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# Optimal Operation of Solar Tower Plants with Thermal Storage for System Design ⋆

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**Abstract:** Concentrated Solar Power CSP plants are increasingly being considered for construction worldwide, in order to meet the demand for renewable power generation. The most promising technology considered today employs a central receiver, illuminated by a heliostat field, using molten salts as working fluid. A distinctive feature of these plant is the possibility of thermal energy storage, providing 15 or more hours of full power operation without solar irradiation. The state-of-the-art SAM software is often use for sizing the plant and evaluating the return on investment, assuming a straightforward and short-sighted control strategy. In this paper, a model similar to that used by SAM is developed and then used to demonstrate the potential advantages of optimal control, in a context of variable tariffs with higher prices during peak hours. The modelling and optimization problems are formulated with the high-level Modelica and Optimica languages, which allows to solve the problem with minimal effort. This paper is a first step to promote the use of optimal control techniques and high-level modelling languages for the correct evaluation of the potential performance of CSP plants with thermal storage during their design phase.

*Keywords:* Control of renewable energy resources; Optimal operation and control of power systems; Solar energy

## 1. INTRODUCTION

For over a century devices have been designed to convert concentrated solar energy into useful work (Pifre, 1882; Francia, 1968; Spencer, 1989). The oil crisis triggered R&D on solar energy and pilot plants were built during the 1980s. In recent years, renewed interest in concentrating solar power (CSP) plants has sparked a new surge in investment; in 2011 there were 1.3 GW of CSP operational worldwide, 2.3 GW under construction, and 31.7 GW planned (Pitz-Paal et al., 2013). An important inherent option for CSP power plants is to incorporate thermal storage, enabling power to be generated when the sun is not shining, and contributing to CSP distinctive ability, in comparison to many other renewable electricity generation technologies, to provide dispatchable power. Recent researches aimed at quantifying the added values of CSP dispatchability, the key findings being: i) the dispatchability of CSP adds quantifiable economic benefits, ii) the flexibility of CSP can aid integration of other renewable energy sources, such as solar photovoltaics (Denholm and Mehos, 2013).

Of all CSP technologies available today, that of central receiver systems (CR, also known as solar towers) is moving to the forefront, and it might become the technology of choice. The interested reader is referred to the paper by Behar et al. (2013) for a thorough review of the history of this technology, the state of the art, and the ongoing R&D efforts. State-of-the-art CR systems use molten salts as the working fluid in both the solar receiver and the Thermal Energy Storage subsytem (direct TES), which may be sized to provide several hours of nominal operation without solar radiation (Turchi and Wagner, 2012). The schematic layout of the first commercial plant of this type, operating since 2011 in Spain, is shown in Fig. 1.

The storage decouples completely the power block from the variable solar resource, which is beneficial for both plant efficiency and reliability. In fact, in order to achieve better overall performance during the day, the control techniques for CSP systems usually aim at maintaining the solar receiver outlet temperature close to its nominal value, by varying the heat transfer fluid (HTF) mass flow rate. However, in the absence of significant energy storage, the operating point of the power block needs to follow the variations of the solar radiation, as discussed by Camacho et al. (2007a,b). On the contrary, adopting a direct TES system introduces an additional control variable, i.e. the mass flow rate from the storage tank to the primary heat exchanger (steam generator). Thus, the receiver outlet temperature and the power delivered to the conversion cycle can be controlled independently. This

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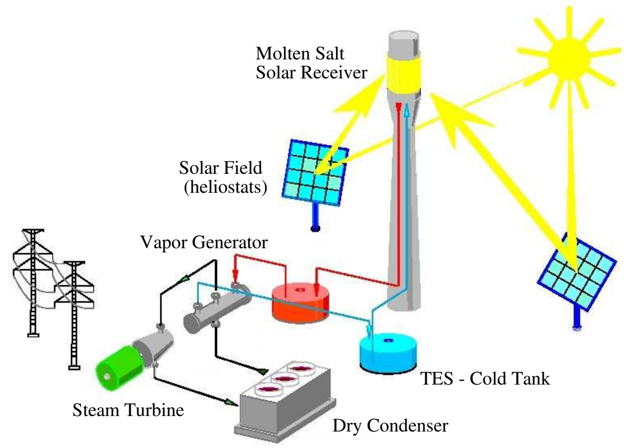



Fig. 1. Schematic layout of the Gemasolar 20 $\mathrm{MW_{el}}$ (15 hours of storage) solar tower plant, adapted from Burgaleta et al. (2011).

makes it possible to sustain constant power output during short transients of the solar field (e.g. cloud passage), or to shift the production to better meet variable-price tariffs.

In this paper, according to a scheme presently adopted mainly in the USA, the produced electricity is supposed to be sold to a utility company at the previously negotiated power purchase agreement (PPA) bid price, multiplied by pre-defined Time-Of-Day (TOD) factors that account for the higher value that the produced power has during peak hours. The PPA price is then negotiated by the producer in order to balance the investment and operational costs, and hopefully make a profit.

The availability of a TES system coupled with variable energy prices obviously calls for an optimized operation of the plant, maximizing the plant revenue by exploiting the TES to shift the production to higher priced time slots. This problem has been considered by many authors in recent times, see, e.g., Garíaa-Barberena et al. (2012); Powell et al. (2012); Nolteernsting et al. (2012).

With reference to real-time operation, Wittmann et al. (2008a) discuss the potential of weather forecast-based operation for CSP plants, stressing the importance of forecast quality. Wittmann et al. (2008b, 2011) present a methodology to maximize revenue for a plant operating in a free energy market; the CSP plant is run with a price-driven strategy and, based on electricity pricing and weather forecasting, an economically optimized bidding strategy for the day-ahead energy market is determined. The authors identify a period comprising the next one or two trading days as a reasonable optimization horizon, considering the trade-off between profit gain and forecast quality.

More recently, Lizarraga-Garcia and colleagues assessed the potential of a solar-thermal generation system in a fluctuating electricity prices context (Lizarraga-Garcia et al., 2013), considering the innovative CSP technology proposed by Slocum et al. (2011). Unfortunately, in most of these works the results of the optimization are presented, but not the full details of the models used to compute them.

When a new CSP plant is being considered at a specific location, models and tools are needed to assesses the potential in power production, and thus eventually compute the PPA price level that can repay for the investment in the specified time horizon. The most well-established, publicly available tool for this purpose is the System Advisory Model (SAM) (Turchi and Wagner, 2012; Wagner, 2008; Wagner and Gilman, 2011). The TES control strategy assumed by this model is short-sighted: for each operational period of one hour, the controller tries to use all the available power from the solar field and from the TES to drive the power block at the maximum possible load. This strategy is easily described by a handful of FORTRAN code lines, but is of course sub-optimal when the TOD factor has significant variations at peak hours.

This paper presents a simple dynamic model that replicates the basic modelling assumptions of the SAM software (with some simplifications), and then employs it to formulate and solve a dynamic optimization problem, that can give a more accurate estimation of the potential of a future CSP plant, assuming optimal control is used for its operation. Object-oriented language and tools are used for this purpose. The main goal of the paper is to show that, by means of these techniques and tools, the effects of optimal system operation can easily be considered when making strategic sizing decisions.

The CSP plant model replicating the main features of the SAM model is introduced in Sec. 2. The control strategy adopted by SAM is described in Sec. 3, while the optimal control problem definition and the way its solution is tackled are detailed in Sec. 4. The main results are presented and discussed in Sec. 5, while Sec. 6 ends the paper with the main conclusions and an outlook to future work.

## 2. PLANT MODEL

### *2.1 Solar Tower Model*

The selected CSP technology is a state-of-the-art molten salts plant with direct storage, briefly described in Sec. 1, and whose layout is shown in Fig. 1. The modelling assumptions are similar to those adopted by the SAM, though a number of parasitic losses has not been considered for simplicity (their weight is about 5% of the total production on a yearly basis):

(1) the temperature levels of the HTF are considered to be constant, neglecting all the heat losses in the system outside the receiver, which is modelled assuming a constant thermal efficiency;
(2) the temperature dependency of the thermodynamic properties of the HTF, i.e., density and specific heat, is neglected;
(3) energy storage is explicitly modelled only in the TES tanks, since the (controlled) dynamics of the receiver system and power block is much faster;
(4) perfect knowledge of future solar irradiation values is assumed

As a consequence, the system model contains a single dynamic equation, describing the state of charge of the TES, and several algebraic equations, describing the power block and the TES operation set points. For simplicity and numerical robustness, all the power variables are normalized to the nominal power block thermal power $Q^0_{\mathrm{PB}}$, and all the mass flow rate variables to the corresponding mass flow rate $m^0_{\mathrm{PB}}$ (the superscript $^0$ hereafter denotes design values).

Table 1. Design data adopted for the solar tower plant, the superscript $^0$ is omitted.

| | | | |
|---|---|---|---|
| Location | Daggett, CA | $\eta_{\mathrm{PB}}$ [−] | 0.4 |
| SM [−] | 2.1 | DNI [kW m$^{-2}$] | 1 |
| $\eta_{\text{rec-th}}$ [−] | 0.88 | $\alpha_{\mathrm{rec}}$ [−] | 0.94 |
| $\eta_{\mathrm{opt}}$ [−] | 0.78 | $\epsilon_{\mathrm{avail}}$ [−] | 0.99 |
| $\epsilon_{\mathrm{refl}}$ [−] | 0.9 | $\mathrm{f}_{\mathrm{MIN},\mathrm{Q}_{\mathrm{rec-inc}}}$ [−] | 0.25 |
| $\mathrm{f}_{\mathrm{MAX},\mathrm{Q}_{\mathrm{rec-inc}}}$ [−] | 1.2 | $\mathrm{f}_{\mathrm{MIN},\mathrm{m}_{\mathrm{PB}}}$ [−] | 0.25 |
| $\mathrm{x}_{\mathrm{TES,MIN}}$ [−] | 0.05 | $\mathrm{x}_{\mathrm{TES,MAX}}$ [−] | 1 |

The considered design data are collected in Tab.1, and are taken after Turchi and Wagner (2012); Wagner (2008); Wagner and Gilman (2011). The plant is assumed to be located in Daggett - CA, latitude 34.87$^o$, longitude $-116.78^o$, average direct normal irradiation (annual) 2791.4 kWh m$^{-2}$.

Apart for the solar multiple SM, the irradiation DNI, and the optical efficiency $\eta_{\mathrm{opt}}$, all the other values are assumed to be constant in the following analysis, $\eta_{\mathrm{PB}}$ is the power block thermal efficiency, $\eta_{\text{rec-th}}$ and $\alpha_{\mathrm{rec}}$ the receiver thermal efficiency and absorptivity, respectively, $\eta_{\mathrm{opt}}$ is the optical efficiency, $\epsilon_{\mathrm{avail}}$ and $\epsilon_{\mathrm{refl}}$ the heliostats availability and reflectivity, respectively. The receiver operating limits may be expressed in terms of the minimum and maximum design value of the incident thermal power $\mathrm{f}_{\mathrm{MAX},\mathrm{Q}_{\mathrm{rec-inc}}}$ and $\mathrm{f}_{\mathrm{MIN},\mathrm{Q}_{\mathrm{rec-inc}}}$, as

$$Q_{\text{rec-inc, MIN}} = \frac{\mathrm{SM}}{\alpha_{\mathrm{rec}}\ \eta_{\text{rec-th}}}\ \mathrm{f}_{\mathrm{MIN},\mathrm{Q}_{\mathrm{rec-inc}}}, \tag{1}$$

$$Q_{\text{rec-inc, MAX}} = \frac{\mathrm{SM}}{\alpha_{\mathrm{rec}}\ \eta_{\text{rec-th}}}\ \mathrm{f}_{\mathrm{MAX},\mathrm{Q}_{\mathrm{rec-inc}}}. \tag{2}$$

$\mathrm{f}_{\mathrm{MIN},\mathrm{m}_{\mathrm{PB}}}$ represents the minimum power block operating limit, in terms of the design mass flow rate of HTF through the primary heat exchanger. $\mathrm{x}_{\mathrm{TES,MIN}}$ and $\mathrm{x}_{\mathrm{TES,MAX}}$ are the storage operative limits, in terms of minimum and maximum normalized level (the tank height and the minimum allowable liquid level are supposed to be fixed at 20 m and 1 m, respectively). Starting from the definition of solar multiple (SM), it is possible to determine the solar field area $A_{\mathrm{SF}}$ and the thermal power transferred to the fluid in the receiver $Q_{\text{rec-HTF}}$, according to the equations

$$\mathrm{SM} = \left.\frac{Q_{\text{rec-HTF}}}{Q_{\mathrm{PB}}}\right|^0 = \left.\frac{Q_{\text{rec-inc-av}}\ \alpha_{\mathrm{rec}}\ \eta_{\text{rec-th}}}{W_{\mathrm{PB}}/\eta_{\mathrm{PB}}}\right|^0 \tag{3}$$

$$Q_{\text{rec-inc-av}} = \mathrm{DNI}(t_{\mathrm{TMY2}})\ \eta_{\mathrm{opt}}(t_{\mathrm{TMY2}})\ A_{\mathrm{SF}}\ \epsilon_{\mathrm{avail}}\ \epsilon_{\mathrm{refl}} \tag{4}$$

where $Q_{\mathrm{PB}}$ and $W_{\mathrm{PB}}$ are the thermal and electric power of the power block, and $Q_{\text{rec-inc-av}}$ is the available solar power which may reach the receiver if the solar field is fully focused.

Both the DNI and $\eta_{\mathrm{opt}}$ are functions of weather data. Following the SAM approach, weather data in the TMY2 format, containing data for various locations with a hourly sampling, are considered for this paper. The value of $\eta_{\mathrm{opt}}$ is evaluated hourly as a function of the incidence angle and of the optimized heliostats field matrix efficiency, whose calculation is based on the DELSOL3 code (Kistler, 1986), as detailed in Wagner (2008). These computations can be carried out off-line, so that $Q_{\text{rec-inc-av}}$ is eventually computed as a known, time-vaying input for the plant model. Also the price $P$ of the produced electricity produced depends on known hourly TOD factors, which in turn depend on the selected tariff, on the hour of the day, on the day of the week, and on the season, according to

$$P = f_{\mathrm{TOD}}(t)\ \mathrm{PPA}. \tag{5}$$

The power actually reaching the receiver $Q_{\text{rec-inc}}$ may then be calculated as

$$Q_{\text{rec-inc}} = Q_{\text{rec-inc-av}} - Q_{\mathrm{def}}\ , \tag{6}$$

where $Q_{\mathrm{def}}$ is the power dumped by heliostat defocusing, which is a control variable of the problem. The following (normalized) equations complete the model:

$$Q_{\text{rec-abs}} = Q_{\text{rec-inc}}\ \alpha_{\mathrm{rec}}, \tag{7}$$

$$Q_{\text{rec-HTF}} = Q_{\text{rec-abs}}\ \eta_{\text{rec-th}}, \tag{8}$$

$$m_{\text{rec-HTF}} = Q_{\text{rec-HTF}}, \tag{9}$$

$$W_{\mathrm{PB}} = m_{\mathrm{PB}}\ \eta_{\mathrm{PB}}, \tag{10}$$

$$T_{\mathrm{TES}}\ \frac{\mathrm{d}x_{\mathrm{TES}}}{\mathrm{d}t} = m_{\text{rec-HTF}} - m_{\mathrm{PB}}, \tag{11}$$

$$x_{\mathrm{TES}}(0) = x_{\mathrm{TES},0}. \tag{12}$$

Eq. (7) gives the thermal power absorbed in the receiver $Q_{\text{rec-abs}}$ and Eq. (8) the power $Q_{\text{rec-HTF}}$ transferred to the HTF. Eq. (9) relates the mass flow rate of HTF through the receiver $m_{\text{rec-HTF}}$ to $Q_{\text{rec-HTF}}$, while Eq. (10) establishes the linear relation between $W_{\mathrm{PB}}$, $m_{\mathrm{PB}}$, and the power block efficiency $\eta_{\mathrm{PB}}$, which is assumed to be constant in this work. Finally, the differential equation (11) describes the dynamics of the TES system, where $T_{\mathrm{TES}}$ is the capacity of the storage tank in terms of hour of operation at nominal power block load. The corresponding initial conditions for the state variable are explicitly defined by Eq. (12).

There are also several constraints which need to be enforced in order to ensure feasible operation:

$$Q_{\text{rec-inc}} \leq Q_{\text{rec-inc, MAX}}, \tag{13}$$

$$0 \leq Q_{\mathrm{def}} \leq Q_{\text{rec-inc-av}}, \tag{14}$$

$$0 \leq m_{\mathrm{PB}} \leq 1, \tag{15}$$

$$\mathrm{x}_{\mathrm{TES,MIN}} \leq x_{\mathrm{TES}} \leq \mathrm{x}_{\mathrm{TES,MAX}}. \tag{16}$$

The first inequality states the maximum power that can be handled by the receiver, calling for a partial defocusing of the heliostat field if the available power $Q_{\text{rec-inc-av}}$ becomes too high; the defocused power $Q_{\mathrm{def}}$ (second inequality) is non-negative and less than the available power. The normalized flow rate of HTF to the power block is comprised between 0 and 1 per unit (third inequality), while the storage tank state of charge $x_{\mathrm{TES}}$ is limited between a lower and an upper bound.

Furthermore, both the solar field thermal power $Q_{\text{rec-inc}}$ and the power block HTF flow $m_{\mathrm{PB}}$ have a minimum operating load, $Q_{\text{rec-inc, MIN}}$ (Eq. 1) and $\mathrm{f}_{\mathrm{MIN},\mathrm{m}_{\mathrm{PB}}}$, respectively, and need to be turned off if the desired load level is lower than that. The first constraint is enforced by subsituting $Q_{\text{rec-inc-av}} = 0$ whenever $Q_{\text{rec-inc-av}} =< Q_{\text{rec-inc, MIN}}$, which is easily done as this quantity is computed offline from weather data. The second constraint is handled by introducing extra terms in the optimization problem, see Sec. 4.

The resulting model has two known, time-varying inputs $Q_{\text{rec-inc-av}}(t)$ and $f_{\text{TOD}}(t)$, and two control variables $m_{\text{PB}}(t)$ and $Q_{\text{def}}(t)$. The model can be encoded using the equation-based, object-oriented language Modelica (Mattsson et al., 1998), see Listing 1 in the Appendix.

## 3. REFERENCE CONTROL STRATEGY

The model described in Sec. 2.1 may be used to predict the performance of the considered solar tower plant working according to a reference operation strategy, defined following Wagner (2008); Wagner and Gilman (2011). This approach aims at satisfying the nominal power cycle demand ($Q^0_{\text{PB}}$), by making use of the available resources, i.e. the solar field (SF) and the TES system, in a prioritized order. A series of logical statements are used to determine whether the power cycle demand can be met with only the solar field, or with the solar field and with the TES, always in this order, while ensuring that the operative constraints (Eqs. 13-16) are satisfied. In other words, the algorithm aims at running the power block at the maximum possible load for every time step, defocusing the solar field when its output $Q_{\text{rec-inc-av}}$ exceeds the sum of the nominal heat consumption of the power block and of the maximum storage charging rate that fulfills the capacity limits over a one-hour horizon. In this way, the values of the decision variables $m_{\text{PB}}$ and $Q_{\text{def}}$ can be determined, disregarding any information about the electricity price and of future availability of solar irradiation.

The SAM software simulates the differential-algebraic equations by assuming that all variables are constant within each hour of operation, i.e. by using forward Euler's method, which will then be used for the simulation of this model. As there is no feedback from $x_{\text{TES}}$ to any other variable of the model, forward and backward Euler's methods give the same results, only shifted by one time step, which is deemed irrelevant when determining yearly revenues.

## 4. OPTIMAL CONTROL

The model described in the previous Section may be used to assess the potential of an optimized operation strategy for the considered solar tower plant, aimed at maximizing the revenue deriving from the electricity sold. The control objective is

$$\min \int_{t_{\text{I}}}^{t_{\text{F}}} -W_{\text{PB}}\, P + c\, \left(\frac{\mathrm{d}u}{\mathrm{d}t}\right)^2 + g\, s\, (u - \mathrm{f}_{\text{MIN},\mathrm{m_{PB}}})\, \mathrm{d}t. \quad (17)$$

The first term in the summation accounts for the normalized instantaneous revenue from electricity selling, which needs to be maximized. The second term, with $c > 0$, is introduced to penalize fast changes and oscillations of the control variable, which might be stressful for the power block (though no explicit cost model is formulated here for such stresses), as well as repeated re-starts of the plant during the same day.

The third term, with $g > 0$, is introduced to avoid the power block operation below the minimum operating load $m_{\text{PB,min}}$, along with the additional constraints

$$u = m_{\text{PB}} + s, \quad (18)$$

$$0 \leq s \leq u. \quad (19)$$

The control variable $u$, which is the output of the dynamic optimization problem together with $Q_{\text{def}}$, is the desired normalized value of the HTF flow to the power block, while $s$ is a slack variable. If $u > \mathrm{f}_{\text{MIN},\mathrm{m_{PB}}}$, the term is minimized by taking $s = 0$, so that $m_{\text{PB}} = u$. If $u < \mathrm{f}_{\text{MIN},\mathrm{m_{PB}}}$, the term is minimized by taking $s = u$, so that $m_{\text{PB}} = 0$

The values of $c$ and $g$ are empirically chosen to be the smallest possible, that actually succeed at avoiding control oscillation, restarting of the power block in the same day, and operation below the minimum operating load, while perturbing as little as possible the optimization of the first term, i.e., the economic revenue of the plant.

An additional constraint $x_{\text{TES}}(t_{\text{F}}) = x_{\text{TES,F}}$ might be added to obtain a specific value of the storage at the end of the operational period; this can be instrumental in comparing the performance of the optimal control to that of the original control strategy on equal grounds.

The above-described optimal control problem can be encoded using the Optimica language (Åkesson et al., 2010), an extension of Modelica that also allows to specify the control objective and the constraint equations. The optimization problem contains an instance of the plant model, as well as all the extra elements required to fully describe the optimization problem, see Listing 2 in the Appendix.

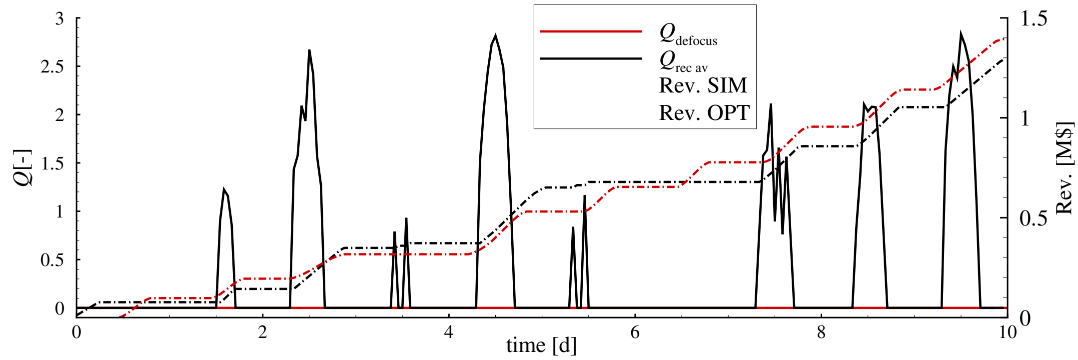
## 5. RESULTS & DISCUSSION

As a case study, the comparison between the reference and the optimized operation was performed. The considered tariff was adopted by the utility company *Pacific Gas and Electric* in 2011, as defined in SAM (Wagner and Gilman, 2011).

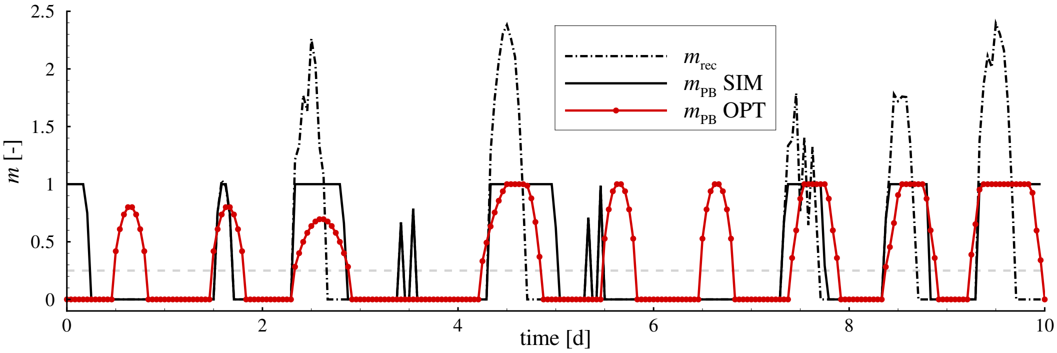
The results regarding a 10-days period from February the $7^{th}$ to February the $16^{th}$ are presented in Fig. 2. The first day is a Thursday, so that the week-end (which has a different $f_{\text{TOD}}$ schedule), shows up in the middle of the considered time period. Here the results of the simulation performed with the control algorithm emulating the SAM control strategy, and the results of the optimized operation are compared. In order to perform the comparison on a fair basis, the initial and final state of the TES in the optimization problem are constrained to be the same as they are in the simulation using the SAM control.

The simulation is performed using Euler's backward algorithm. The optimization is performed by the JModelica tool (Åkesson et al., 2010), which transcribes the optimal control problem into a finite-dimensional NLP program using a first-order collocation strategy that eventually boils down to using Euler's backward algorithm, so that an unbiased comparison between the two cases can be performed. The NLP program is then solved by the well-established interior-point IPOPT solver (Wächter and Biegler, 2006).

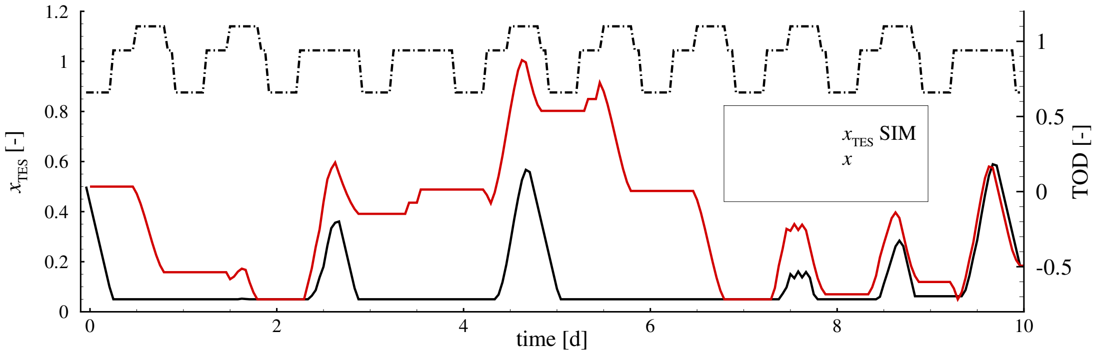
First of all, it can be noted from Fig. 2(a) that the use of optimal control allowed to increase the revenue of the period of more than 7%, passing from 1.292 to 1.394 M$.




(a)




(b)




(c)

Fig. 2. Comparison between reference and optimized operation for a solar tower plant during a 10-days period from February the $7^{th}$ to February the $16^{th}$ (location Daggett - CA, weather data in the TMY2 format). The considered system features solar multiple SM $= 2.5$ and storage capacity $T_{\mathrm{TES}} = 15$.

Even though the plant model considered here does not account for all the details of the SAM model (parasitic losses, start-up costs, variable power block efficiency), that might account for a few percent points of power production, it is reasonable to assume that the *relative* difference between the revenue obtained with the standard control and with the optimal control would be roughly the same when considering the full-fledged SAM model.

Furthermore, no defocusing is needed in either case during the considered period, which takes place during the winter season, when the available solar power is lower. As a consequence, the mass flow rate through the receiver is the same in the two cases, while the operation of the power block is managed differently, as shown in Fig. 2(b). Note that the hourly values of $m_{\mathrm{PB}}$, represented by the red dots, never fall in the forbidden region between zero and $m_{\mathrm{PB,min}}$, as expected from the problem formulation.

The effects of the optimized control strategy can be clearly understood by looking at Fig. 2(c), whereby both the storage level and the TOD factor are shown. The optimal controller tends to shift the production towards the afternoon hours of working days (when the TOD factor is highest) by reducing (or avoiding entirely) the production during the week end, i.e. limiting it to a value sufficient to prevent storage overloading while avoiding the need to dump solar energy by defocusing. This kind of optimal behaviour is typical of winter months, when the available solar power is scarce. Unfortunately, due to space constraints, it is not possible to show the details of a summer day, when defocusing is required due to the large value of the solar multiple SM.

As already pointed out in previous works, see e.g. Wittmann et al. (2008b), the storage size has a large influence since it determines the quantity of production that can be deferred. On this regard, Fig. 3 shows the plant yearly revenue as a function of the storage capacity, with and without optimal control. The optimal control result has been obtained by separately optimizing each month of operation, and then summing the resulting monthly revenues. It can be noted that adding storage capacity initially allows to notably increase the revenue, while this effect vanishes when exceeding a certain storage capacity which, in this case, is approximately 15 hours.

It is also confirmed that the optimized strategy allows for an increased revenue with respect to the reference one. It is interesting to note, though, that the advantage grows with the size of the storage. This means that a correct evaluation of the amount of storage to be installed in the plant, which depends on the trade-off between the increased revenue and the increased cost of a larger storage system, needs to consider the effects of optimal control, which is the main result of this paper.

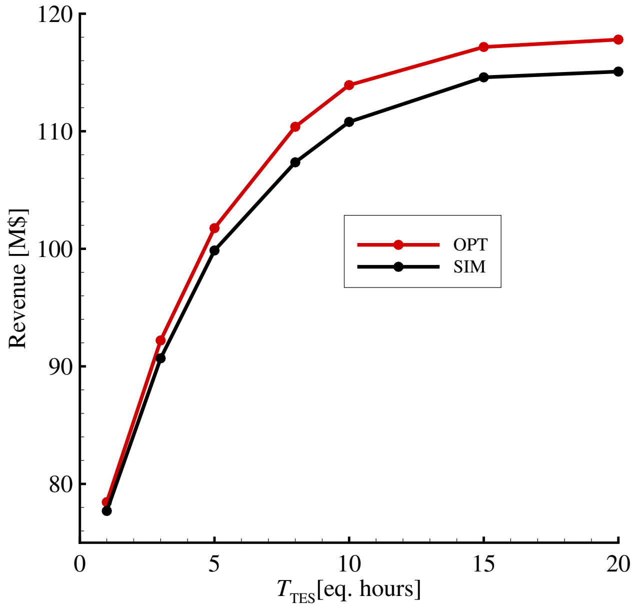



Fig. 3. Plant yearly revenue vs. storage capacity.

## 6. CONCLUSIONS

Concentrated Solar Power plants with thermal storage are a promising technology, that is increasingly considered as an option for mass production of renewable energy. In a context of time-varying tariffs, the storage system can be used to shift the production to more profitable hours. In this work, the model of an exemplary plant based on data available in the SAM software has been developed using the high-level Modelica language. Optimal control problems have then been formulated in Optimica and solved with the JModelica tool, showing that the impact of optimal control on the estimated yearly revenue of the plant is indeed significant.

The main conclusion of this work is that optimal control should be taken into account when estimating the potential plant revenue during the plant design and sizing phase. It is also argued that modern, high-level, object-oriented languages (such as Modelica and Optimica) and tools can be used effectively for this purpose, lowering the access barrier to an otherwise rather unfriendly world of numerical optimization software.

Future work will aim at increasing the accuracy of the model to match that of the SAM software, while ensuring that the problems remain numerically tractable.

## ACKNOWLEDGMENT

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## APPENDIX

Listing 1. Plant model in Modelica.

```
model CSP_tower
 input Real Q_rec_inc_av ;
 input Real m_PB(min=0,max=1);
 input Real Q_def(min=0) ;
 output Real x_TES(min=0.05,max=1);
 Real m_rec_HTF;
 Real Q_rec_inc(min=0,max=Q_rec_inc_max);
 Real Q_rec_abs, Q_rec_HTF, Q_rec_HTF, Q_lost, W_PB;
 parameter Real alpha_rec = 0.94;
 parameter Real eta_rec_th = 0.88;
 parameter Real eta_des = 1;
 parameter Real f_max_Q_rec_inc = 1.2,
 parameter Real f_min_Q_rec_inc = 0.25;
 parameter Real SM = 2.1;
 parameter Real T_TES;
 parameter Real x_TES_0;
 final parameter Real
  Q_rec_inc_max =
    SM/alpha_rec/eta_rec_th*f_max_Q_rec_inc,
  Q_rec_inc_min =
    SM/alpha_rec/eta_rec_th*f_min_Q_rec_inc;
equation
 Q_rec_inc  = Q_rec_inc_av - Q_def;
 Q_rec_absv = Q_rec_inc * alpha_rec;
 Q_rec_HTF  = Q_rec_abs * eta_rec_th;
 m_rec_HTF  = Q_rec_HTF;
 W_PB       = m_PB * eta_des;
 T_TES * der(x_TES) = m_rec_HTF - m_PB;
initial equation
 x_TES = x_TES_0;
end CSP_tower;
```

Listing 2. Optimization problem in Optimica.

```
optimization optim(objectiveIntegrand =
  -plant.W_PB*f_TOD + c*du_dt^2
  + g*s*(u-plant.f_min_m_PB),
  startTime = 0,finalTime = 1);
 CSP_tower plant(T_TES=15*3600);
 parameter Real g = 1, c = 2250000;
 // Known inputs
 input Real Q_rec_inc_av, f_TOD;
 // Unknown control variables
 input Real f(min=0, free=true);
 input Real du_dt (free=true, nominal = 4e-5);
 // Other extra variables
 input Real s(min=0, free=true);
 Real u (min=0,max=1.0);
equation
 Q_rec_inc_av   = plant.Q_rec_inc_av;
 TOD            = plant.TOD;
 u              = plant.m_PB + s;
 der(u)         = du_dt;
 f              = plant.Q_def;
initial equation
 plant.m_pb=0;
constraint
 s <= u;
 f <= plant.Q_rec_inc_av;
 plant.x_st(finalTime) = 0.05;
end optim;
```

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