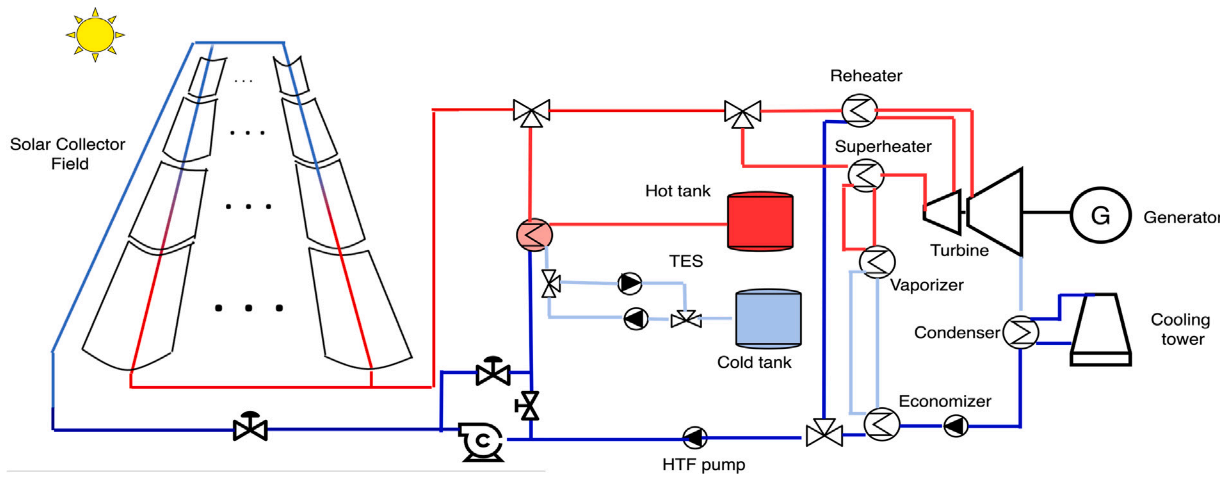

Fig. 1. Parabolic trough concentrating solar power plant schematic.

of electricity prices, taking into account its behavior during the last seven days and the meteorological conditions of the following days. The results obtained using the MS-MPC controller have been contrasted with other techniques to expose and compare their performance and advantages. The results show that higher revenues are obtained from this technique applied to energy scheduling in a generic 50 MW solar plant. The objective is to receive a more significant income from the energy sold, formulated through an MS-MPC controller, which also considers a variation in electricity market prices and uncertainties in solar production.

As previously mentioned, the proposed MS-MPC strategy is compared to four scheduling approaches. These techniques are described below:

- **Heuristic method:** It consists of a simple storage policy. Energy is stored if there is an excess of solar energy that cannot be delivered to the grid.
- **Standard MPC:** It is an MPC controller that uses the mean value of all scenarios as input to the model to compute the sequence of control actions.
- **Min–max MPC:** It is a stochastic MPC controller that considers two optimization problems. On the one hand, the first one maximizes the objective function to obtain the worst case. The second step solves the optimization problem using the parameters given by the first one [31].
- **MS-MPC algorithm:** This approach computes a sequence of control actions valid for all scenarios in terms of their likelihood.

In this context, the benchmarks to evaluate the performance of the MS-MPC are based on specific criteria defined in this document. Guidelines are given for setting, tuning, and implementing controllers in a CSP system. Finally, the results obtained by simulation highlight the advantages of handling disturbances and uncertainties within scheduling in a parabolic trough concentrating solar plant with thermal storage using an MS-MPC method.

2. Solar plant description

This section presents the solar plant and the models of its main components, including the power cycle, solar collector field, and thermal storage units (TES). Fig. 1 shows the overall scheme of the plant considered in this work.

Remark 1. A lumped-parameter model is used to describe the solar collector field behavior. This kind of model, as proposed in [9], provides a good description of the plant for control purposes.

The models used are simple but precise enough for the objectives of this work and are depicted below.

2.1. Solar collector field model

The solar collector field considered in this paper corresponds to a 50 MWe solar power plant. It is formed by 150 EuroTrough ET150 loops of 630 m each one, as described [32]. Most 50 MWe solar trough plants are formed by 90 loops, but since TES systems are considered, a higher number of loops are needed. When the incident solar irradiance is high enough, the field can feed the power conversion system (PCS) at its maximum capacity and also load the TES if possible.

$$C_{th}\frac{dT_{\text{out}}}{dt} = K_{\text{opt}}cos(\theta)SI - q\rho_f C_f(T_{\text{out}} - T_{\text{in}}) - H_l S(\bar{T} - T_a). \tag{1}$$

where T_{out} is the average of the outlet temperature of all loops of the plant and T_{in} is the inlet temperature of the solar field.

The density and specific heat of the oil depend on the working temperature. They can be approximated by the following expressions [9]:

$$\rho_f = 1061.5 - 0.5787\ T - 9.0242e - 4\ T^2, \tag{2a}$$

$$C_f = 1552.049 + 2.38501\ T + 0.0010558\ T^2. \tag{2b}$$

The thermal losses coefficient was obtained using real field data, as mentioned [9]. It can be approximated by the following expressions:

$$H_l = 11.7e - 9\ (\Delta T)^3 - 2.81e - 6\ (\Delta T)^2 + 1.44e - 4\ \Delta T + 0.081 - \frac{3.21}{\Delta T}, \tag{3a}$$

$$\Delta T = \bar{T} - T_a. \tag{3b}$$

To regulate the outlet temperature T_{out} around the desired set-point given by the energy scheduling. Using Eq. (1), a relation between the working temperature and the flow needed to achieve that can be obtained in steady-state as follows.

$$q = \frac{K_{\text{opt}}cos(\theta)SI - H_l S(\bar{T} - T_a)}{Pc_p(T_{\text{out}} - T_{\text{in}})}. \tag{4}$$

This flow can be used to compute the thermal power produced in the solar field as follows.

$$P_{\text{th}} = q\ C_f\ \rho_f(T_{\text{out}} - T_{\text{in}}). \tag{5}$$

2.2. Rankine power cycle

In this subsection, the mathematical model of the power conversion system is presented. The PCS is modeled as an efficiency based on the working temperature as follows.

$$\eta_{\text{rank}} = K\left(1 - \frac{T_a}{T_{\text{out}}}\right). \tag{6}$$

Table 1
Variable description.

Variable	Description	Variable	Description
α	Thermal losses coefficient in the storage system.	E_{st}	Stored energy.
β	Storage system efficiency.	E_{grid}	Delivered energy to the utility power grid.
η_{rank}	Thermo-electric conversion efficiency.	E_{s_+}	Energy extracted from the storage system.
E_{sol}	Solar field energy.	E_{s_-}	Energy delivered to the storage system.

Here, the constant K is computed to make that the Rankine efficiency is 0.38 at 390 °C, approximately [32]. Its value is 0.695.

Using Eq. (6), the electrical power can be obtained by means of the thermal power.

$$P_e = P_{th}\,\eta_{rank}. \tag{7}$$

2.3. TES model

This subsection describes the thermal storage system model used in this paper. The TES system is considered to have a storage capacity of 300 MWh.

The storage system is composed of two tanks, cold at 295 °C and hot at 388 °C. Molten salts are used as storage medium [33]. When the TES stores energy, part of the oil from the solar field is sent to the heat exchanger. This hot oil transfers heat to the cold salt pumped from the cold tank and is stored in the hot tank. When the tank is operating in discharge mode, the hot salts are sent to the heat exchanger, and heat is transferred to the cold oil, increasing its temperature. This oil is then used in the turbine to produce electricity when the field cannot do it [34].

The model used in this paper considers the amount of energy available in the tanks as a function of time. Tanks are considered cylindrical with a volume of

$$Vol_{tank} = A_{tank} h_{tank}. \tag{8}$$

Here, A_{tank} is the base area and h_{tank} is the height of the tanks. In this paper, the values $h_{tank} = 12\,\mathrm{m}$, $A_{tank} = 855.29\,\mathrm{m}^2$, and α_{cd}, which can be computed as

$$\alpha_{cd} = \frac{q_{salts}}{A_{tank}}, \tag{9}$$

are used.

The energy available in the tanks depends on the height level of salts stored in the hot and cold tanks (Eq. (10b)):

$$Hot_{level} = Hot^0_{level} + \alpha_{cd} t, \tag{10a}$$

$$Cold_{level} = Cold^0_{level} - \alpha_{cd} t. \tag{10b}$$

where Hot_{level} is the salt height level of the hot tank at instant t, Hot^0_{level} is the salt height level of the hot tank at instant 0. $Cold_{level}$ is the height level of the cold tank at the instant t and $Cold^0_{level}$ is the height level of salt of the cold tank at the initial instant. α_{cd} is the rate of charge or discharge of energy from the TES. If power is stored, α_{cd} is positive and negative if energy is extracted.

The charging/discharging rate can be computed considering the energy being extracted or sent to the TES. The flow of molten salts can be computed using Eq. (11):

$$q_{salts} = \frac{P_{salt}}{\rho_{salts} Cf_{salts} (T_{hot} - T_{cold})}. \tag{11}$$

where P_{salt} is the energy stored or extracted from the tanks. ρ_{salts} is the salt density, Cf_{salts} is the salt specific heat, T_{hot} is the temperature of the hot tank and T_{cold} is the temperature of the cold tank.

The density and specific heat of the molten salts can be calculated by the following expressions [35]:

$$\rho_{salts} = 2090 - 0.636 \cdot T \ \frac{\mathrm{kg}}{\mathrm{m}^3}, \tag{12}$$

$$Cf_{salts} = 1443.2 - 0.172 \cdot T \ \frac{\mathrm{J}}{\mathrm{kg}\ ^\circ\mathrm{C}}. \tag{13}$$

3. Methodology

In this section, the mathematical formulation of the algorithms used in this paper is developed.

3.1. Stochastic optimal energy scheduling

Here, a stochastic MPC is developed to carry out the energy scheduling in a solar plant. It addresses the operation of the solar plant and planning for four days and determines the optimal stored and delivered power each day using MS-MPC. The main idea behind this approach is to maximize energy production, considering the unpredictable behavior of solar production and prices in the electrical market. The MS-MPC controller is in charge of optimal energy scheduling by computing the energy that can be delivered to the UPG or stored in the TES. In this sense, it calculates the energy that the solar plant must deliver to the electrical network, considering the price in the energy market and the weather forecast along the prediction horizon. To this end, a multistage optimization problem based on MS-MPC is calculated at each instant time, considering the possible evolution of the price market and the weather conditions based on historical data.

3.2. Energy power balance: Linear model

It is necessary to consider a discrete-time linear model of the system to design and implement an MPC controller. This model represents the energy power balance in a solar plant for each time instant $k \in \mathbb{Z}_+$, can be expressed as

$$x(k+1) = A \cdot x(k) + B \cdot u(k) + D \cdot \omega(k), \tag{14a}$$

that is,

$$x(k+1) = \begin{bmatrix} 1-\alpha & 0 \\ 0 & 0 \end{bmatrix} x(k) + \begin{bmatrix} 1 & -\beta \\ -1 & 1 \end{bmatrix} u(k) + \begin{bmatrix} 0 \\ \eta_{rank} \end{bmatrix} \omega(k). \tag{14b}$$

where $x(k)$ is the state vector, which consists of $[E_{st} \quad E_{grid}]^T$, $u(k)$ is the control variable described by $[E_{s_+} \quad E_{s\_}]^T$, and $\omega(k)$ represents the disturbances of the system given by E_{sol}. Table 1 gives in more detail a description of all variables used in Eq. (14b).

The solar plant must be subject to constraints that limit the energy due to the physical limitations of the storage system, i.e.,

$$0 \le E_{s_+} \le E_{s_{max}}, \tag{15a}$$

$$0 \le E_{s_-} \le E_{s_{max}}, \tag{15b}$$

$$E_{st_{min}} \le E_{st} \le E_{st_{max}}. \tag{15c}$$

Furthermore, the energy delivered to the UPG must be constrained. It could be penalized when it produces a lower or higher quantity than contracted. It can be written as

$$E_{grid_{min}} \le E_{grid} \le E_{grid_{max}}. \tag{16}$$

The control variables given by Eqs. (15a) and (15b) can be expressed as

$$u(k) \in \mathcal{U} \subseteq \mathbb{Z}^{n_u}. \tag{17}$$

While the constraints on the state variables, that is, Eqs. (16) and (15c) are rewritten as follows.

$$x(k) \in \mathcal{X} \subseteq \mathbb{Z}^{n_x}. \tag{18}$$

Here, n_x and n_u are the numbers of state variables and control inputs, respectively. In this case, $n_x = n_u = 2$.

3.3. Model predictive control formulation and the optimization problem

Optimization problem to maximize the amount of income in terms of energy at each time instant along the prediction horizon by computing a sequence of control inputs $\{u(k), u(k+1), \dots, u(k+N_p-1)\}$ and applying only the first component $u(k)$, i.e.,

$$\max_{\{u(k),u(k+1),\dots,u(k+N_p-1)\}} \sum_{i=k}^{k+N_p-1} J\left[x(i), u(i)\right], \tag{19}$$

subject to

$$x(i+1) = Ax(i) + Bu(i) + D\omega(i), \quad \forall i \in [k, k+N_p-1], \tag{20a}$$

$$x(i+1) \in \mathcal{X}, \quad \forall i \in [k, k+N_p-1], \tag{20b}$$

$$u(i) \in \mathcal{U}, \quad \forall i \in [k, k+N_p-1]. \tag{20c}$$

The objective cost function to be maximized is defined as

$$J\left[x(k), u(k)\right] = E_{grid}(k)c(k) + \left(E_{s_-}(k) - \beta E_{s_+}(k)\right)\alpha^{N_p-k}. \tag{21}$$

Here, c represents the prices for selling energy to the UPG, which correspond to the electrical price market. The optimization problem (19) is repeated at each time instant k.

This MPC formulation will be called Standard MPC. This type of MPC solves the optimization problem for one solar production scenario, represented by the mean value of the considered scenarios.

3.4. Heuristic method

This method delivers the maximum energy to the grid provided by solar energy. When the amount of solar energy exceeds the total capacity of the turbine, the remaining energy is stored in the TES. Until solar energy decreases to less than the maximum capacity of the grid, the TES must dispatch power until it reaches the lowest allowed value. This technique represents an intuitive way to deliver maximum energy to the grid without considering electricity prices. The optimization problem to be solved at each time instant is given by Eq. (19) subject to (20). However, the cost function does not consider the behavior of the electricity price market, i.e., the prices are deemed static values over time. Therefore, the cost function is defined as

$$J\left[x(k), u(k)\right] = E_{grid}(k) + \left(E_{s_-}(k) - \beta E_{s_+}(k)\right)\alpha^{N_p-k}. \tag{22}$$

As mentioned in the previous section, energy scheduling can be developed using an MPC formulation. However, solar irradiance has a non-deterministic behavior; therefore, stochastic MPC formulations are suitable in this context.

3.5. Min–max model predictive control approach

This method is a stochastic MPC formulation that is used to deal with disturbances. This approach solves a double optimization problem. In particular, it computes the set of control inputs that maximizes the objective function while minimizing the effects of the disturbances. It can be formulated as follows.

$$\max_{u[k:k+N_p-1]} \left(\min_{\omega[k:k+N_p-1]} \sum_{i=k}^{k+N_p-1} J\left[x(i), u(i)\right] \right), \tag{23}$$

subject to (20).

3.6. Multiple-scenario based model predictive control formulation

Multi-scenario MPC consists of computing a unique control action that satisfies all scenarios evaluated based on their probability of occurrence [20,36]. This approach has been widely used due to its versatility in implementation, resulting in a very intuitive technique [19,37]. One of the advantages of MS-MPC is that it does not need a preliminary characterization of the uncertainty using a probability distribution function. Therefore, the optimization problem can be written as an equivalent deterministic problem. Furthermore, this approach ensures a convex solution to the optimization problem that guarantees robustness for all likely disturbance evolutions.

Here, a point that deserves special attention is the generation of scenarios, which can be obtained based on previous knowledge or by generating random scenarios [38].

The optimization problem to be solved at each time instant $k \in \mathbb{Z}_+$, consists of considering a certain number of disturbance scenarios (N_s) and computing a single control sequence. The MS-MPC is formulated as follows.

$$\max_{\{u[k],u[k+1],\dots,u[k+N_p-1]\}} \sum_{j=1}^{N_s} \rho_j \left(\sum_{i=k}^{k+N_p-1} J\left[x_j(i), u(i)\right] \right), \tag{24}$$

subject to

$$x_j(i+1) = Ax_j(i) + Bu(i) + D\omega_j(i), \quad \forall j \in [1, N_s], \quad \forall i \in [k, k+N_p-1], \tag{25a}$$

$$x_j(i+1) \in \mathcal{X}, \quad \forall j \in [1, N_s], \quad \forall i \in [k, k+N_p-1], \tag{25b}$$

$$u(i) \in \mathcal{U}, \quad \forall i \in [k, k+N_p-1], \tag{25c}$$

$$\omega_j(i) = \omega(k), \quad \forall j \in [1, N_s]. \tag{25d}$$

where, N_s is the finite number of scenarios, ρ_j is the probability of the occurrence of scenario j, and $\omega[k]$ is the disturbance measured at each time instant k, which is common for all scenarios at the current time, the set of scenarios is updated at each time step with the known disturbance. Therefore,

$$\sum_{j=1}^{N_s} \rho_j = 1.$$

3.7. Perfect forecast model predictive control

Perfect forecast MPC (PF-MPC) is an ideal controller in which the best behavior is expected because it assumes that the disturbances are perfectly known over time. This kind of controller can give a theoretical bound and an idea of how much other controllers can achieve compared to the best performance determined by the PF-MPC. However, the implementation of this controller is unrealistic because a perfect forecast cannot be provided.

4. Experimental setup

This section presents a case study composed of parabolic CSP with a capacity of 50 MW to provide power to the grid, similar to that described in [9], and a thermal storage system of 300 MWh. In this solar plant, the proposed method has been tested and compared with other well-known techniques to show the benefits of the proposed approach via simulations. Furthermore, the experiments were tested using the corresponding data on solar generation and electricity prices[1] for the first six days of April 2022.

4.1. Multiple-scenario model predictive control configuration

The experimental setup consists of a four-day prediction horizon with a sample time of $T_s = 20$ min. Moreover, the constraints given by Eq. (15) can be formulated as follows.

$$-50 \text{ MWh} \le E_s \le 50 \text{ MWh}, \tag{26}$$

$$5 \text{ MWh} \le E_{st} \le 300 \text{ MWh}. \tag{27}$$

[1] https://www.omie.es/es/market-results/daily/daily-market/daily-hourly-price.

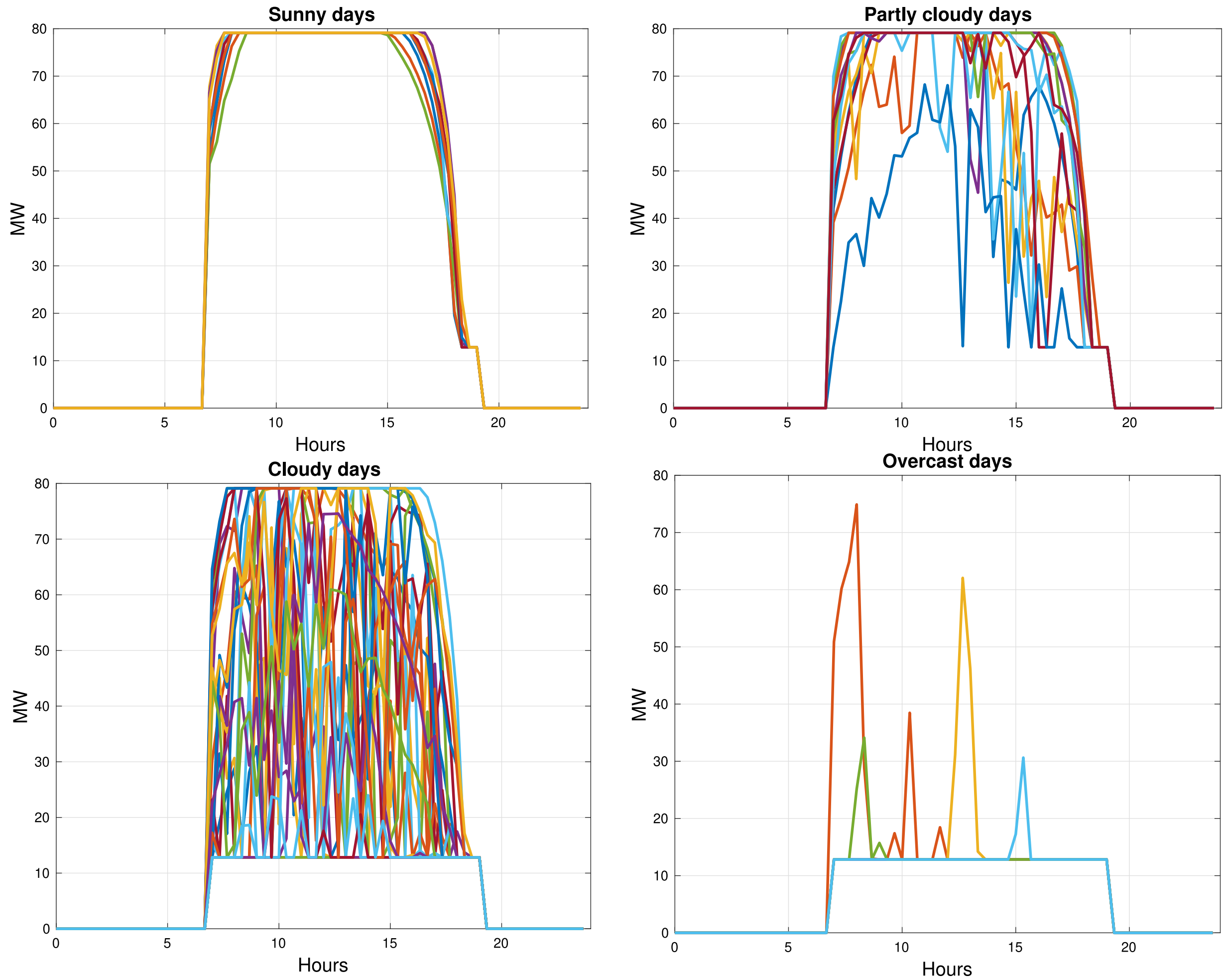

Fig. 2. Power generation scenarios.

For simplicity, E_{s+} and E_{s-} are joined in one variable, as seen in Eq. (26), which is greater than zero ($E_s > 0$) when the TES is charging; otherwise, the TES delivers energy to the grid. E_{st} is constrained by a maximum capacity of 300 MWh and a minimum value of 5 MWh. The minimum value in the TES is to take advantage of the residual heat of the salts and preheat the oil before starting it again. Moreover, it is necessary to consider that the TES cannot change between charge and discharge modes immediately. It takes about 20 min to change the TES operating mode.

The maximum capacity of the turbine limits the energy delivered to the grid. It is,

$$0 \le E_{grid} \le 50 \text{ MWh}. \tag{28}$$

On the other hand, the number of scenarios must be selected according to a certain level of risk-constraint violation (δ_x) [39]. This number has to be chosen to guarantee a trade-off between robustness and computational burden.

$$N_s > \frac{1}{\delta_x} - 1.$$

In this sense, since the level of risk violation is $\delta_x = 0.1$.

$$N_s > 9.$$

In particular, for this simulation, the number of scenarios has been set to $N_s = 15$. The optimization problem to be solved is (19) subject to (26)–(28).

4.2. Power generation scenario forecasting

In order to conduct experiments using the MS-MPC approach, a collection of scenarios has been collected from historical data, which can be found in the SOLARGIS Web service.[2] The collected scenarios correspond to solar irradiance for every day in April 2019 and 2020. These scenarios have been grouped into four types of days: sunny, partly cloudy, cloudy, and days completely covered in clouds, called overcast days. There are 60 scenarios to consider when applying the MS-MPC approach. Fig. 2 shows the historical power production of the solar plant grouped according to the classification days, as mentioned above. The set of scenarios for each day is selected based on forecast weather conditions.

4.3. Electrical energy price forecasting

The energy market is regulated by supply and demand. Therefore, it is a non-deterministic variable whose values are known 24 h in advance. However, the prices for the following days are not known and have a stochastic evolution.

Electricity prices are correlated with the volatility of changes in demand, spot prices, and the total capacity of renewable energy, mainly wind and solar thermal [40]. In this work, the electrical prices along the prediction horizon were obtained using the mean value for the last

[2] https://solargis.com/es/products/time-series-and-tmy-data/useful-resources.

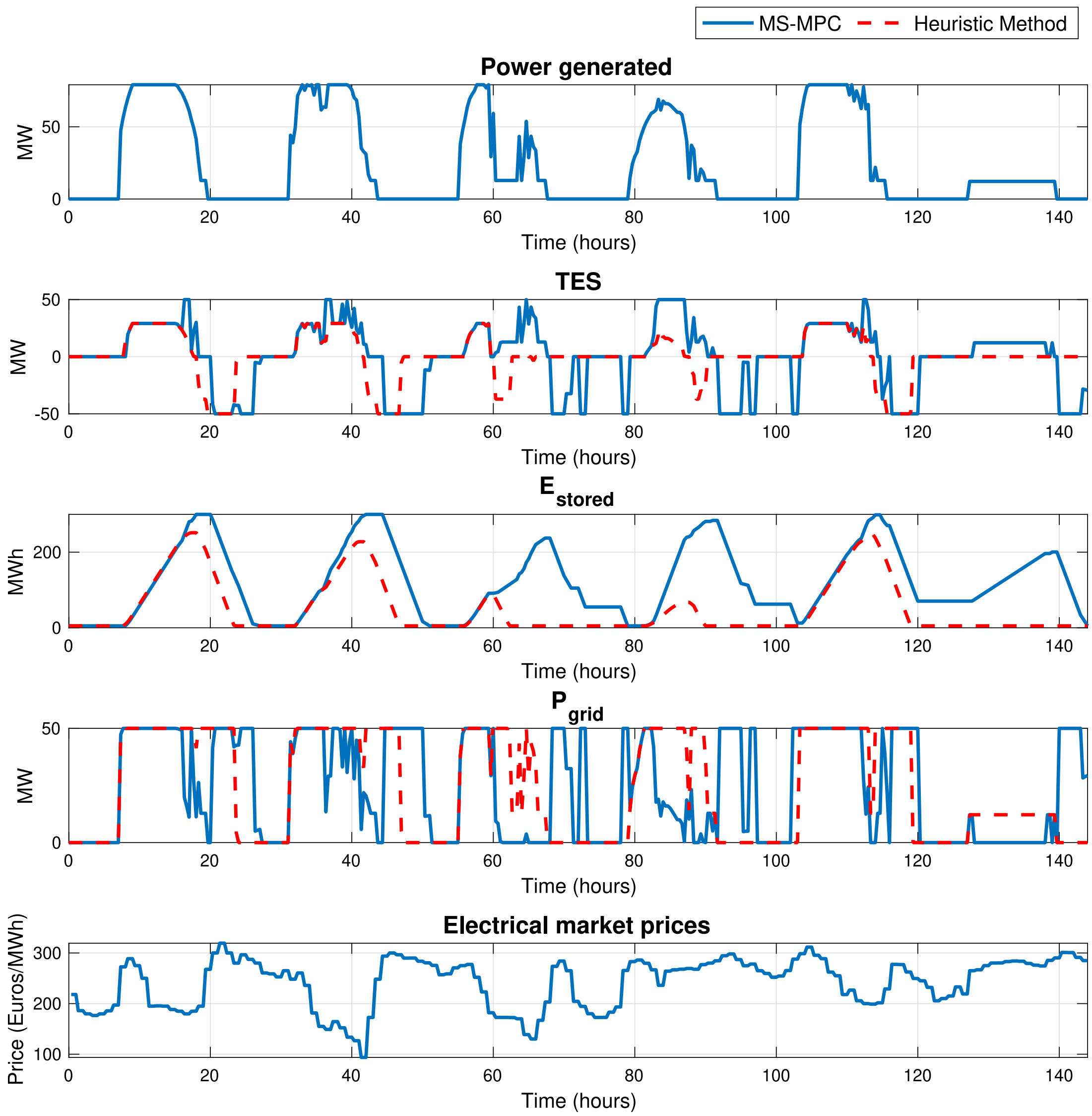

Fig. 3. Comparison planing energy management by using a heuristic method and a MS-MPC approach.

Table 2
Weight factors considering forecast meteorological conditions.

Solar irradiance	Wind speed	Weight factor
↑	↑	0.85
↑	↓	1.10
↓	↑	0.90
↓	↓	1.15

seven days. They have been multiplied by a weight factor given by the meteorological conditions, as seen in Table 2. Variation in prices is subject to solar irradiance conditions and wind speed. That is, prices are on a downward trend as long as there is a prognosis of high solar irradiance and wind speed.

Remark 2. There are many techniques for forecasting energy prices in the electricity market; see, e.g., [41]. Still, in this work, for the sake of simplicity, a straightforward heuristic rule will be used, since prices are updated every 24 h.

5. Results and discussion

To achieve a reliable performance evaluation of the MS-MPC controller, this approach has been compared with other methods described earlier.

Fig. 3 shows the comparison of energy scheduling behavior between the MS-MPC controller and the heuristic method. The top figure represents the power generated by the CSP for the six days mentioned above. These days are classified as sunny, partly cloudy, the second and third days, cloudy, partly cloudy, and over-coast days. The second figure represents the power acquired or delivered to charge or discharge the TES. The energy behavior in the TES is shown in the third figure, the power delivered to the grid is represented in the fourth figure, and finally, the electrical energy prices are shown at the bottom of the figure. MS-MPC is represented by a solid line, whereas a dashed line characterizes the heuristic method.

As seen in the heuristic method, while solar power is enough to be delivered to the grid at its maximum capacity, the TES is charged, as happens during the first five days. Until the power generated is lower than the total power that admits the turbine, the TES is discharged to supply the most energy; in contrast, when an over-coast day, all produced power generated is delivered to the grid, and the TES remains at the minimum value.

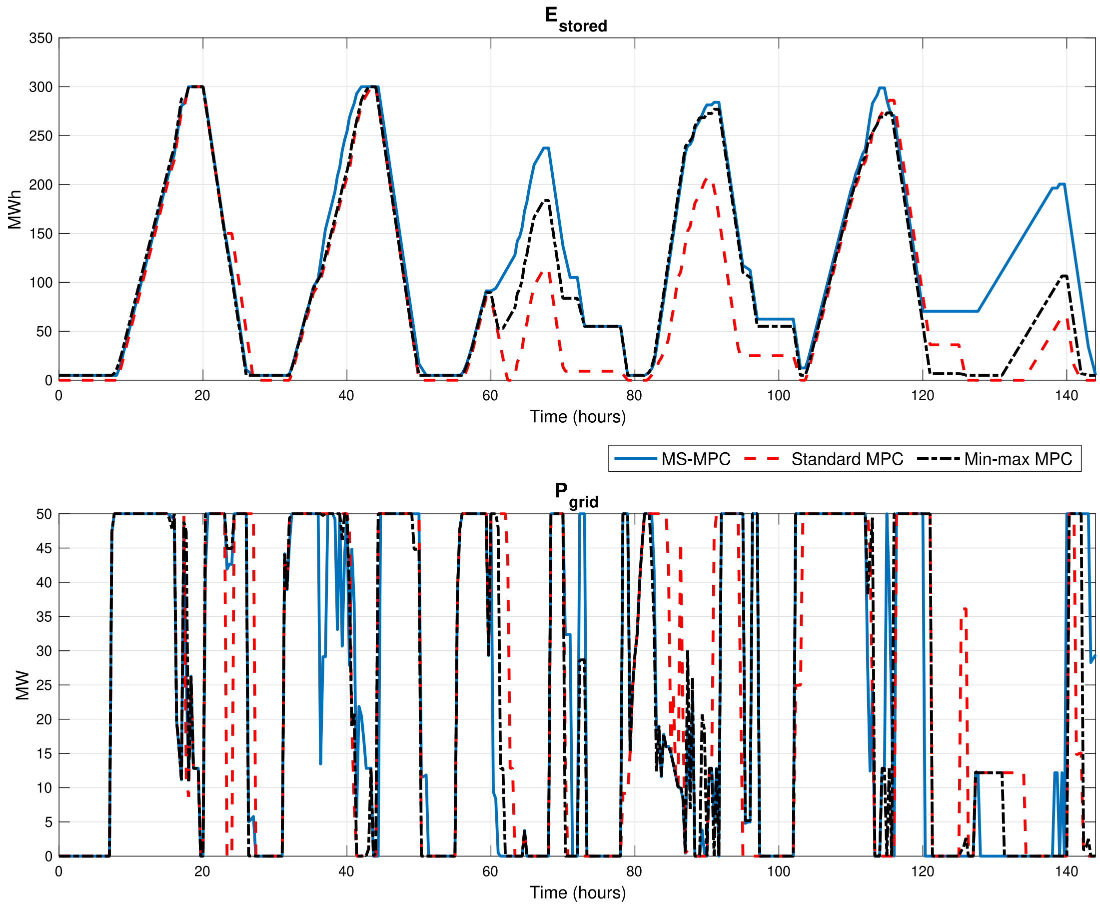

Fig. 4. Comparison of the energy stored in the TES and energy delivered to the grid by using MPC-based approaches.

On the other hand, the MS-MPC effectively uses the TES capacity. Therefore, low prices mean that energy is stored and no power is delivered to the grid. Another remarkable fact is that electrical energy is delivered to the grid when the TES is fully charged. However, when there is not enough power to be delivered to the grid, energy must be stored in the TES until prices increase, as seen on the last day.

The main differences among the applied algorithms can be seen when using the TES and the energy sold to the grid. The usage of batteries and the energy delivered to the grid using MPC-based approaches are depicted in Fig. 4. The standard MPC shows the poorest behavior compared to the Min–Max MPC and the MS-MPC. As expected, the standard MPC discharges the batteries fully, giving more energy despite the prices not increasing. Meanwhile, the Min–max MPC has a pretty conservative way of acting at the time of charge or discharge of batteries. However, the energy given to the UPG is sold more effectively. In this case, the contrast is observed during the last day, when the MS-MPC approach shows the best performance compared to these MPC algorithms. Here, it is notable for its role in considering some possible evolution of uncertainty, resulting in a considerable improvement in the storage of energy in the TES and selling it to the grid.

A comparison made with PF-MPC is shown in Fig. 5 to establish the goodness of the MS-MPC approach. As mentioned above, the PF-MPC is an ideal approach with perfect disturbance knowledge. Thus, it achieves the best performance for scheduling energy, providing an ideal upper bound. As can be seen, the MS-MPC has a behavior closer to the theoretical implementation.

To compare MS-MPC with other methods in terms of energy delivered to the grid and incomes obtained, Fig. 6 shows, on the left side, the amount of energy produced to the primary grid, and on the right side, the incomes obtained for each of the four described methods are represented for each day. Here, it is noticeable that the most energy sold does not mean the highest income because prices are dynamic, and it is better to sell power when prices are increasing. These results are summarized in Table 3 as well as the total amount of energy exchanged (charged or discharged) with the TEST. In addition, the profit increment for each method can be seen in comparison to that of the heuristic method.

Table 3
Comparison of the energy sold, the energy exchanged with the TES, the expected income, and the profit increment for each method.

Method	Sold energy (MWh)	Exchanged energy with the TES (MWh)	Incomes (Euros)	Profit increment (%)
Heuristic	3506.90	1719.10	821,220	0
Standard MPC	3489.50	2711.10	871,240	6.09
Min–max MPC	3497.20	2893.80	878,410	6.96
MS-MPC	3482.80	3035.70	883,450	7.58
PF-MPC	3477.80	3076.40	894,660	8.94

As expected, the best performance comes from PF-MPC. It is obtained with complete knowledge of solar production and prices. Second, the MS-MPC is situated with results very close to those of the PF-MPC. The Min–Max MPC shows higher income but sells more energy to the grid than the standard MPC. This particular demonstrates the over-conservatism of this type of controller despite having to deal with uncertainty. As expected, the policy of selling as much energy as possible, as is done in the heuristic method, offers the poorest results. Overall, MS-MPC provided a better performance assessment in dealing with uncertainties and providing the lowest amount of energy to the grid, generating the highest income after the theoretical limit (PF-MPC).

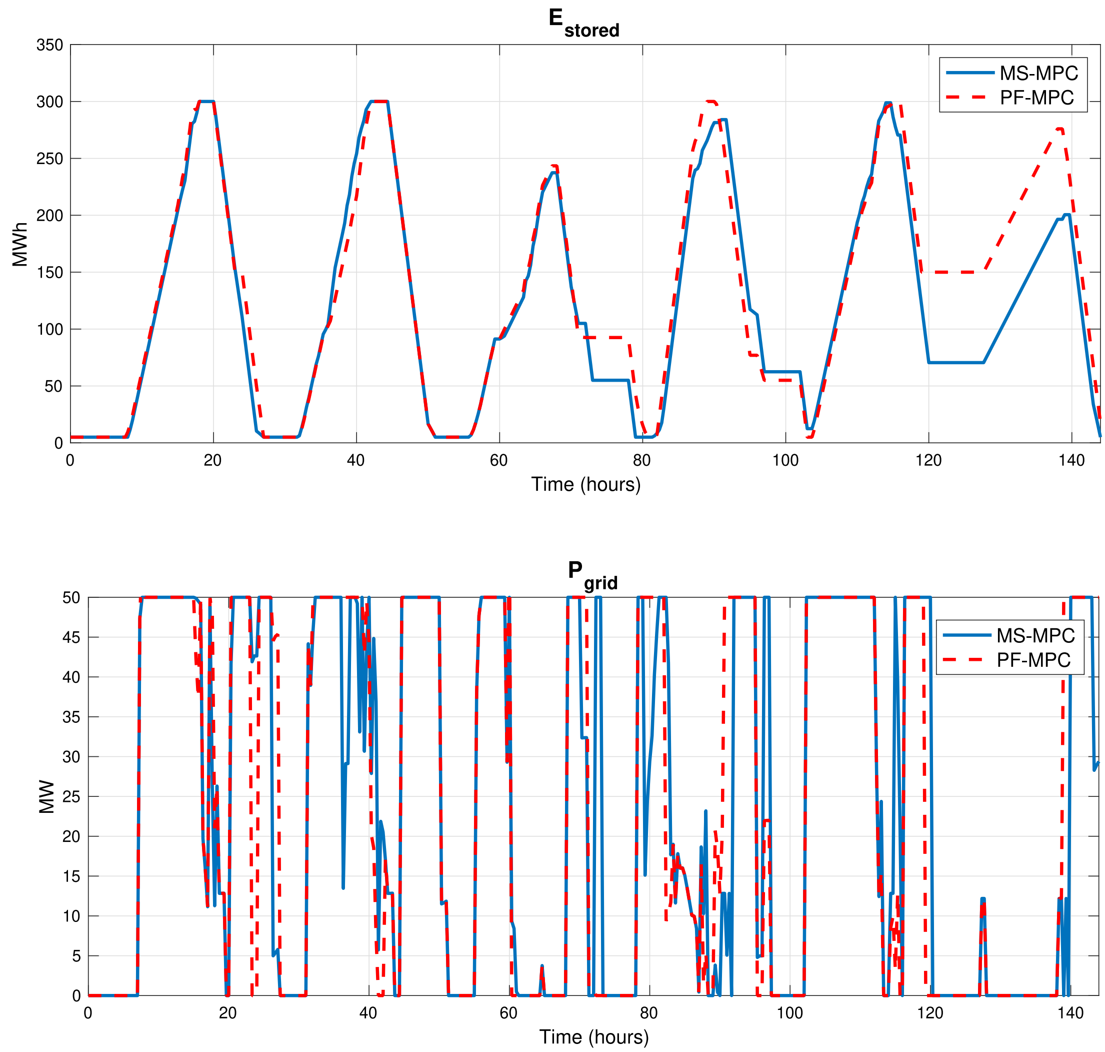

Fig. 5. Comparison of the energy stored in the TES and energy delivered to the grid by using MS-MPC and PF-MPC.

Table 4
Advantages and drawbacks of the proposed algorithms.

Approach	Advantages	Drawbacks
Heuristic method	Easy implementation.	Do not optimize the economic benefits.
Standard MPC	It carries out a finite horizon optimization problem.	It does not consider the uncertainty in the formulation of the optimization problem.
Min–max MPC	It considers the stochastic implementation of the uncertainty.	It results in a quite conservative behavior by considering the worst case scenario realization.
MS-MPC	It takes into account some scenarios in the optimization problem, formulating a stochastic version of an MPC controller.	Collecting a sufficient number of scenarios by gathering historical data or randomly generating them is necessary. It could result in a higher computational burden.

Finally, some advantages and drawbacks deduced from the algorithm formulations are summarized in Table 4.

6. Conclusions

This work has developed an approach based on scenarios in which uncertainties in solar irradiance and variability of electricity prices for a 50 MW solar trough plant are considered. Simulations show that while the PF-MPC approach yields an ideal result, the MS-MPC approach presents results that are very close to the ideal result after a performance comparison with other techniques, such as a heuristic method, a standard MPC, and a min–max MPC. However, the scenario-based stochastic approach guarantees a certain degree of robustness that is not considered by either the heuristic formulation or a classic MPC. Furthermore, it can be deduced from the results that the best policy is obtained when the stochastic characteristic is used to formulate the optimization problem. The results show that the proposed method performs better in dealing with uncertainties by providing the lowest amount of energy to the grid (3482.80 MWh) while generating the highest income (894,660 euros). The proposed method attains

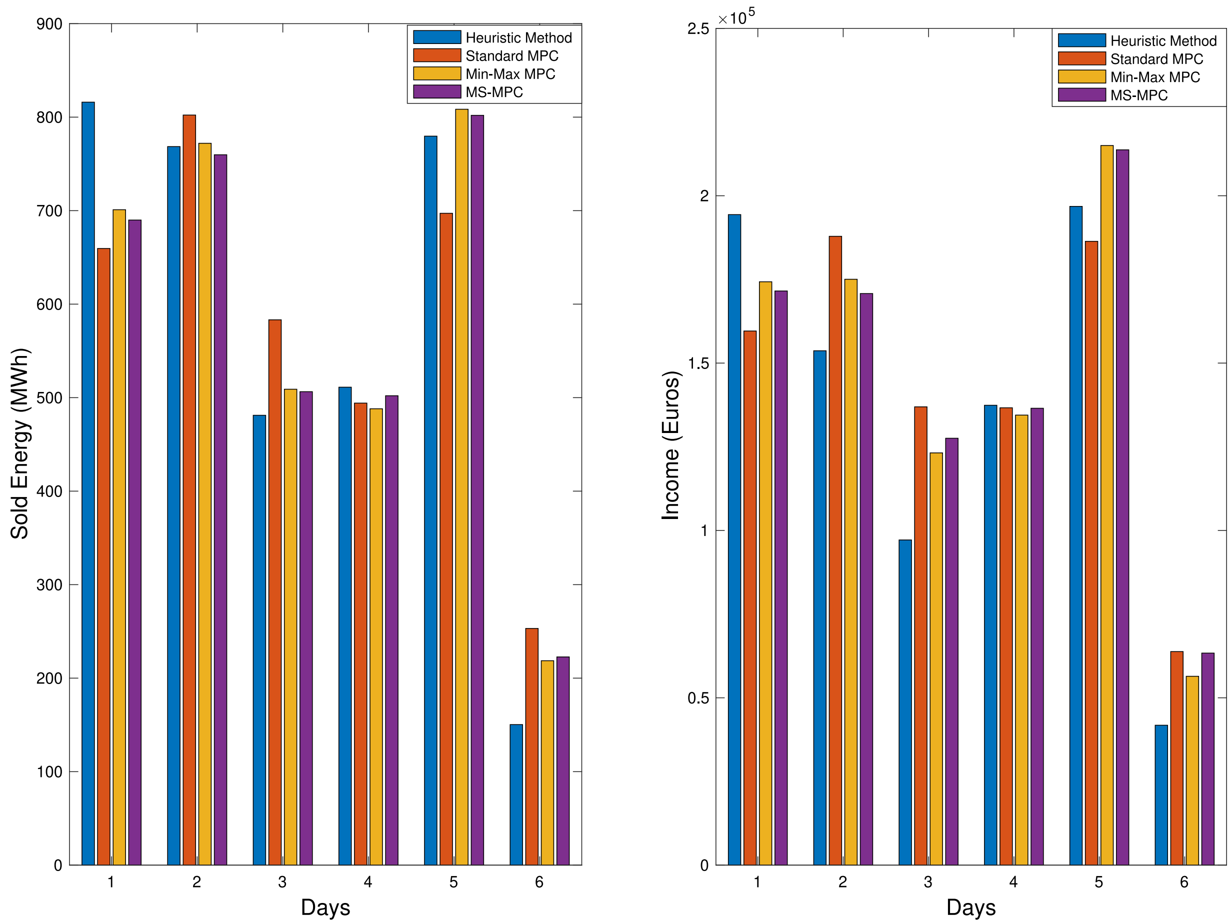

Fig. 6. Comparison of sold energy at each day and income obtained by using different approaches.

the closest performance compared to the theoretical optimal schedule and represents a profit increase of approximately 7.58% more than a heuristic method.

CRediT authorship contribution statement

Pablo Velarde: Writing – original draft, Methodology, Software, Investigation. **Antonio J. Gallego:** Writing – original draft, Methodology, Validation. **Carlos Bordons:** Validation, Writing – review & editing. **Eduardo F. Camacho:** Conceptualization, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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