Dynamic Optimization Approach to Coordinate Industrial Production and Cogeneration Operation Under Electricity Price Fluctuations

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Abstract

Industrial processes working with cogeneration utilities can coordinate their operation to take advantage of Demand Response programs to reduce their cost, while making the grid more stable and secure. Simplified steady-state and transition models are usually employed in a mathematical scheduling fashion to deal with this problem in process plants with small inertia. Here, however, we propose the use of a dynamic-integrated optimization approach that considers the dominant process dynamics jointly with the heat and power coupling in the cogeneration unit. The methodology meets the related European legislation and it has been tested in a simulated sugar factory that has a cogeneration system with connection to the external grid. The operation under two tariffs (TOU and Spanish Day-Ahead prices) was compared to the traditional policy of maximum production and fixed electricity prices, showing that a reduction of up to 5.41% of the costs is possible for the considered case study.

Keywords: Demand Side Management, Cogeneration, Sugar Industry, Dynamic Optimization, Day-Ahead Market.

1. Introduction

In a world facing such environmental challenges as climate change, air pollution or deforestation among others, the way energy is generated and consumed has become a topic of extraordinary relevance in our society. In the case of electricity, the penetration of intermittent renewable energies and the high fluctuations in demand due to the incorporation of new electricity-demanding consumers, like electric vehicles for example, are posing a real challenge to the grid operator, who must ensure the matching of electricity supply and demand in real time.

It is in this context that smart grids arise, where generation, transport, distribution and consumption are performed in an optimal and coordinated way (Fang et al., 2012). A major innovation of this concept is the consideration of a flexible demand subject to modifications through incentives, a topic commonly known as Demand Side Management (DSM) (Meyabadi and Deihimi, 2017). Among the different activities proposed by the DSM policies, price-based Demand Response (DR) programs aim to flatten the electricity demand curve changing the end-user consumption pattern through stimulus in the electricity price. Some examples of the programs proposed are: Time Of Use (TOU) rates, where prices are fixed by blocks depending on the time of the day; Critical Peak Pricing (CPP), where consumption peaks are charged with an extra-high rate; and Real-Time Pricing (RTP), where consumers are charged with prices that vary over short time intervals, typically hours, and are quoted one day or less in advance to reflect the real cost of electricity in the wholesale market (Albadi and El-Saadany, 2008; Galen L Barbose, Charles A Goldman, 2004).

Industrial facilities, who require a huge electricity consumption to produce goods and services, are natural candidates for participating in this kind of programs, reducing their operating cost while making the grid more stable and secure. Intuitively, under DR operation, an industrial consumer would increase production (and therefore its power consumption) when the electricity price is lower, storing products in excess and releasing them later when the electricity price is higher. Consequently, in order to participate in DR programs, an industrial site must be able to store products safely and efficiently, and be capable of adapting its production rate within a time scale similar to the variations in the electricity price. This requires the process to be “flexible”, that is, capable of operating in a wide-enough range without incurring big efficiency losses. Therefore, although at first sight production scheduling and energy management may have competing goals, their integration enables the participation of industrial sites in price-based DR programs, so they have become a topic of interest for a variety of industrial processes in the research community (Merkert et al., 2015).

In many cases, stationary mathematical models were used to find the optimal production schedule, where transitions between different operating points and/or modes were neglected or simplified using tabulated values or pre-defined functions to reduce the computational cost. While this approach may be enough in some cases, depending on the process inertia and on the DR program selected, the electricity prices may change with a frequency that is comparable to the dominant dynamics of the process. If that is the case, simplifying transition times may lead to computing a suboptimal or even infeasible sequence of operating points (Tsay et al., 2019). Moreover, it must be ensured that the benefit from changing the plant set points outweighs the additional effort in terms of extra labor, potential productivity and efficiency losses in transient states. That is the reason for including more precise dynamic information in the optimal scheduling problem. This topic is known as integrated scheduling and process control, and a complete review can be found in (Baldea and Harjunkoski, 2014).

Dynamic process scheduling

Ideally, a full integration of the scheduling and control problems would lead to the best sequence of operating points that fulfils an economic objective, while the dynamics of the plant would also be adapted to reach such points in the shortest possible time. Currently, two approaches can be found to deal with this problem: Top-down approaches, which consider dynamics and control elements in a scheduling problem formulation, and bottom-up approaches, where the control layer itself accounts for the scheduling problem.

The most developed bottom-up approach is Economic Model Predictive Control (EMPC), where the typical tracking objective function found in a Model Predictive Controller (MPC) is substituted by an economic one (Ellis et al., 2014; Rawlings and Amrit, 2009). The rolling-horizon nature of EMPC makes its application interesting in problems where external variables cause fluctuations in the economics of the process, and operational decisions can be adapted within a time horizon. This is especially interesting when a real-time tariff is considered, and its implementation has been studied in some works (Caspari et al., 2019; Schäfer et al., 2019). The main drawback of this approach is that a dynamic optimization problem must be solved online. This is an important limitation, given the mathematical complexity often needed to represent the full process behavior of many industrial plants. In ((Schäfer et al., 2019), some model reduction approaches were mentioned, and they proposed the use of data-driven models for the optimal operation of an air separation process in real-time electricity markets. Although this is a promising approach, a lot of work is still needed in this topic to assure accurate-enough real-time solutions when more complex processes are studied.

When the implementation of TOU and DA tariffs are studied, power related decisions are implemented only once a day, so top-down approaches become more interesting. Given the computational complexity of dynamic scheduling problems, a trade-off between detailed solutions and computational complexity is usually considered. Time-scale bridging models (Du et al., 2015) use a low-order representation of the dynamics of the process and its control system, so they can be considered in the scheduling problem. Thus, a closed-loop model that represents the dependence of the process outputs with respect to the inputs is used instead of the whole dynamic model. Using closed-loop low-order models introduces enough information of the plant dynamics in the scheduling problem to avoid infeasible operation strategies. This approach has recently been studied and compared to other solutions (Kelley et al., 2018; Pattison et al., 2016; Schäfer et al., 2019; Tsay et al., 2019). As a main advantage, we could say that it can reduce the complexity of the Mixed Integer Dynamic Optimization (MIDO) calculations if needed, but at the expense of not optimizing the dynamic behavior of the plant, which is still managed by an independent control layer. Furthermore, they allow the use of rescheduling strategies to account for low frequency disturbances (such as modifications in electricity prices or process demand) that may cause suboptimal process operations if neglected (Pattison and Touretzky, 2016). For a full comparison between the top-down and bottom-up performance, the reader is referenced to (Caspari et al., 2020).

Integration of process and cogeneration scheduling

When industrial processes have on-site generation systems, the possibilities with price-based DR programs are wider, but the scheduling becomes even more complex. Cogeneration, or Combined Heat and Power (CHP), is one of the most used on-site generation systems in the process industry. This is mainly because it is a very well-known technology and it provides much higher efficiency values than traditional generation systems, thanks to the simultaneous production of heat and power from only one source of energy (Kehlhofer et al., 2009).

In the literature, we can see that the *sequential* approach is the most widely used in industry to deal with the operation of cogeneration systems. In this approach, the industrial operation is first scheduled without energy considerations to minimize the production cost, and a scheduling problem of the utility system is performed later to satisfy the energy requirements of the production system while minimizing the energy cost (Agha et al., 2010). In this last step, the Economic Dispatch (ED) and Unit-Commitment (UC) problems are solved (Conejo and Baringo, 2018), computing the amount of electricity that must be bought, sold, or generated while fulfilling the industrial process demands and selecting which units must do it.

The main advantage of the sequential approach is that, for realistic problem sizes, the computational cost is relatively low, but the solution may lead to suboptimal or even infeasible points. The alternative is the use of an integrated approach where both problems are tackled simultaneously. This approach was firstly considered by (Agha et al., 2010), where its performance was compared against the sequential approach, concluding that the integrated fashion led to significant reductions in the energy costs while decreasing the emissions of harmful gases for the case studied. Later, the idea of optimizing the participation of energy intensive processes with on-site generation systems in Demand Response programs was studied in (Wang et al., 2013). In this way, the implementation of a TOU tariff along with a load tracking problem was proposed. A DR program based on day-ahead hourly electricity prices was implemented with an MILP model in (Ding et al., 2014). On the other hand, (Zhang et al., 2013) studied the use of a mixed integer nonlinear programming model to solve the integrated approach in two real refineries coupled to cogeneration systems. A similar approach was also taken in (Sun et al., 2015), although in that case a heuristic method (Particle Swarm Optimization) was used to solve the optimization problem. A bi-level heuristic problem was proposed by (Hadera et al., 2015) to optimize the melt shop section of a stainless steel plant. In this study, the authors considered different sources of power and the possibility of selling back the electricity to the external grid. (Zulkafli and Kopanos, 2016) proposed a model where performance degradation and different types of cleaning were considered for the utility system. Later, the same authors extended their approach to propose a rolling-horizon optimization to cope with demand uncertainty (Zulkafli and Kopanos, 2017). Equipment breakdowns and deviation price uncertainty were considered by (Leo and Engell, 2018). In this work, the authors presented a stochastic mixed-integer linear programming model to simultaneously determine the optimal production schedule of a power-intensive plant with on-site generation capabilities and the optimal day-ahead electricity commitment.

The main drawback of the integrated approach is the bigger computational effort needed to solve the problem with respect to the sequential approach. In order to deal with this issue and to take advantage of the problem structure, an iterative strategy, also called the decomposition approach, has recently been proposed by some researchers. (Hadera et al., 2019) proposed the use of the Mean Value Cross Decomposition, and they tested their approach in a pulping and steel production process. A game theory approach was proposed in (Leenders et al., 2019), where the Stackelberg game was applied to two case studies taken from the literature. A three-stage mixed-integer programing decomposition strategy was proposed in (Zulkafli et al., 2020), showing that optimal or near-optimal solutions can be obtained four times faster than with the integrated approach.

Article scope

In CHP systems, the limit of power generation depends on heat production and vice versa. This coupling between heat and power generation makes the participation of industrial sites with CHP plants in electric markets more difficult. One way to deal with this problem is the use of cogeneration plants with different generation technologies (steam turbines, gas turbines, or combined cycles), where each technology presents a different relation between power and heat generation. Therefore, a good scheduling of their operation may lead to important savings. Another solution, which is gaining popularity with the incorporation of renewable energies, is the use of Thermal and Electric Storage Systems (TSS and ESS). With these systems, thermal energy and power can be used and generated when more convenient and stored until needed. Thus, the problems related to an uncertain demand can be drastically reduced.

However, there are still industries with cogeneration units, where a strong coupling between power and heat generation exists and could take advantage of DR programs. In these cases, the strong interaction between the heat demand of the main process and the power generation in the utility system makes the use of an integrated approach advisable. Furthermore, in many of these factories, the dominant dynamics of the main process may force response times close to the frequency at which electricity prices change, so dynamic features should be incorporated to obtain the optimal operation scheduling.

To the best of our knowledge, no dynamic scheduling has been proposed where the production process and cogeneration system are integrated; this is probably due to the expectation of an intractable problem size. In this work, we propose a dynamic scheduling with a top-down approach, where the closed-loop dynamics of the system with control is considered using a time-scale bridging model. Then, we test our approach in a simulated sugar factory with a CHP plant able to export or import power from the external grid. Moreover, we evaluate the operation of the process under two different price-based DR programs (TOU and RTP) and we also consider the legislation constraints regarding cogeneration utilities. Although some studies have already evaluated the influence of such constraints (Tina and Passarello, 2012), the laws they considered have already been derogated, so we study the implementation of the current legislation in the optimization problem. To show the benefits of using the proposed program, the results obtained are compared to a typical scenario where the production is maintained at the maximum value during a whole campaign, and the electricity is bought or sold from the external grid using a flat tariff. This study serves as proof of concept for other industrial processes which share similar features with the presented case study, so that the adoption of the proposed approach could be beneficial.

The innovative contributions of this paper are:

1) A new methodology is proposed for obtaining the optimal operation scheduling of industrial processes with coupled cogeneration systems under price-based DR programs.
2) Formulation of the problem using a dynamic-integrated approach in order to consider the slow dynamics present in many industrial processes, such as large chemical plants.
3) Evaluation in a seasonal production process, the extraction of sugar from beet.
4) Explicit consideration of the current European legislation related to efficient cogeneration systems.

The rest of this paper is organized as follows. In the next section, a motivating example is given. Then, the proposed methodology is explained in Section 3. We apply the dynamic-integrated approach to the sugar extraction case study in Section 4. In Section 5, the results are presented and discussed and, finally, in Section 6, the conclusions and some future research lines are outlined.

2. Motivating case study

The progressive trade liberalization of the sugar market worldwide has caused the closure of many European sugar factories since 2005, essentially due to the end of the quota system and a big drop in the price of sugar (Maitah et al., 2016). In order to subsist, sugar industries have been forced to find ways to reduce their costs to be more competitive and, in this framework, the enrollment in price-based DR programs is presented as an interesting possibility. Hence, sugar production and power consumption must be adapted to the price of electricity provided by the different tariffs, while also exploiting the possibilities given by cogeneration systems, which are usually part of the classical configuration of these processes. Traditionally, numerous businesses gave up on this possibility, due factors like the impact of the uncertainty present in the production process, the lack of knowledge about the operation of the electricity market, or the European legislation related to cogeneration. In this paper, two price-based DR programs are considered in a simulated sugar factory operating in Spain, via a decision support system whose core is an optimization model.

In the Spanish electricity system, regardless of whether you are an industrial generator or consumer, there are essentially two ways to buy or sell electricity: Directly in the wholesale electricity market, or through a retailer. Considering that going without an agent requires the presence of market experts in the company staff (rarely found in small-medium size factories), this option has not been considered in this work. With an intermediary, companies can choose between different tariffs to buy or sell electricity, where some of them come from price-based DR programs and are negotiated under bilateral contracts. In this work we have considered: the Base Load (BL) tariff, where prices are maintained constant during big periods of time; TOU, which was explained in the previous section; and Day-Ahead prices, where the hourly market prices are given to final consumers a day in advance.

Regardless of the selected tariff, the intermediary always buys or sells the requested power from the wholesale market, so a brief description about the Spanish electricity market is given next. In the Day-Ahead market, supply and demand bids are sent to the market operator (OMIE) until 10 AM of the day before the price is negotiated. At that time, after matching electricity supply and demand, and having considered different technical constraints, the electricity price is fixed for each hour of the next day. If the participants do not fulfill the electricity-consumption commitments, penalties are applied. So, considering that industrial consumers need great quantities of electricity to run their processes, it is essential for them to inform their agents before 10 AM about the electricity consumption and selling previsions, so that the intermediary may bid in the market with enough confidence.

On the other hand, Directive 2012/27/UE (Official Journal of the European Union, 2012) is one of the tools used by the European Commission to achieve the objectives fixed towards 2050 relating to energy efficiency and the reduction of carbon emissions. The requirements laid down in that Directive are minimum requirements for the Member States, which must transpose the directive, adapting measures specifically for each state. Among the different rules provided by the Directive, it establishes a method for measuring the efficiency of cogeneration plants and defines the concept of high-efficiency cogeneration. In Spain, the Directive 2012/27/UE was transposed by Royal Decree 56/2016 of 12 February 2016 relating to energy efficiency. It dedicates Chapter IV and, specifically, Article 13, to promoting the efficiency in the production of energy use in heating and cooling. Furthermore, it modifies Royal Decree 616/2007 of 11 May 2007, which provides a framework for promoting high-efficiency cogeneration in Spain and defines a method for calculating the Primary Energy Savings (PES) in its annex III. This index has been used in this work to measure the efficiency of the integrated cogeneration system, and its application is explained in detail in Section 4.

As in many other industries, a sugar production process needs heat and power to transform raw materials into products. Particularly, in the plant studied, sugar is obtained from beet using the heat and power provided by a cogeneration system, which can import or export electricity to the external grid if necessary. A diagram of the studied case is presented in Figure 1. Beet is first piled in a big esplanade outside the factory (storage area). The time the beet spends there is a crucial variable because, due to such diverse problems as rotting or frosts, much of the raw material can be lost if this waiting time is extended too much. Therefore, long storage times should be avoided a priori. However, beet harvesting can be delayed because of rain, so this uncertainty, in many cases, means that industry managers prefer to increase the storage time to dissipate the possibility of running out of raw material. Inside the factory, the beet is first washed and sliced into cossettes, from which sugar is extracted by putting them in countercurrent contact with hot water to obtain a juice. Next, a purification stage is carried out, where impurities are removed using physical and chemical separation techniques. Once the juice is composed essentially of water and sugar, an evaporation phase takes place, removing a great part of the water present in the solution. This is the part of the production process that needs more heat, as it is fed directly with Low Pressure (LP) steam coming from the cogeneration plant. Finally, a crystallization stage takes place, and the sugar grains are obtained, ready to be dried and stored. In Figure 1, all process stages have been summarized under the main process black box. For the considered factory, the beet processing rate must be established between 8880 t/d (370 t/h) and 10320 t/d (430 t/h).

The installed CHP plant has three different boilers and three backpressure turbines, able to produce up to 11 MW of power. Only one of each is represented in Figure 1. Natural gas is used in the boilers, obtaining superheated High Pressure (HP) steam from its combustion. The temperature of the obtained steam can be controlled using a heat exchanger (ATP), where it is put into contact with a manipulated flow of fresh water. Next, the steam is expanded in the turbines or passed through a bypass valve if necessary, obtaining superheated LP steam, which must be saturated before sending it to the evaporation stage. The power generated in the turbines can be controlled manipulating the steam flow passing through. During normal process operation, if all the steam obtained in the boilers is used to obtain electricity, more power than that needed for the factory is generated. Therefore, if the connection with the external grid is not considered, part of the steam needed by the process is bypassed to avoid electricity surpluses.

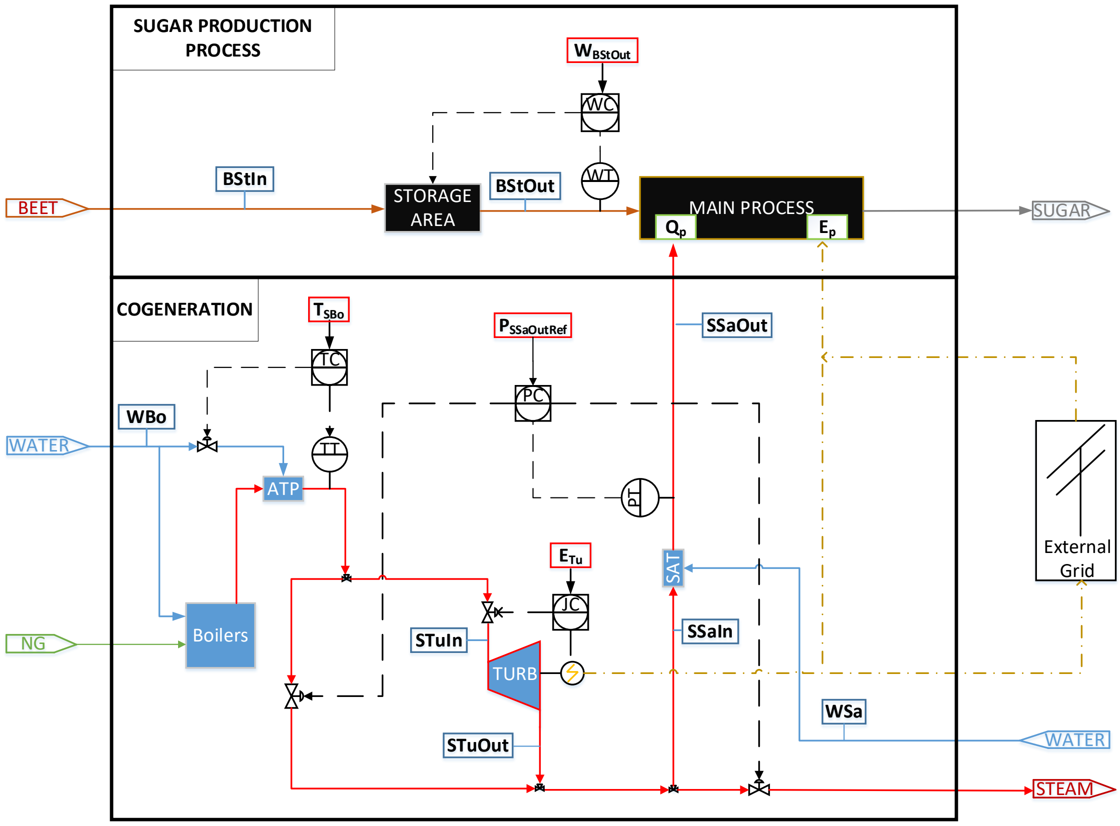

Figure 1. Simplified process flow diagram of the considered case study with the main existing instrumentation and power connection to the external grid.

Traditionally, sugar processes present an excellent energy integration, taking advantage of the vapor obtained in the evaporation stage to provide the heat energy demanded by the rest of the process (Urbaniec, 1989). In the plant considered, there are six co-current evaporation stages, whose vapor is used to fulfill the steam demand, mainly from the extraction, purification and crystallization stages, the last being the biggest consumer. This feature makes the pressure inside each evaporator a critical variable for control, and hence, the pressure steam is delivered to the evaporation from the cogeneration plant. In the case studied, a split range controller is used to control this pressure, manipulating the amount of steam that passes through the bypass and a relief valve placed before the saturator. More details about the sugar production process can be found in (Asadi, 2005; der Poel, 1998).

Given the strong coupling between heat and power generation in the CHP system, the operation of the main process and cogeneration cannot be considered independently. Additionally, given the slow dominant dynamics of the industrial process when changes in the operational point are carried out, dynamic features must be explicitly incorporated in the optimization framework.

3.Dynamic-Integrated Scheduling approach

In order to tackle the above highlighted problem features, we propose an integrated scheduling approach of the process and the utility system (i.e., in a simultaneous fashion) that also incorporates the dominant dynamics of the process.

Methodology

Consider an industrial process that produces a single product in one production line, and whose dominant dynamics is close to the frequency of changes in electricity prices. Product storage is assumed not to be a problem, considering space, quality and security issues. Furthermore, the process has access to a CHP plant where heat and power generation are strongly coupled, while, in the whole system (process + CHP), only continuous operating decisions can be taken. Electricity can be imported and exported to the external grid through a retailer, and the current legislation related to the efficient generation in CHP systems must be met. A scheme of the proposed workflow can be found in Figure 2. The first step is to study the features of the selected case study. Each system is different in many ways, so a good understanding of the process itself and its relationship with the utility system is key for an effective model formulation. In this step, the optimization aim, the outputs, and the decision variables must be defined.

In the model formulation stage, we propose the use of time-scale bridging models, which consist of a reduced-order representation of the dynamics of the system. This way, a closed-loop model that shows the dependency of the process outputs with respect to the inputs is used instead of the rigorous plant dynamic model. The so-called grey-box modelling approaches are recalled for such a task, where first principles equations, such as mass and energy balances, are merged with experimental approximations from plant data (Pitarch et al., 2019). In this modelling framework, the amount of first principles or experimental equations must be chosen according to the system complexity and the data available from measurements. It is advisable to look for control volumes to disaggregate the model and make the task easier.

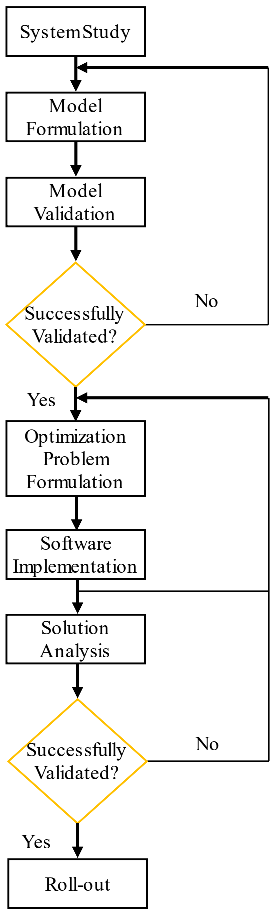

Figure 2. Methodology Scheme

A model customization to fit the actual plant is essential. For this purpose, a data-reconciliation problem with a backbone of first principles equations is stated in the first step to estimate all model variables and parameters over time (measured and unmeasured). Then, upon the said set of coherent estimations, input-output experimental relationships between some of these variables must be sought to complete the model. The next step is model validation. If data collection is a limiting factor for any reason, a qualitative verification can be done instead with the help of a process expert. Otherwise, a quantitative validation, where the model response is directly compared to the real system outputs, is always recommended. In any case, the model needs to be dynamically simulated for different scenarios. To do so, we recommend the use of a specialized software like EcosimPro (Empresarios Agrupados, 2018), where possible algebraic loops or high-index problems can be handled in an easier way.

Once the model has been successfully validated, a dynamic-optimization problem in the general form (1) is formulated.

$$\min_{u(t)} J := \int_{t_0}^{t_f} L\big(u(t)\big)dt \tag{1a}$$

$$s.t. \quad \dot{x}(t) = f(x(t), u(t), z(t)), \qquad x(t_0) = x_0 \tag{1b}$$

$$h(x(t), u(t), z(t)) = 0 \tag{1c}$$

$$g(x(t), u(t), z(t)) \leq 0 \tag{1d}$$

$$x \in \mathcal{X}, \qquad u \in \mathcal{U}, \qquad z \in \mathcal{Z} \tag{1e}$$

Where $x(t) \in \mathbb{R}^n$ are the state variables, $u(t) \in \mathbb{R}^m$are the input decision variables for optimization, and $z(t) \in \mathbb{R}^l$ are algebraic variables, each of them belonging to bounded compact regions $\mathcal{X}, \mathcal{U}$ and $\mathcal{Z}$, respectively. The Dynamic Algebraic system of Equations (DAE) that model the behavior of the plant (1b) – (1c), together with the initial condition, define an initial-value problem (IVP) which is solved from time t_0 to t_f. This IVP is also subject to additional specific constraints $g(\cdot)$, such as the electricity market interactions and legislation limits. While the main process and CHP model depends on each case study, the electricity market and legislation constraints can be applied to any other industrial plant with a cogeneration facility.

There are mainly two different approaches to solve (1): sequential or simultaneous (Biegler, 2010). Each approach has its pros and cons. In the sequential one, the use of a DAE solver provides accurate time evolutions of the state. However, depending on the model size, the computational cost for simulating in each iteration of the optimizer can be unacceptable. Hence, this approach is adequate when the accuracy of the solution is key. In the simultaneous approach, time dynamics are discretized (via orthogonal collocation for instance), so the size of the algebraic optimization problem increases, and the solution may not be so accurate. On the other hand, the many calls to a numerical simulator are avoided and much lower computational times are reached. Since computational time is key for our purposes in this application, we decided to follow this last approach. In addition, the employed reduced-order models are easier to maintain by the plant personnel. The optimization problem (1) can thus be coded in any modern programming language for numerical optimization such as Pyomo (Hart et al., 2011), CasADi (Andersson et al., 2018), or GEKKO (Beal et al., 2018).

In order to validate the results obtained from the optimization, a simulation test for several representative operation days is first performed. Here, the optimization is launched several times with different values for the exogenous parameters in a preselected operating scenario, and the optimization results are validated by experts. Special attention must be paid to the results obtained at the end of the day, since the turnpike property may cause some problems (Faulwasser et al., 2017). If the one-day validation is positive and the optimizer provides acceptable solutions, a long-term validation should be performed, so the optimizer is tested for several days or even months, checking the transition results between different days and operating scenarios. After the validation stage, the prototypical tool is ready to be rolled out. A scheme of the proposed process interaction with the optimizer can be found in Figure 3.

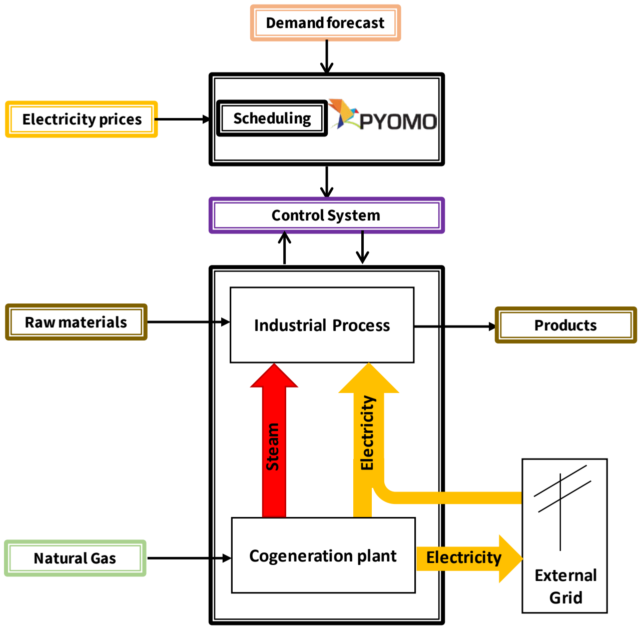

Figure 3. Scheme of the proposed process interaction with the optimizer.

4. Application to the case study

In this section, the proposed methodology is applied to the case study presented in Section 2. The sugar extraction is a seasonal business which, in the north of Spain, is typically carried out from approximately October to February. A common way of working is to fix the sugar production before starting the campaign, so in this work an objective of 138000 t of sugar has been established. For an average polarization of 16º and 90% of purity, it has been assumed that 959760 t of beet are necessary to obtain the sugar target. If profit is defined as the difference between the incomes from sugar sales and the costs expended to produce it, having fixed the total amount of sugar that will be produced; the only way to increase profit is by reducing costs, which can be divided into operating and fixed costs. The minimization of the operating costs may lead to an extension of the campaign duration, and therefore, an increment in the fixed cost. Given that the difference between the minimum and maximum production rate in the factory is 1440 t/d, for 959760 t of beet, the maximum increase in the campaign duration can be 15 days. For this short period of time, it has been assumed that the rise of the fixed cost comes essentially from the extension of the workers' salary, which will be considered in the results. In this and many other processes as well, a great part of the operating costs are due to the energy needed to transform the raw materials into products. With this in mind, the specific energy cost, defined as the energy costs for a given production rate, is proposed to be minimized by taking advantage of the electricity price variations. Considering that the heat and power energy are provided by a CHP system, the energy costs will come essentially from the natural gas flow needed, and the electricity imported from the external grid. Therefore, the objective has been established to reduce the energy cost while the campaign duration is considered.

The beet processing rate and the electricity exchanged in the market are the most important variables that can be manipulated to reach the above objective. In addition, the steam pressure received by the evaporation is a key variable too, as it can sharply modify the operation of the whole process. Other extra decision variable is the temperature of the outlet steam of the boilers, which may modify the electricity produced without changing the steam flow passing through.

4.1 Model formulation

The plant can be represented by a non-linear dynamic grey-box model, built upon equations obtained from plant data and completed with energy and mass balances. Thus, the model is less complex than if only first principles are used, and an adequate matching with the plant in the operating region where data is collected is maintained. The details about the model formulation and validation can be found in (Pablos et al., 2019). However, in that model, we find a split-range controller using discrete equations that need to be suitably reformulated to be handled by gradient-based optimization algorithms. Furthermore, some new variables must be added to represent the storage zone behavior and limit the time the beet spends in stock.

Split-range PI controller

In the system considered, a split-range PI controller is used to control the steam pressure produced in the cogeneration unit. It must decide the opening of the bypass and relief valve, considering that only one of them can be opened at the same time, or both must be closed. In the original model, the controller is represented as follows:

$$e(t) = P_{SSaOutRef}(t) - P_{SSaOut}(t) \tag{2}$$

$$v(t) = kp \cdot e(t) + v_i(t) \tag{3}$$

$$\dot{v_i}(t) = \frac{kp}{Ti} \cdot e(t) \tag{4}$$

$$Op_{By}(t) = \max\left(0, min\left(100, \frac{v_{max}}{v_{max} - 45} \cdot (v(t) - 45)\right)\right) \tag{5}$$

$$Op_{Re}(t) = \max\left(0, min\left(100, \frac{-v_{max}}{45} \cdot (v(t) - 45)\right)\right) \tag{6}$$

where:

$$0 \leq v(t) \leq 100$$

The list of variables and their units can be found in Appendix A. Equation (2) computes the error between the actual and desired pressure. Equations (5) and (6) are used to find the opening of the valves as a function of $v(t)$, which is obtained as the output of the PI controller equations. If the value of $v(t)$ is greater than 45, the bypass will be opened, and the relief valve will be closed. If the value of $v(t)$ is 45, both will be closed; and if it is less than 45, the relief valve will be the only one opened. To introduce this in the optimization code, the use of 'if' statements is necessary, which must always be avoided for gradient optimization. Hence, to implement the split-range controller, complementarity conditions (Biegler, 2010) have been used, and equations (5) and (6) have been modified as follows:

$$Op_{By}(t) = \frac{v_{max}}{v_{max} - 45} \cdot (v(t) - 45) \cdot y(t) \tag{7}$$

$$Op_{Re}(t) = \frac{-v_{max}}{45} \cdot (v(t) - 45) \cdot \big(1 - y(t)\big) \tag{8}$$

$$45 - v(t) = S_0 - S_1 \tag{9}$$

Where:

$$0 \leq y \perp S_0 \geq 0$$

$$0 \leq (1 - y) \perp S_1 \geq 0$$

$$S_0 \geq 0, \quad S_1 \geq 0, \quad 0 \leq y(t) \leq 1$$

$$0 \leq Op_{By}(t) \leq 100, \quad 0 \leq Op_{Re}(t) \leq 100$$

and $\perp$ is the complementarity operator, enforcing at least one of the bounds to be active. In (Biegler, 2010), four different formulations for the complementarity conditions were compared, and whether they should be implemented as constraints or as additional terms in the objective function was discussed. The results showed that the best way to deal with them is using a penalty term in the objective function and solving the problem for a penalty parameter ρ. Therefore, this approach has been followed, and the implementation of these conditions will be addressed in the objective function section.

Storage zone

In the storage zone, beet is accumulated until it can be processed in the sugar plant. To model the accumulation of beet, a first-order mass balance was stated.

$$\dot{m}_{St}(t) = W_{BStIn} - W_{BStOut} \tag{10}$$

The more time the beet spends inside the storage zone, the more sugar losses it experiences, so it is important to predict how a proposed policy will affect the time the beet is in there. To measure this, the storage residence time (τ_{St}) was defined as the mass of beet inside the storage zone over the beet processing rate.

$$\tau_{St} = \frac{m_{St}(t)}{W_{BStOut}(t)} \tag{11}$$

To limit the residence time, two variables are defined to detect whether the residence time is greater than 30 hours, or less than 15 hours (equations (12) and (13) respectively). While the upper limit has been established to avoid sugar losses because of beet degradation and limit the duration of the campaign, the lower limit corresponds to a safety bound, set to protect the process from running out of beet. In the objective function, these defined variables will be used to penalize undesired behaviors.

$$StoPenUp(t) = \max(\tau_{St}(t) - 30,\ \ 0) \tag{12}$$

$$StoPenLo(t) = \max(15 - \tau_{St}(t),\ \ 0) \tag{13}$$

Since they involve the use of max and min terms, they have been reformulated again using complementarity conditions, as suggested in (Biegler, 2010). Analogous to equations (7) and (8), the complementarity has been enforced including an extra penalty in the objective function.

$$StoPenUp(t) = \ \tau_{St}(t) - 30 + S_3(t) \tag{14}$$

$$StoPenLo(t) = 15 - \ \tau_{St}(t) + S_5(t) \tag{15}$$

$$\tau_{St}(t) - 30 = S_2(t) - S_3(t) \tag{16}$$

$$15 - \ \tau_{St}(t) = S_4(t) - S_5(t) \tag{17}$$

Where:

$$0 \le S_2(t) \perp S_3(t) \ge 0$$

$$0 \le S_4(t) \perp S_5(t) \ge 0$$

$$S_2 \ge 0, \quad S_3(t) \ge 0, \quad S_4(t) \ge 0, \quad S_5(t) \ge 0$$

4.2 Specific constraints

In this section, the generic constraints regarding the cogeneration legislation and electricity market interaction are defined.

Directive 2012/27/UE: Application

To measure the efficiency of cogeneration processes, Directive 2012/27/UE defines the Primary Energy Savings (PES) index, which represents the savings of a cogeneration unit against the production of heat and electricity separately in a reference plant.

$$PES = \left(1 - \frac{1}{\frac{\mu Q_{CHP}}{\mu Q_{Ref}} + \frac{\mu E_{CHP}}{\mu E_{REf}}}\right) \cdot 100 \tag{18}$$

Any cogeneration system with an installed capacity of more than 1 MWe is considered as highly efficient if the primary energy savings are at least 10% with respect to the separate generation. The PES index is evaluated yearly, so its enforcement within optimization routines with shorter prediction horizons can be a challenge. To make sure the legislation is respected, the index is calculated for each instant (t), and the integral of the index throughout the prediction horizon must be greater than the minimum accepted value (0.10) times the prediction horizon. Thus, the optimizer has freedom to find solutions which can eventually go below the lower bound.

$$\int_0^T PES(t)dt \geq 0.1 \cdot T \tag{19}$$

To obtain the PES index for each instant, the values used as reference for the separate generation $(\mu Qref, \mu Eref)$ were obtained from Regulation 2015/2402, which depend on the construction date of the cogeneration unit and on the fuel type used. The reference values taken for the case study can be consulted in Table 4 (Appendix A). Regarding the heat and electricity efficiencies through cogeneration $(\mu Q_{CHP}, \mu E_{CHP})$, they are defined as the heat and electricity obtained in cogeneration mode, divided by the total fuel used to obtain such heat and electricity.

$$\mu Q_{CHP}(t) = \frac{Q_{CHP}(t)}{F_{CHP}(t)} \tag{20}$$

$$\mu E_{CHP}(t) = \frac{E_{CHP}(t)}{F_{CHP}(t)} \tag{21}$$

According to Directive 2012/27/UE, a cogeneration plant can be divided into two different parts, CHP and non-CHP. For the case studied, if the global efficiency (μ_G) of the plant is equal to or greater than 75%, then it is considered that all the fuel, heat, and electrical energy is generated in the CHP part. However, if the efficiency goes below 75%, then, part of the fuel and electrical energy is obtained in the non-CHP part. The efficiency bound has been acquired from the Directive considering a cogeneration plant with counter pressure turbines and no condensation. Again, the global efficiency of the plant is evaluated annually so, in order to ensure that this efficiency is always above 75%, the same approach carried out for the PES index has been used.

$$\mu_G = \frac{E_{Tu}(t) + Q_{CHP}(t)}{F_{plant}(t)} \tag{22}$$

$$\int_0^T \mu_G(t)dt \geq 0.75 \cdot T \tag{23}$$

The heat obtained in the cogeneration system can be calculated as the difference between the steam heat at the inlet of the saturator and the water heat used in the boilers, assuming that water losses are negligible.

$$Q_{CHP}(t) = W_{SSaIn} \cdot (H_{SSaIn} - H_{WBo}) \tag{24}$$

Since the global efficiency constraint must be respected in the optimal solution, the electricity generated in the plant can be computed with equation (25), and the fuel energy obtained using equation (26).

$$E_{Tu}(t) = \mu_{Tu} \cdot W_{STuIn}(t) \cdot \left(H_{STuIn}(t) - H_{STuOut}(t)\right) \tag{25}$$

$$F_{plant}(t) = W_G(t) \cdot LHV_G = F_{CHP}(t) \tag{26}$$

$$E_{Tu}(t) = E_{CHP}(t) \tag{27}$$

Electricity market

For the electricity market, it has been assumed that the electricity bids sent to the market operator are always accepted. This assumption has been done based on the idea of the retailer bidding for the electricity needed or the remnant with a sufficiently low price with respect to the expected matching value (or even zero). Since the electricity market is marginalist, the final market price will be the same for every agent, and the price paid or obtained for the electricity negotiated will depend on the tariff used and the exact conditions negotiated. Therefore, in this work, three different possibilities have been considered. Two are based on tariffs with fixed prices, and the last one is directly based on the market electricity prices. These options cannot be combined, so only one of them will be used at a time.

- Base Load Contract (BL)
- Time of Use (TOU)
- Day-Ahead Market

One of the main features of the optimization problem presented in this work is its capability to calculate the amount of electricity that the intermediary should bid for in the market based on the predictions made regarding the electricity price and beet availability. The electricity generated in the turbines must always be equal to the beet-sugar process demand (E_p) plus the power committed with the external grid (E_C), which considering that the market bids are hourly based, must remain always constant within an hour:

$$E_{Tu}(t) = E_p(t) + E_c(t) \tag{28}$$

Considering the big process inertia, and the sharpness of changes in the electricity commitment, the split-range pressure control system is used to absorb the oscillations in the steam generation caused by the perfect matching of electricity generation and demand.

4.3 Objective Function

In the objective function, apart from the specific energy cost, four more different terms have been added with diverse aims. Each one is fully explained below.

$$\begin{gathered} J \coloneqq Specific\ Cost + Complementarity\ term + Moving\ Cost \\ + Storage\ Penalty + Turnpike\ \text{Cost} \end{gathered} \tag{29}$$

Specific Cost

As mentioned in Section 4, the objective of the optimization problem is to minimize the specific energy cost, which can be defined as the cost of the energy needed to process a certain amount of beet. First, in the numerator, the natural gas cost is represented. Since its price is expressed in [€/kWh] but the natural gas flow is obtained in [kg/s], it is converted using its density (d_G) and its Higher Heating Value (HHV_G). Then, the electricity incomes appear. If electricity is sold to the market, the electricity commitment (E_C) will be positive, and since it means a cost reduction, the whole term will represent a negative contribution to J. Otherwise, if the electricity is bought, the cost will increase. To express everything normalized with the same time scale [€/s], the electricity commitment is divided by 3600. In the denominator, the beet that leaves the storage zone and is, therefore, processed in the sugar plant, appears. Finally, the integral of this quantity is computed along the whole prediction horizon.

$$Specific\ Cost = \int_0^T \left(\frac{\frac{W_G(t)}{d_G} \cdot HHV_G \cdot Pr_G - \left(\frac{E_C(t)}{3600} \cdot Pr_e(t)\right)}{W_{BStOut}(t)} \right) dt \tag{30}$$

Complementarity term

In order to model the split-range controller and the storage penalty, complementarity conditions have been used, as previously mentioned. Hence, to implement these constraints in the optimization problem, a penalty term has been added to the cost function. Thus, the problem feasibility is not compromised, avoiding the inclusion of tight equality constraints into the optimization problem. Therefore, two different terms have been added, each one with a different weight ρ.

$$Complementarity\ term = \sum_0^T \left(\rho_{SR}\left(y(t)\cdot S_0(t) + \left(1-y(t)\right)\cdot S_1(t)\right) + \rho_{SP}\left(S_2(t)\cdot S_3(t) + S_4(t)\cdot S_5(t)\right)\right) \tag{31}$$

Smoothing term

To avoid high frequency oscillations in the solution, a penalty term on the variation of some of the decision variables is added to the objective function. The weights of this term must be used carefully, since very high values deeply affect the original solution given by the optimizer.

$$Moving\ Cost = \sum_0^T \Big(\rho_{W_{BStOut}}\left(W_{BStOut}(t) - W_{BStOut}(t-1)\right)^2 + \rho_{T_{SBo}}\left(T_{SBo}(t) - T_{SBo}(t-1)\right)^2 + \rho_{P_{SSaOut}}\left(P_{SSaOut}(t) - P_{SSaOut}(t-1)\right)^2\Big) \tag{32}$$

Storage penalty

This term is added to penalize values of the beet residence time outside the pre-established bounds. With equations (14)-(15), high or low residence time is calculated for each time t. Then, the integral of that term is computed, so the longer the residence time is out of bounds, the higher the penalty applied, allowing a small violation of the limits if necessary.

$$Storage\ Penalty = \rho_{St}\int_0^T \left(StoPenUp(t) + StoPenLo(t)\right)dt \tag{33}$$

Turnpike cost

The turnpike property (Dorfman et al., 1958; Ellis et al., 2014; Faulwasser et al., 2017) is used to describe the response that appears in many finite-horizon dynamic optimization problems, where the solution is forced to pass through the optimal steady-state before reaching the final point, which gives a better economic result. This behavior appears when the prediction horizon is large enough, so the optimizer "pays" the cost of the turnpike (the optimum steady-state) to reach the final point with the least possible cost. Thus, if the predicted trajectory stayed at the final point for too long, the overall cost would be higher than passing through the optimal steady-state point for some time.

In this case study, the prediction horizon is one day, which is long enough to let the turnpike property appear and, at the end of the predicted state trajectory, the optimizer moves the plant away from the optimum steady-state point. The problem with this behavior is that the optimizer does not know that another optimization will be run the next day, so it moves the plant to a point that is hardly convenient to be the starting point for that day. To deal with this problem, two complementary strategies are proposed. The first one aims to assure that the final point suggested by the optimizer is a stationary point. Thus, the solution can be bad, but at least it is not a transient to an unknown destination. The implementation has been performed using terminal constraints on the end state, which ensure that the gradient w.r.t the decision variables is zero. Next, the steady state achieved is desired to be the best possible one. To do so, a final term is added to the cost function which represents the cost of maintaining the process at such a state during the first five hours of the next day, assuming the electricity price and beet arrival to be the ones already used for the first five hours of the current day. Five hours have been used because that is the slowest plant dynamics.

$$Turnpike\ Cost = \rho_{Tp} \int_0^{18000} \left(\frac{\frac{W_G}{d_G} \cdot PCS_G \cdot Pr_G - \frac{E_C}{3600} \cdot Pr_e(t)}{W_{BStOut}} \right) dt \tag{34}$$

Note that a good selection of the penalty values for (31) – (34) is essential for the performance of the described methodology. A wrong choice could lead to suboptimal or infeasible solutions. This is critical in the case of the complementarity terms since, otherwise, the split range would not be correctly modeled, and the compliance of the storage penalty could not be ensured. In Table 4 (Appendix A) the values selected for our case study can be found and, in Appendix B, a description of the methodology followed to select such values is shown.

5. Results and discussion

This section corresponds to the solution analysis of the methodology proposed in Section 3. It has been divided into two different parts. In the first subsection, a single day prediction is used, and the response of the optimizer is shown for different scenarios where the electricity prices and the beet input vary within usual ranges. In the second subsection, the results using the optimizer for a whole campaign are presented and compared to the scenario traditionally used in sugar factories, where the production rate is kept at its maximum, and the electricity excess is exported to the grid under a BL tariff with fixed prices.

5.1 Single-day response

In the considered case study, there are two exogenous parameters: the electricity price and the raw material received (beet-input). The price of the electricity is key to determine the convenience of selling or buying electricity from the external grid. Monitoring the arrival of raw material is also essential, in order to maintain the beet residence time between limits, thus, minimizing the sugar losses and preventing the situation where no raw material is available for production.

To test the behavior of the optimizer, some scenarios with different electricity prices and beet inputs were selected. Different experiments were carried out by fixing either the price or the beet-input profile, in order to evaluate the optimizer solutions with respect to each non-influential factor. The starting point was the same for all the cases, which corresponds to the classical policy where production is carried out at the maximum rate, in order to finish the campaign as soon as possible so as to reduce fixed expenses.

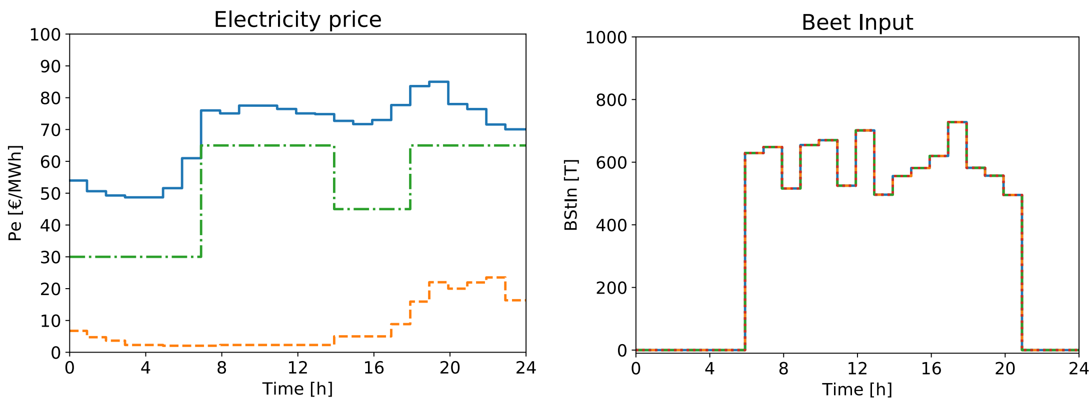

Figure 4. Scenarios used to test the response of the optimizer against different electricity prices. TOU (dashed-dotted green), Market high (solid blue) and Market low (dashed orange).

First, the beet input was fixed. As can be seen in Figure 4, trucks only deliver beet from 6 AM to 9 PM. The corresponding graph represents the total amount of beet received each hour. Three different electricity-price scenarios, obtained from the considered DR programs, were tested:

- Time of Use tariff: with three different price zones [30, 45, 65] €/MWh depending on the hour.
- Spanish DA market prices for two different days: One with higher prices (10/12/2017), and another with much lower prices (30/12/2017).

Due to the large number of variables defined in the optimization problem, only the most important ones are shown here to present the results. Among them, the beet processing rate and the electricity commitment are key, of course. Moreover, as the way to deal with the legislation is one of the contributions of this work, the value of the Primary Energy Saving index is also presented. Yet, importantly, the policy followed to store the raw material is analyzed, given that a lack or an excess of stocked beet can invalidate the proposed management policies. The computed solutions for this first test with the above scenarios are depicted in Figure 5.

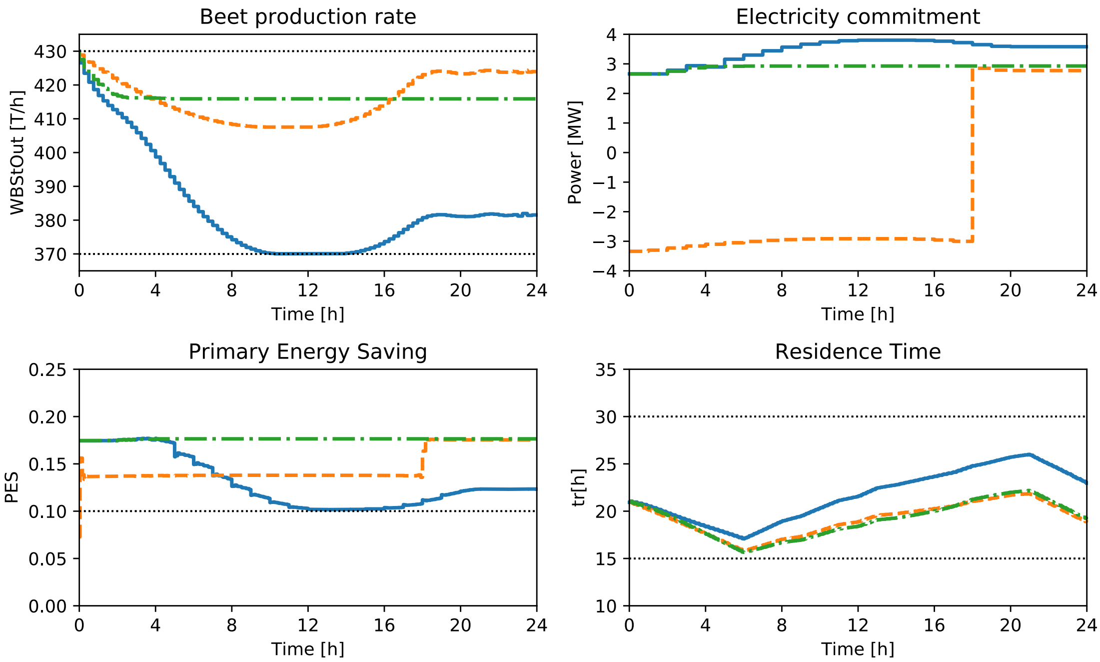

Figure 5. Results obtained for different electricity price scenarios. TOU (dashed-dotted green), Market high (solid blue), Market low (dashed orange).

From the results, it is observed that the computed response varies significantly, depending on the price policy. For example, if the market case with the highest electricity prices is taken, it can be noticed that the production rate goes for some hours to the minimum allowed. This is done to sell as much electricity as possible to the external grid (almost 4 MW) during that period, which makes sense considering its high price. Note that the PES value goes to the 0.1 limit from approximately the 10th until the 14th hour of the day; however, the integral of the index is above 0.10, so equation (19) is not violated. Concerning the residence time, despite the aggressive policy suggested, it is easily kept between the bounds. From the 15th hour, the optimizer suggests increasing the production in order to be prepared for the next day. Recall the turnpike cost, which considers the five hours of the next day for the optimization final point using the electricity price and beet input of the current day. In this case the electricity price is considerably smaller for the first hours of the day, so the optimizer moves the process to an intermedium point. In the lowest price scenario, the results are quite the opposite, and the production rate is maintained closer to its upper limit. Furthermore, the electricity price is so cheap that until the 18th hour the algorithm suggests importing power from the external grid and operate the boilers at a lower rate. Note that the beet processing rate is lowered until the 6th hour approximately, when new beet arrives to the plant (Figure 4), in order to keep the residence time above the lower limit of 15 hours. Then, production is kept nearly constant during some hours to regain stock for the next day, until, in the last hours, when enough stock is accumulated, the optimizer suggests increasing the production to an upper value. This analysis is key on order to understand that the optimizer suggest the highest possible production rate without violating the residence time constraint.

Regarding the TOU tariff, despite the price variations in the considered scenario, the optimizer suggests moving the plant to a stationary point. This can be justified considering that the process needs almost five hours to reach a steady state when operational changes are made in the production rate, so the algorithm needs the price to be maintained close to one point for several hours to consider the change of operating point worthwhile. This is observed in the market cases where the price is maintained high and low, respectively, almost the whole day. However, in the case of the TOU tariff, the price is only kept for a few hours and then suddenly changes, making the optimizer suggest an intermediate operational point. Nevertheless, note that the selected point is not just any random one, as it corresponds to the case where the bypass and relief valves are both closed, and the turbines are generating the maximum power. Intuitively, this is the point where less energy is wasted and, given that it can be considered as the optimum stationary operation from an energy point of view, the optimizer exploits it in several scenarios. From this operating point, if the optimizer suggests a lower production rate, maintaining the electricity production, the relief valve has to be opened and, if the production rate is increased, the bypass valve has to be used, which is the case in the "market high" scenario.

In the second set of scenarios, the electricity price is fixed to the values of the "market high" scenario, and variations are made in the expected beet input. This price profile was selected to show the response of the optimizer when the electricity price is very convenient, but the beet storage is close to its limits. Again, all tests started from the plant at the same operating point, and three different scenarios were considered (Figure 6):

- Standard input: the beet-input profile is the same as in the previous test.
- High input: the input profile is higher because of the good weather conditions.
- Low input: due to adverse weather conditions, a small quantity of beet could be harvested and not many trucks arrived with raw material.

The predicted optimal policies for these scenarios are shown in Figure 7. Again, the same variables have been selected to evaluate the suggested solutions.

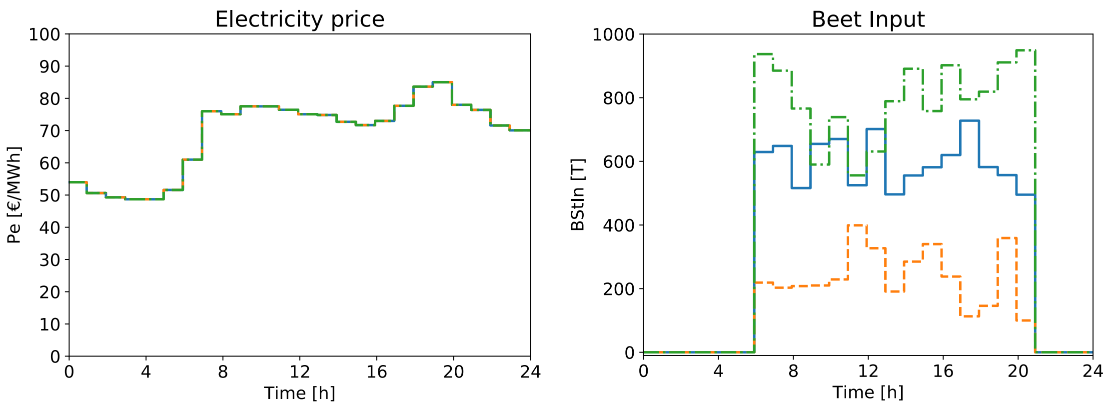

Figure 6. Scenarios used to test different beet inputs. Standard input (solid blue), High input (dashed-dotted green), Low input (dashed orange).

From the results, several interesting conclusions can be extracted. Firstly, the blue evolution in Figure 7 is the same as the response seen in the previous test for the market high scenario. This case serves as reference, since it is the free response of the optimizer when the residence-time constraints are not active. If we look at the high beet-input scenario, the reader can note how, despite the convenient electricity price, the production rate is much higher than for the nominal beet-input case. Of course, since less electricity is being sold, the cost function is penalized, but this is done to maintain the residence time just below its upper limit. It must be noticed in this case that, if only the electricity price were considered, the storage area would be overwhelmed. In the opposite case, due to the low input of beet, the optimizer suggests going to the minimum operational point as fast as possible to keep the residence time above the lower limit. Despite all efforts, due to the extreme low input of beet, surpassing the minimum value set for the residence time cannot be avoided, but at least the least bad possible operation is suggested.

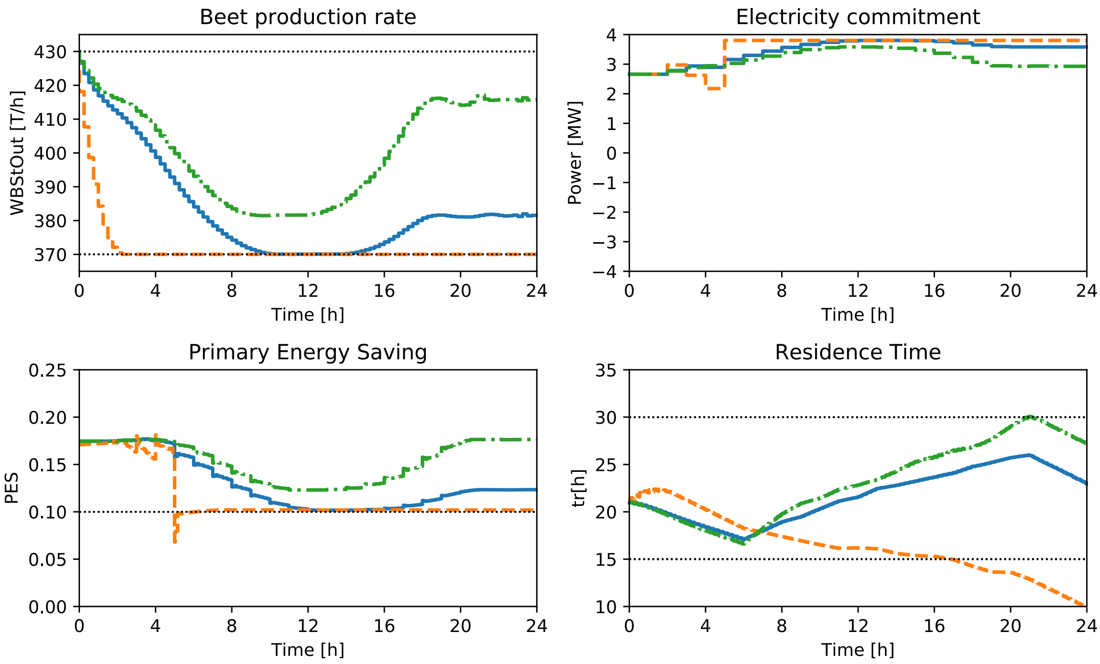

Figure 7. Results obtained for the beet arrival test. Standard input (solid blue), High input (dashed-dotted green), Low input (dashed orange).

5.2 Campaign results

The policies proposed by the optimizer during a whole campaign (using the TOU and DA market tariffs) are now compared to the usual policy where the production rate is maintained at its maximum, and the electricity surplus is sold to the external grid using a fixed price (BL tariff). For this comparison to be fair, the beet storage upper bound was set to 30 hours, in order to allow some freedom for the optimizer, but maintaining the campaign duration so that the fixed expenses (salaries, service access fees, etc.) do not vary at all.

With the approach proposed in Section 4, three different cases were compared:

- **Base case:** Beet processing rate is set to the maximum, and the electricity surplus generated is sold under a Base Load tariff with a fixed price of 50 €/MWh for the whole day.
- **Case 1:** The electricity prices are set by a TOU tariff with three different price zones [30, 45, 65] €/MWh depending on the hour.
- **Case 2:** The electricity prices are taken from the Spanish DA market, including from 30/09/2017 to 17/01/2018.

Note the reader that our approach is implemented in a moving-window fashion with a prediction horizon of 1 day, and no rescheduling is performed during the whole operation. Apart from the energy cost, the following indicators are also presented to analyze the suitability of each solution: the campaign duration, the natural gas consumption, and the incomes provided by the electricity sale.

From the results presented in Table 1, it can be observed how the use of DR programs can significantly reduce the energy cost of the studied sugar factory, while maintaining the duration of the campaign (it is extended by just a few hours, which does not affect the fixed costs). This has mainly been achieved because of two different factors: a) the modification of the price tariff and b) the use of the proposed optimization approach. To measure the contribution of each factor, two extra tests were carried out where the operation strategy of the base case was implemented but using the TOU and DA market tariffs. These results show that, for the TOU case, 0.60% of the improvement comes from the change of tariff, while the rest (0.50%) comes from the use of the optimizer. In the second case, the DA market tariff reduces the energy cost by 2.95%, and the optimizer gives an extra improvement of 1.01%. At this point, it can be noted that the results show a commonly accepted trend, where the base load tariff gives the lowest gains with its conservative electricity prices, the TOU tariff gives intermediate results, and the spot market yields the greatest benefits at the expense of assuming a greater risk in the price. Regarding the rest of the analyzed variables, a significant reduction in the natural gas needed by the production process is obtained in both cases. This can be justified by the smarter use of the cogeneration system suggested by the optimizer, which is able to propose solutions where the energy is fully leveraged, as shown in the previous subsection. With respect to the electricity incomes, the new policies which allow a larger amount of electricity to be sold, together with the better exploitation of the electricity prices, make the incomes obtained for selling the electricity far better than the ones obtained when the production rate was fixed at its maximum.

Table 1. Campaign results. The percentages show the difference with respect to the base case.

Tariff	Energy Cost (€)	Campaign length (d)	Natural Gas (m^3)	Electricity incomes (€)
Base Case				
Base Load	1,442,645	94	3,426,901	300,009
Case 1				
TOU	1,422,730 (-1.39%)	94 (-)	3,410,315 (-0.48%)	311,488 (+3.82%)
Case 2				
DA Market	1,387,647 (-3.96%)	94 (-)	3,406,464 (-0.60%)	344,613 (+14.86%)

One drawback in the considered case study is that, due to the seasonal factor, if the production rate is greatly lowered for several days, the campaign length increases and some of the fixed expenses do too. With this in mind, the storage constraint was introduced to maintain the campaign duration almost constant for all the cases. However, if the solution is analyzed in depth, it can be observed how, for most of the days, the response provided by the optimizer is to operate the plant at the highest possible rate, in most of the cases ignoring the profits that could be obtained from selling more electricity. Only if the price profile is clearly beneficial does the optimizer suggest moving the process to a new working point. Hence, to test what the penalty for including that constraint is, a last test has been carried out where the upper storage penalty is removed, and both DR programs are used without restrictions (case 1* and 2*).

In this case, the energy cost can no longer be a representation of the overall cost of the campaign, and now total expenses must be considered to compare each strategy. For that purpose, it was considered that, since the maximum campaign extension is 15 days, the most important increment that may suffer the fixed costs comes essentially from the salary that must be paid to the workers during that period (as was indicated in the beginning of this section). During the campaign season in a traditional sugar factory of the size considered in this work, around 100 temporary workers are hired for the operation of the plant. If it is assumed that the company has to pay 1710€/month for each worker, corresponding to a typical net salary of 1000€/month, the wage for the total temporary staff per day can be established at 5700 €. Note that salaries for permanent personnel were not included in this computation, because these remain as fixed expenses. Therefore, in order to compare which strategy is the more convenient, the possible reduction in the energy cost is balanced with the extra salaries that should be paid with respect to ending the campaign in 94 days (the shortest possible).

From Table 2, the first aspect that can be noticed is that, if the upper storage constraint is removed and the selected DR programs are used, the results still remain better than those obtained for the base case. If we take a closer look to the Case1*, we can observe that expanding 3 days the total duration of the campaign, the costs have been reduced w.r.t case 1 (1.16%). Due to a more aggressive strategy in the electricity production, the natural gas consumption has increased (0.27%), but the incomes have been drastically increased from the exchange of electricity with the external grid (12.64%). Regarding case 2*, as with case 1*, the optimizer suggests extending the duration of the campaign 3 days, but in this case the cost is reduced even more (1.45%), partially due to an increasement in the electricity sale of 13.71% w.r.t case 2. Again, the natural gas consumption is increased (0.29%), but still lower than case 1* and the base case.

Table 2. Campaign results without the upper storage constraint. Percentages show the difference with respect to the base case.

Tariff	Energy cost + salary inc. (€)	Campaign length (d)	Natural Gas (m^3)	Electricity sale (€)
Base Case				
Base Load	1,442,645	94	3,426,901	300,009
Case 1*				
TOU	1,406,698 (-2.55%)	97 (+3.19%)	3,419,649 (-0.21%)	349,366 (+16.45%)
Case 2*				
DA Market	1,368,622 (-5.41%)	97 (+3.19%)	3,416,265 (-0.31%)	385,722 (+28.57%)

5.3 Computational features

To give some information about the size of the optimization problem, a degree-of-freedom analysis was performed, and some numbers are given next. In this case study, the optimization with a prediction horizon of a single day involves 25127 variables and 23671 equality constraints, which gives a total of 1456 degrees of freedom. To discretize the optimization model, the orthogonal collocation method (Biegler, 2010) was chosen, using Radau roots for collocation, and 97 finite elements with 3 collocation points per element. Thus, a total of 289 collocation points with a finite element of 15-minutes in length was considered enough to obtain a good solution in a reasonable time, given the slow dynamics of the system.

The solver IPOPT was used in Pyomo 5.5.2 under Python 3.7.3 on an Intel i7-7700 (3.60 GHz) CPU, with 32 GB RAM and Windows 10. The CPU time for solving this optimization varies greatly, depending on the scenario and the initial guess. The average CPU time in case 2 was 123.4 s, the maximum being 1633 s corresponding to day 73, and the minimum 15 s for day 17. The optimizer must be run at least once per day before 10 AM. The electricity price and beet reception forecast must be introduced by the operator, so the optimizer computes the production and energy generation policy that must be followed during the next day. Hence, the computational time is not a limitation for the case study considered.

6. Conclusions

In this work, the dynamic-integrated scheduling operation of an industrial process working with a cogeneration system is presented for fully exploiting price-base Demand Response programs. A simulated sugar factory that has an on-site cogeneration plant has been used for testing a model-based optimization methodology, which aims to apply a Time of Use and a Day-Ahead market tariff in the best possible way, while respecting the European legislation on the efficient use of cogeneration systems. Thus, a decision-support solution for reducing costs in a real sugar factory has been presented in order to better face the new challenges raised by the worldwide liberalization of the sugar market.

The presented analysis proves that the optimal use of DR programs might reduce the energy costs up to 1.39% in the considered factory if the TOU tariff is selected, and up to 3.96% if the Day-Ahead Spanish market prices were used. These potential savings are estimated by comparing them with the classical policy, where the production is maintained at its maximum value and a fixed price electricity tariff is used. Moreover, the values are computed without increasing the duration of the campaign, thanks to the use of an upper storage constraint in the optimization problem. Therefore, while the use of a TOU tariff reduced the uncertainty in the electricity price, the DA market gave a better performance in the selected time horizon, the solution being greener in both cases thanks to a 0.54% average reduction in the natural gas consumption. If the constraint in the beet storage is removed, results improved up to 2.55% in the case of a TOU program, and up to 5.41% with a DA market tariff, as compared to the base case.

Although the results are satisfactory, we think that the seasonal feature of the case study and the storage policy limit the degrees of freedom for optimization too much, and therefore, the potential benefits of the proposed methodology. This is why, we consider that better results could be obtained if this very same approach would be adopted in other industries with higher flexibility in their storage and production policy. On the other hand, the methodology proposed in this work is valid for the assumptions indicated at the beginning of Section 3. The points referring to the process dynamics as compared to the electricity price variations are especially relevant. As relevant as the straightforward aspect of considering CHP systems where heat and power generation are indeed strongly coupled. Note that, if the main process dynamics is much faster than the changes in the electricity price, it can be neglected, and the optimization problem would be much easier to formulate and solve. Furthermore, if no coupling exists in the cogeneration process, its operation can be separated from the industrial process, and a sequential or iterative approach should be taken. Of course, the proposed approach (as well as other DR programs) may not be effective in large plants where the electricity price fluctuations have a low impact on the plant economics, either because of a lack of data on the actual power consumption of the equipment inside individual plants, or because the contribution of the electricity price is small compared to raw material costs and product revenues.

If discrete operating decisions need to be considered during normal operation, the presented approach is not directly applicable (unless some suitable reformulation/approximation of these can be done), and the optimization problem must be reformulated as a dynamic MINLP problem. This would be the case if different products could be produced in the industrial plant in one or more operating lines, or the CHP system had the possibility of turning some equipment on or off. The efficient formulation of such problems is also a relevant research problem nowadays, so future work could be oriented in this direction. Furthermore, uncertainty in such diverse aspects as the electricity price or demand forecast could also be considered in the formulation. Thus, the dynamic optimization problem would have to be solved using a robust or stochastic optimization approach, and an efficient formulation for such an aim could be studied.

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Appendix A. Variables and parameters.

Table 3. Model variables notation.

VARIABLES		
Name	**Description**	**Units**
Op_{By}	Opening of the bypass valve	%
Op_{Re}	Opening of the relief valve	%
e	Split-range controller error	barA
E_C	Electricity commitment	kW
E_{CHP}	Power generated in cogeneration mode	kW
E_{Tu}	Power generated in turbines	kW
m_{St}	Accumulated mass beet in the storage zone	T
F_{CHP}	Energy obtained from fuel in cogeneration mode	kJ/s
F_{plant}	Energy obtained from fuel	kJ/s
H_{STuIn}	Enthalpy of the steam that enters in the turbines.	kJ/kg
H_{STuOut}	Enthalpy of the steam that leaves the turbines.	kJ/kg
H_{SSaIn}	Steam enthalpy at saturator input	kJ/kg
H_{WBo}	Boiler water enthalpy	kJ/kg
μE_{CHP}	Power efficiency of the CHP	%
μ_G	Global efficiency	%
μQ_{CHP}	Heat efficiency of the CHP	%
PES	Primary Saving Energy index	
P_{SSaOut}	Pressure of the steam leaving the saturator	barA
$P_{SSaOutRef}$	Split-range controller reference	barA

T_{SBo}	Temperature of the steam leaving the boilers.	ºC
Q_{CHP}	Heat generated in cogeneration mode	kJ/s
$S_0, S_1, S_2, S_3, S_4, S_5$	Auxiliary variables for complementarity constraints	
$StoPenUp$	Measures the residence time excess w.r.t the maximum value	
$StoPenLo$	Measures the residence time defect w.r.t the minimum value	
τ_{St}	Storage residence time	h
v	Split-range controller output signal	%
v_i	Split-range controller integral action	%
W_{BStIn}	Beet mass flow entering in the storage zone	kg/s
W_{BStOut}	Beet mass flow leaving the storage zone	kg/s
W_G	Natural gas mass flow entering in boilers	kg/s
W_{SSaIn}	Steam mass flow at saturator input	kg/s
W_{STuIn}	Steam mass flow entering in the turbines	kg/s
y	Binary variable used for complementarity	

Table 4. Parameter values and notation.

Name	Description	Value	Units
d_G	Natural Gas density for the input conditions	3.65	kg/m^3
H_{WBo}	Specific enthalpy of the water used in the boilers	550.52	kJ/kg
kp	Split-range controller proportional gain	140	%/bar
μE_{Ref}	Reference cogeneration power efficiency	0.53	
μQ_{Ref}	Reference cogeneration heat efficiency	0.87	
μ_{Tu}	Efficiency of the steam turbine	0.95	
LHV_G	Natural Gas Lower Heating Value	47,100.00	kJ/kg
HHV_G	Natural Gas Higher Heating Value	52,200.00	kJ/kg
Pr_G	Natural Gas Price		€/kWh
Pr_E	Electricity Price		€/kWh
ρ_{SR}	Split-range controller complementarity weight	1	
ρ_{SP}	Storage penalty complementarity weight	250	
$\rho_{W_{BStuOut}}$	Production rate moving weight	1	
$\rho_{T_{SBo}}$	Steam boilers temperature moving weight	1	
$\rho_{P_{SSaOut}}$	Evaporation working pressure moving weight	1000	
ρ_{St}	Storage penalty weight	0.5	
ρ_{Tp}	Turnpike penalty weight	0.2	
T	Prediction horizon time	86400	s
Ti	Split-range controller integral gain	10.00	s
v_{max}	Maximum output signal of the split-range controller	100.00	%
W_{BStIn}	Arrival of beet to the storage zone		T/h

Appendix B. Methodology to select the penalties used in the objective function.

The selection of the penalty values used in (31) – (34) is critical for obtaining good solutions. The methodology that we have followed for finding such suitable values is presented below.

1) Select some representative scenarios that cover the full operation spectrum in one day. In our case, considering that we have 2 exogenous input variables, the electricity price and the beet arrival, we have selected four representative scenarios corresponding to the extreme cases:
   a. High market price and low beet arrival (PHBL).
   b. High market price and high beet arrival (PHBH).
   c. Low market price and low beet arrival (PLBL).
   d. Low market price and high beet arrival (PLBH).

   The values of the price and beet arrival are the ones used in Section 5.1.

2) Find the minimum penalty value that affects the solution. For such task, the iterative bisection method can be recalled for each scenario with all penalty values set to 0, except the one being tuned of course. To evaluate if the solution is affected or not, look if values for some relevant output variables remain constant between iterations or not. In our case study, the relevant variables (those that are directly affected by each penalty) are:

   - ρ_{SR}: The opening of the bypass and relief valve (Op_{By}, Op_{Re}).
   - ρ_{SP}: Computation of the variables $StoPenUp$ and $StoPenLo$.
   - $\rho_{W_{BStuOut}}$: Beet mass flow leaving the storage zone (W_{StuOut}).
   - $\rho_{T_{SBo}}$: Temperature of the steam leaving the boilers (T_{SBo}).
   - $\rho_{P_{SSaOut}}$: Pressure of the steam leaving the saturator (P_{SSaOut}).
   - ρ_{St}: Storage residence time (τ_{St}).
   - ρ_{Tp}: Decision variables at the end of the prediction horizon ($W_{StuOut}, T_{SBo}, P_{SSaOut}, E_{Tu}$).

   The minimum penalty value will be the supreme of the values found for all scenarios.

3) Afterwards, this minimum value can be increased ad-hoc to cope with the designer preferences. Note that, for the complementarity penalties, an increment from the above minimum values may cause distortions in the problem geometry without potential benefits, so we strongly recommend keeping such values to the minimum found.

When a penalty nominal value is found, a local sensitivity test is performed to check if small variations around such value have important effects on the optimization results. To do so, we followed this procedure:

a) Numerically evaluate the optimization results for each of the previously selected scenarios using the nominal penalty value. In our case we looked into the energy cost.
b) Set a 1% increment w.r.t the candidate value and evaluate numerically the solution again for each scenario.
c) Compute the sensitivity as the percentage ratio of the output (energy cost) variation computed for each scenario w.r.t the corresponding nominal value obtained in step a). If the highest sensitivity obtained for all scenarios is small enough (e.g., <0.1%), the optimization with the proposed penalty value appears to be locally robust. Otherwise, a new candidate must be found by alternative methods.

The results obtained from the above described sensitivity analysis around the penalty nominal values in Table 4 are summarized below, in Table 5.

Table 5. Local sensitivity analysis results. The absolute values in the even columns are the energy costs, nominal and with penalties numerically disturbed, for each scenario.

	PHBL (€)	*Sensitivity (%)*	*PHBH (€)*	*Sensitivity*	*PLBL (€)*	*Sensitivity (%)*	*PLBH (€)*	*Sensitivity (%)*
Nominal	11668,43	-	12026,69	-	15106,35	-	16776,30	-
ρ_{SR}	11668,30	<0.01	12027,84	0,01	15106,35	<0.01	16776,30	<0.01
ρ_{SP}	11668,43	<0.01	12025,70	-0,01	15106,35	<0.01	16775,15	-0,01
$\rho_{W_{BStuOut}}$	11668,43	<0.01	12026,77	<0.01	15106,35	<0.01	16776,30	<0.01
$\rho_{T_{SBo}}$	11668,43	<0.01	12026,91	<0.01	15106,35	<0.01	16776,31	<0.01
$\rho_{P_{SSaOut}}$	11668,43	<0.01	12025,25	-0,01	15106,35	<0.01	16776,31	<0.01
ρ_{St}	11668,41	<0.01	12025,74	-0,01	15106,39	<0.01	16775,59	<0.01
ρ_{Tp}	11668,07	<0.01	12027,03	<0.01	15106,35	<0.01	16776,31	<0.01

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