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Plant-wide hierarchical optimal control of a crystallization process

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Abstract: This paper deals with the dynamic real time optimization of a benchmark model that represents a genuine problem found at the crystallization section of sugar factories. A most relevant characteristic of the control problem is given by its hybrid nature, mixing continuous control and the scheduling of the crystallizer batch units. The plant-wide optimal control task is approached in a non-centralized hierarchical way with two-layers. The lower layer consists of a set of MPCs, one for each crystallizer, and is in charge of taking the local decisions that minimize an index related with the economic behavior of each unit. The higher level coordinator layer drives the state of the whole plant near the overall economic optimum, while respecting the constraints imposed by the existence of shared resources.

Keywords: Predictive control, process control, hierarchical control, integrated scheduling and continuous plant control, hybrid optimal control.

1. INTRODUCTION

A typical beet sugar factory can be viewed as the series connection of two main departments. The first one is in charge of extracting and pre-processing the beet sucrose juice and consists mainly of continuous operations. The downstream section, on the other hand, receives the incoming juice to proceed with the crystallization of the commercial product, a process which is carried out, discontinuously, in semi-batch crystallizers.

A particularly interesting plant-wide control problem is found precisely at the interface between these two main sections, where the multiple interchanges of mass and energy between the continuous and discrete units need to be coordinated. A benchmark model (fig. 1), which has been used by the FP7, EU Network of Excellence "Highly-complex and Networked Control Systems (HYCON2)" (HYCON/WP5, 2014), captures the essential characteristics of the real plant. The problem described in the sugar benchmark is important in its own right but it can be considered as a specific example of a more general situation occurring in process industries, where it is not uncommon to have some downstream section consisting of batch or semi-batch units, (e.g. reactors, membrane filters) whose operation need to be coordinated in order to keep pace with the flowrate coming from the upstream plant.

This article describes the application of a plant-wide non-centralized hierarchical optimizing control strategy to the problem presented by the sugar crystallization benchmark. The novelty of the article resides, on one hand, on the fact that the hybrid nature of the plant and its specific characteristics requires a very tight integration between the discrete decisions, related to the scheduling of the batch crystallizers, with the continuous decisions taken for their optimal intra-run operation. On the other hand, a new coordination scheme is used in the upper level of the controller hierarchy, that involves the on the fly creation of a very simple continuously updated linear model of the subordinate units.

The paper is organized as follows: in section 2 a description of the benchmark model is given; in section 3 the plant-wide control task is posed as a mathematical optimization problem and the proposed non-centralized control strategy is discussed, while, finally, in section 4, implementation details are given and simulation results are discussed.

2. PROCESS AND BENCHMARK DISCUSSION

Super-saturation (s), here defined as the excess concentration of sucrose over the solubility of that substance in water at the current values of temperature, is the driving force of the sugar crystallization process. The solubility of sucrose in industrial syrups depends on its concentration and on the temperature and the purity of the solution. The latter defined as the mass of sucrose with respect to the masses of all the dissolved substances. For moderately supersaturated syrups, where s is inside the so called metastable zone, the crystallization occurs basically as the growing of the already existing crystals. For higher values of s, however, the labile zone might be entered, and this would imply the spontaneous appearance of new crystals directly out of the solution.

The sugar crystallizers here described, use evaporation as the mechanism for creating super-saturation. They work in a seeded semi-batch fashion. The seed of crystals is introduced at the beginning of the crystallization process, and this initial population is made to grow along the cycle. The objective is to avoid both dissolution and spontaneous nucleation, by always keeping the super-saturation inside the meta-stable zone. If this goal is achieved, then the crystal size distribution (CSD) of the resulting population would have the desired quality characteristics: a narrow width and the right mean size. A typical beet sugar crystallizer is operated by enforcing a configurable recipe consisting of the following main steps: initial charge of syrup, concentration, seed, crystal grow, tightening and mass discharge. All the steps,

except mass discharge, are carried out while keeping vacuum condition in the chamber, so that mass boiling would occur at low temperatures, preventing *caramelization*. The energy for heating the mass is provided by a heat exchanger incorporated in the design of the unit. The exchanger's primary receives saturated steam from the common source.

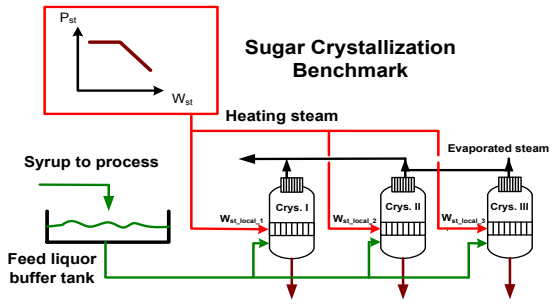

Fig.1. Sugar crystallization benchmark

The pressures of the heating steam at exchanger's primary and of the evaporated steam inside the crystallization chamber are both enforced by their respective PI type controllers. The set-points of these controllers are provided by the sequencing program implementing the recipe. In addition to pressure sensors, the unit is also equipped with online measurements of the level attained by the mass in the chamber and for its concentration. This last variable takes into account the presence of the dissolved substances (sucrose plus impurities) and of the sugar crystals suspended in the solution or *mother liquor* which appear after the seeding step. The first three steps of the recipe are in charge of loading the initial amount of feeding syrup to approximately half its capacity, to proceed next with its concentration for achieving a super-saturation capable of hosting the initial seed.

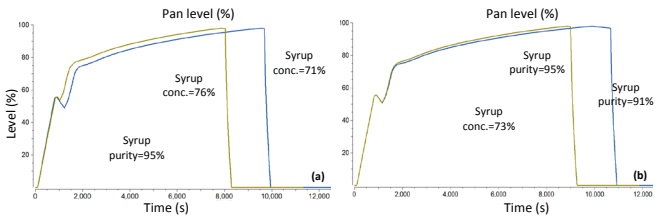

Fig.2. Impact on batch length of syrup (a) conc. (b) purity

The crystal-growing step is the lengthier and most important of the cycle. The goal is keep super-saturation in the meta-stable zone by manipulating the amount of syrup fed to the chamber. This syrup input seeks to compensate the dissolved sucrose that migrates to the surface of the growing crystals and the water that is evaporated by boiling. Super-saturation control is indirectly achieved by stipulating the concentration of the mass to enforce at each point of the evolution of the cycle. Super-saturation and the suspension concentration are obviously correlated but the relation is not so straightforward. Both depend on the *mother liquor* concentration but the slurry concentration also takes into account the presence of the mass of crystals. Super-saturation, on its turn, depends on temperature and on purity. In the industrial crystallizer here taken as reference, the total mass concentration is used nonetheless for conducting the process. At each point in the evolution of the batch (corresponding to a different level in the chamber) a specific set-point for the concentration is given, chosen in such a way as to approximately discount the expected increase in the mass of crystals and the decrease in solution purity, so that the resulting conditions translate into a sucrose super-saturation in the meta-stable zone. When the level reaches its maximum value, the slurry is concentrated further and, finally, is discharged.

The benchmark that has been put forward (fig. 1) consists of three identical crystallizers that are fed from the common source represented by a buffer tank of the syrup to process. This vessel seeks to accommodate the continuous upstream syrup processing units with the discontinuous crystallizers. The latter have also to compete for the needed heating steam. The basic problem to solve is that of proposing a schedule for the crystallizer's cycles, so that the buffer tank is not overflowed nor drained. This has to be done while trying to solve, at the same time, the difficulties imposed by the limited availability of the heating steam. So, in this context, it is illustrative to understand the impact that the properties of the incoming syrup, disturbances from the benchmark's point of view, have on the duration of the crystallizer cycle. Figure (2) shows that an increase of the concentration and of the purity of the syrup leads both to a reduction of the cycle duration, provided that the evaporation rate is not changed.

But the cycle duration, and thus the throughput of the crystallizers, can also be influenced by modifying the evaporation rate imposed in the units. This can be achieved, for example, by adjusting the set-points to the heating steam pressure regulatory loops. This is here accomplished by multiplying the nominal profile used by the sequencing program of the crystallizer by a factor p_F centered at one. The effect of this factor is shown in fig. (3.a). It is important to notice that this acceleration comes at a price: since the crystallization kinetics has its own rhythm, which depends also on the purity of the *mother liquor*, an attempt to rush-up the strike beyond a certain limit would imply an increase in super-saturation (fig. 3.b), since the aggregate surface of the mass of crystal will not grow at the rate needed to keep up with the increasing presence of sucrose.

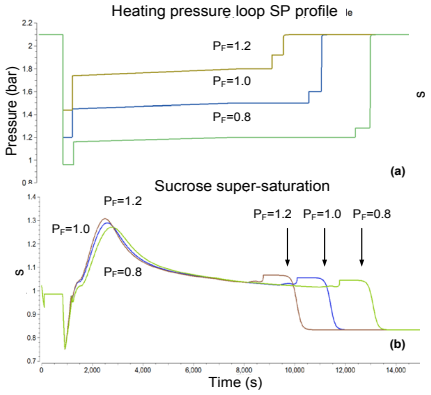

Fig.3. Impact of p_F on a) batch length and b) super-saturation

The first-principles model of the benchmark is described in Mazaeda et al, (2014) and the references therein. It includes the dynamic models of each crystallizer, and of the buffer tank. It also incorporates a very simple model of the saturated

steam source. The latter represents the limited availability of this resource by means of a linear static law relating an increase in the consumed steam flowrate with a decrease of the provided pressure. The model of the crystallizers and of the tank includes the needed mass and energy balances. Mass balances to the syrup include the balances to its three components: water and dissolved sucrose and impurities. In the crystallizer, after seeding, there is also the need to follow the evolution of the sugar crystals mass. The crystallizer model requires balances to the steam evaporated in the chamber and for the heating steam in the primary of the heat exchanger. The objective of the model is to serve as a test case for evaluating plant-wide control strategies. The emphasis has been mainly put in capturing the relation of the batch crystallizers with the common resources represented by the syrup tank and the steam source. Then, special care has been taken, for example, to reflect the non-linear and time-varying behavior of the equivalent global heat transfer coefficient of the heat exchanger. This coefficient, and thus the steam consumed by the crystallizer, diminishes along the strike as the level of the mass in the chamber and its viscosity increases, affecting mass circulation. The heating steam profile also determines the shape of the syrup input profile, due to the presence of the suspension concentration regulatory loop. So it has a similar diminishing pattern, parallel to of the one exhibited by the evaporation rate. The growing of the crystals is customarily described in the population balance framework. Here however, for the sake of simplicity, a lumped model describing the aggregate mass of sugar grains has been used, as in Lauret *et al*, (1998).

3. PLANT-WIDE OPTIMAL CONTROL PROBLEM

The sugar benchmark problem exhibits a pattern that can be found in process industries with some frequency. The general situation is the following: there is a downstream sub-plant, consisting of a group of batch or semi-batch parallel units (the sugar crystallizers), whose combined throughput needs to match the flowrate (syrup) arriving from the upstream factory. Since the match has to be found between continuous and discrete units, it should be understood in some average sense, typically by requiring for the level of an intermediate buffer vessel to be kept between safe limits. In addition to depend of a common stock to process, it is not rare for the discrete units to compete for some limited shared auxiliary resource (steam). In general, the duration of the cycle of the semi-batch units, and thus their throughput, would depend on some properties of the stream to process (concentration and purity of the syrup). In some cases, there exists a margin for impacting the duration of the cycle by manipulating some control inputs (the heating pressure set-points factors $\boldsymbol{p_F}$).

So, from the point of view of control, and turning again our attention to the specific sugar crystallization case, the throughput of the parallel crystallizers should be regulated to match the flowrate of incoming syrup, or equivalently to avoid the overflow or draining of the buffer tank, by choosing appropriately the short-time scheduling of the semi-batch units. The scheduling task can be eased by shortening the duration of the individual cycle at the expense of increasing the consumption of steam.

We have both, the scheduling of the crystallizers and the three individual p_F acceleration/delaying factors, for specifying the average combined throughput of the parallel units. This gives flexibility but it is redundant. In cases like this, it is reasonable to choose the existing degrees of freedom optimally. In plant-wide problems, a profit related performance criterion is usually taken: prices of the products minus costs of raw materials and auxiliary resources. Typically, the value of products far outweighs the costs, so the optimal solution is equivalent to maximize production, a value determined by the bottleneck of the whole factory. But in the case of partial downstream plants, however, since the attainable production rate is determined by the upstream plant, a reasonable optimal strategy will be one that minimizes the costs of ancillary resources (steam in the benchmark considered) as highlighted in (Skogestadt, 2004).

$$\min_{u} J = \min_{\mathrm{P_{f\,i}},\mathrm{Load_i}} \int_{t=0}^{t=t_{end}} W_{st}\,dt \tag{1}$$

$$f_{overall}(\dot{x}, x, u, p, t) = 0 \tag{2}$$

$$L_{\min} \le L_{Buf}(t) \le L_{\max} \tag{3}$$

$$s_{\min,i}(t) \le s_i(t) \le s_{\max,i}(t) \tag{4}$$

$$\mathrm{P}_{f\,\min,i} \le \mathrm{P_{f}}_i(t) \le \mathrm{P_{f\,max},i} \tag{5}$$

$$Load_i \in \{0,1\} \quad \mathrm{i} \in \{1,2,3\} \tag{6}$$

In view of the above, the dynamic plan-wide optimal control for the sugar benchmark is stated as shown in equations (1)-(6). The cost to minimize is related to the consumption of heating steam mass flowrate (W_{st}) along the entire exercise considered. This steam flow can be put in relation with the cost of the required energy; but there are, also other benefits in working at lower values. For example, a lower steam flowrate means that the crystallizer is conducted at a slower pace, and at correspondingly lower super-saturations, resulting in a more uniform CSD.

The decision variables are the discrete variables (6) on when to start each cycle ($Load_i$) and the continuous accelerating/delaying factors (p_{Fi}) limited to lie in some range (5). In (3), $f_{overall}$ represents the dynamical equations modelling the entire plant. The level of the buffer tank should remain between the specified limits [L_{min},L_{max}].

At this point, some considerations related to the scope of the optimal control for the sugar crystallization benchmark are in order. Notice that a problem such as (1)-(6) would, in general, require the optimal intra-run control of each of the semi-batch crystallizers. This task is, by itself, quite challenging, see for example, (Mesbah *et al*, 2012). The optimal control of the crystallizer should, in general, strive for maximizing the yield, guaranteeing some target CSD characteristics related with the quality of the product while minimizing the cost of processing the batch. Batch crystallization processes are complex, highly non-linear and uncertain. This last characteristic is aggravated in the industrial context due to the lack of enough sensors. The access to on-line information on the CSD is typically absent, especially in food processing industries. Important variables such as, for example, the super-saturation need to be inferred

from others. The use of observers, as part of the optimal control strategy, in this type of setting, is a necessity.

In the context of the sugar crystallization benchmark, however, the interest is in the global aspect of the problem. In conformity with this, and to avoid obscuring the plant-wide strategy with complex details which are very specific of the crystallization example, it is assumed that the original recipe-based control is good enough. The factors (p_{Fi}), are, however, available for adjusting the duration of the cycles. Since an undue acceleration could cause the increase of super-saturation (s) in a way that would compromise quality, the controller manipulating the p_{Fi} commands, should assume the responsibility of guaranteeing that s remains always on safe limits, well within the meta-stable zone, as expressed by the path restrictions (4). Notice that we are considering, for the sake of simplicity, that the super-saturation is directly available.

3.1 Hierarchical plant-wide optimal control solution

Plant-wide problems, such as the one represented by our case study, have been traditionally approached in a hierarchical fashion. A well-known strategy is the Real Time Optimization scheme (**RTO**), which assumes the existence of at least two layers combining an economic optimization with a static model in the upper layer and Model Predictive Controller (**MPC)** type of controller in the lower one (Engell, 2007).

The **RTO** approach has the drawback of having to keep two different models of the same process. An alternative that is rapidly gaining interest is the use of economic **MPC** (**e-MPC**). This is a single layer approach where the receding horizon scheme is directly applied to the optimization of the economic index. Economic **MPC** has been the subject of recent academic interest, concerning, among other issues, the topic of guaranteeing stability (Ellis, *et al*, 2014).

For the plant-wide case, however, the use of a single, monolithic **e-MPC** controller approach might work fine for small plants; but for real-sized problems it could rapidly become computationally challenged.

In (Hernández, *et al*, 2014) an essentially equivalent variant of the sugar crystallization optimal control problem has been satisfactorily solved using an original two-level strategy. The authors propose to solve the complete continuous dynamic problem optimally, choosing the p_{Fi} factors that minimize a cost related index for a fixed given scheduling in the lower layer using the complete dynamical model of the plant. Then, the upper layer uses a static model for refining the current scheduling by guarantying the global mass-balances. The problem has been solved off-line for the entire fixed horizon of several cycles into the future. For on-line application, the described strategy would probably require a receding horizon type of scheme (**e-MPC** type controller) in the lower layer as means of incorporating disturbances. Note that also in this case, the dealing with large plants remains a problem.

In order to cope with this scale problem, a non-centralized strategy is followed in this paper. It uses a hierarchical architecture that has three independent **e-MPC** controllers, one for each batch crystallizer, in the bottom layer and then a higher level coordinator, also implemented as an **e-MPC**, in charge of the scheduling of the batch units and of the tuning the local problems to drive the plant's state near the optimal operation.

It seems reasonable to state the local problem as solving the trade-off between the throughput of the unit (which could be increased by reducing the duration of batch assuming an approximately constant sugar yield) and the consumption of heating steam (W_{st_local}). This kind of compromise is usually solved using the prices of the product and costs of auxiliary resources. In this case, however, this approach would not work for fixed prices: nothing is gained by rushing unnecessarily the batch because the objective is, for the parallel crystallizers, to match the incoming syrup. On the contrary more steam would be wasted without obtaining any global benefits. There are also restrictions on the availability of syrup and of steam that can only be assessed form the plant-wide perspective. What is needed is some kind of artificial knob for each local optimal problem, adjusted by the global coordinator in a way that leads the solutions of the subordinate problems to approach the plant-wide optimum of minimizing the total steam consumption. In the case at hand the, the role of this adjusting knob is played by the parameter T_{Batch_max}, the maximum allowed duration of the batch.

$$\min_{\mathrm{p_f}} J_{\mathrm{single}} = \min_{\mathrm{p_F}} \int_0^{T_{Batch}} W_{st\_loc}\, dt \tag{7}$$

Subject to:

$$T_{Batch} < T_{Batch\_\max} \tag{8}$$

$$f_{\mathrm{single}}(\dot{x}, x, u, p, t) = 0 \tag{9}$$

$$s_{\min}(t) \le s(t) \le s_{\max}(t) \tag{10}$$

$$\mathrm{p_{F\min}} \le \mathrm{p_F}(t) \le \mathrm{p_{F\max}} \tag{11}$$

Thus, each local **e-MPC** should seek to minimize its consumption of heating steam (W_{st_loc}) (7) by manipulating its corresponding p_F variable between the stablished limits (11), provided that it complies with requirement (8) for the actual duration of the batch ($\mathrm{T_{Batch}}$) to be below a certain maximum value ($\mathrm{T_{Batch\_max}}$). The optimization must be carried out subject to the dynamic equations of the unit's model (9) and it should comply with the path restrictions on super-saturation (10).

The coordinator's task is also approached in an economic optimal control setup as the minimization of the total consumption of steam in the prediction horizon (h), as in (12)-(17).

$$\min_{\mathrm{T_{Batch\_maxi}}, T_{Load\_i}} J_{\mathrm{cost\_all}} = \min_{\mathrm{T_{Batch\_maxi}}, \Delta T_{ini\_i}} \int_{t=0}^{t=h} W_{st}\, dt \tag{12}$$

Subject to:

$$L_{\min} \le L_{Buf}(t) \le L_{\max} \tag{13}$$

$$\frac{dm_{buffer}}{dt} = w_{syrup\_in} - w_{syrup\_out} \tag{14}$$

$$f_{st\_src}(P_{st}, W_{st}) = 0 \tag{15}$$

$$w_{syrp_i} = w_{syrp_{0i}} + \frac{\partial w_{syrp_i}}{\partial T_{batch\_mx_i}} \left(T_{batch\_\max_i} - T_{batch\_mx_{0i}} \right) \quad (16)$$

$$w_{st\_loc_i} = w_{st\_loc_{0i}} + \frac{\partial w_{st\_local_i}}{\partial T_{batch\_\max_i}} \left(T_{batch\_mx_i} - T_{batch\_mx_{0i}} \right) \quad (17)$$

At the coordinator level, the decision variables are the mentioned tuning parameters for each of the three crystallizers ($T_{Batch\_max\_i}$) and the time of occurrence of the starting commands for each batch (T_{Load_i}).

Notice that for this coordinator-subordinate non-centralized solution to work, the global and local problems should be consistent (Findesein, 1982), which is the case at hand: compare (12) with (7).

The optimal problem posed in the coordination layer should enforce the restriction of the buffer tank level (13). It should also include, as restrictions, the dynamic model of the same vessel (14) and the static model (f_{st_src}) expressing the real source steam relation between the common pressure (P_{st}) and the total mass flowrate of steam drawn by the three crystallizers (15).

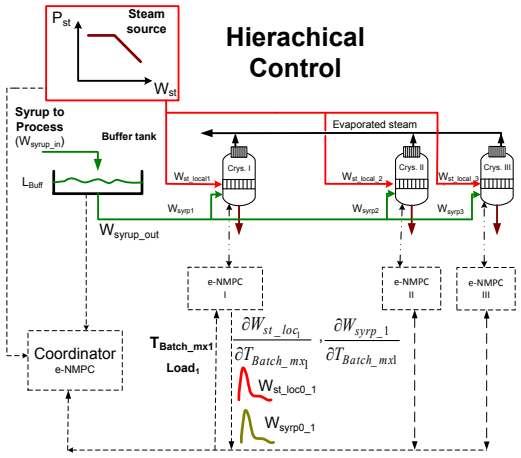

Fig. 4. Hierarchical plant-wide optimizing control.

But the models of the tank and of the steam source are not enough. The coordinator has to have information on the future profile of the demands of syrup and steam for each of the subordinate crystallizers and on how these requirements on the common resources would change with respect to the duration of the individual batches. This information could be obtained, of course, if the coordinator had access to the complete model of the factory but that is what we strive to avoid for guaranteeing the computational scalability of the proposed solution. The strategy proposed in this paper consists in having the subordinate **e-MPC**s to send to the coordinator, at each sampling interval, updated information on the predicted profiles of the demands of the common resources (W_{syrp0i}, W_{st_loc0i}) (obtained as part of the **MPC** solution), along with information on the sensitivity of those profiles to changes in the individual crystallizer tuning parameter ($T_{batch\_max\_i}$). The sensitivities are calculated by finite differences: once the current solution is obtained, a simulation with a slightly changed value for the batch duration is carried out. This information should be incorporated as restrictions (16)-(17): a very simple model expressing a linear approximation of the predicted common resource requests of the subordinate units (W_{syrpi},W_{st_loci}) as a linear function of the adjusting parameters (fig. 4).

Notice that in (12), the original mixed-integer non-linear program (1)-(6), defined in terms of the discrete decisions ($Load_i$), has been reformulated into a completed continuous one using instead the starting time of each batch (T_{Loadi}). This kind of reformulation is well posed (Prada et al, 2008) when the number of switches to apply is known beforehand. This is exactly the case, since the prediction horizon (h) used by the e-MPC of the coordinator, would be chosen, at each sampling interval, so as to encompass a future fixed number of complete cycles for each subordinate crystallizer (fig. 5).

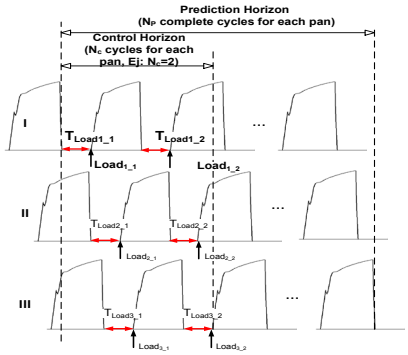

Fig. 5. Prediction horizon used in coordinator.

4. IMPLEMENTATION AND RESULTS

The plant-wide control strategy described in the previous section has been tested in the benchmark simulator. The local **MPC**s use control vector parametrization and a sequential approach in order to solve the optimization stated in (7-11). The numerical mathematical programming algorithm used is of the **SQP** type as developed in **SNOPT**. Since the process to be controlled is of the semi-batch type, the very simple intra-run optimization has been performed using a prediction shrinking horizon that reaches the end on the current cycle. In order to keep the problem simple, the control horizon has been taken as equal to one. The interval for performing the optimization has been chosen to be of 30 minutes, but data has been gathered with intervals of 300 s. For this simulation test, the model of the crystallizers are considered as perfect and it is assumed that the controllers has full access to the state of their respective unit. Of course, as justified previously, a real implementation would need to consider more sophisticated intra-run optimization strategies and the use of observers.

The coordinator **MPC**, solving problem (12-17), is also executed every 30 minutes and is also implemented in sequential fashion. The prediction horizon is variable since it is stretched for one entire cycle into the future for each of the subordinate crystallizers (see Fig. 5). The control horizon is of one sampling interval and an evolutive optimization algorithm was used at this level.

The first optimal control simulation has been carried out along 48 hours. The disturbances to the process are represented by the incoming syrup that should be processed on time. The concentration and purity are considered to be fixed at typical values of 76% and 95% respectively, while

the syrup mass flow-rate undergoes a important abrupt change, going from 14.5 kg/s to 18.5 kg/s at the hour 24 (86400s).

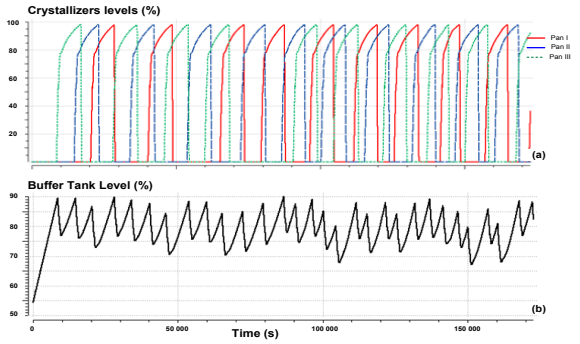

Fig. 6. (a) Level of batch units. (b) Level of buffer tank.

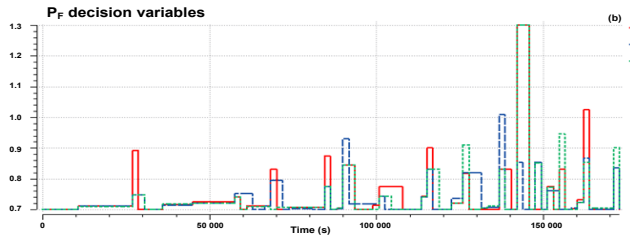

Fig. 7. Local units P_F factors.

In fig. 6.a, the profile of the level inside each batch crystallizer is shown, representing the attained schedule. The evolution of the level of the buffer tank is depicted in fig. 6.b, making evident that the task of processing all the syrup has been accomplished along the exercise.

Figure 7, shows the p_{Fi} for each crystallizer Notice that in the second half of the exercise, for higher values of the syrup input to the plant, the coordinator issues the starting commands at a higher frequency while the lower level controllers decide to use a greater amount of heating steam, to keep pace with the higher flowrate of syrup into the plant.

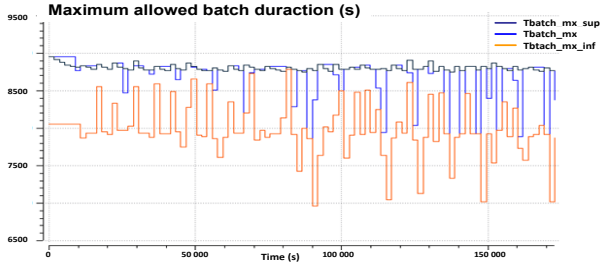

Fig. 8. Coordinator tuning parameter T_{batch_max1}.

Figure 8 shows the T_{batch_max} coordinating parameter for the case of the first pan, along with the dynamically calculated band that limits the size of its excursions to keep the linear approximation valid. Notice that as the conditions are more demanding to the end of the exercise, the coordinator requests from the subordinates a shorter batch to increase throughput at the cost of using more steam. The fig. 9 shows the evolution of the pressure in the common steam source.

Finally, it is of interest to mention that the total amount of processing time for all the controllers is always much less that the considered sampling interval of 30 min. Simulation experiments has been carried out using a single computer for running three subordinate controllers and coordinator. With the use of a distributed computer platform, now possible due to the non-centralized approach, the situation would be even more favourable.

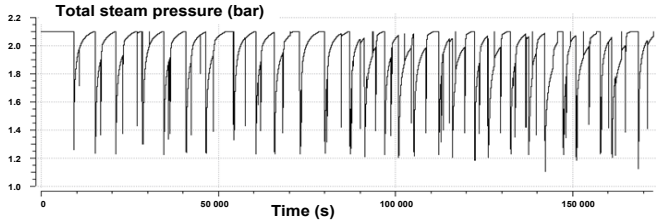

Fig. 9. Heating steam pressure.

6. CONCLUSIONS

A novel hierarchical plant-wide economic optimization scheme has been developed. It has been applied to a sugar crystallization process. Each batch crystallizer is operated by its own **e-NMPC** seeking to optimize an index related to the local economic performance of the unit, while the upper layer takes care of the scheduling and the management of common resources while minimizing the total consumption of steam.

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