Robust Multi-objective Scheduling in an Evaporation Network

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***Abstract*— Considering uncertainty in continuous production processes is key to compute short-time optimal schedules which can be trusted in practice. This paper proposes a two-step stochastic approach to the robust scheduling of several evaporation plants. This approach considers the possibility of reacting in the future once the uncertainty materializes. Each evaporator has different features (capacity, equipment, etc.) and the individual performance is affected by external factors and fouling effects. Moreover, a multi-objective analysis has been carried out to provide a decision support for the operator who must take the concrete decisions about load allocation and cleaning tasks along a time horizon. The problem has been solved by discretizing the time horizon and adapting the general-precedence method to deal with an unknown number of tasks. The nonlinear behavior of each plant is approximated by surrogate linear models obtained experimentally, providing thus solutions in acceptable time.**

I. INTRODUCTION

Problems of short-term scheduling often appear in industry [2], which require computing real-valued quantities (efficiency indicators, control set points, etc.) as well as choosing between many different discrete options (assignment of resources, task execution, etc.). Although, scheduling is sometimes still done manually in industry, it can be translated to optimization problems which involve both binary/integer and real decision variables, and solved using mixed-integer programming (MIP) [4]. There is specific software to formulate and solve such problems (e.g. GAMS, CPLEX, BONMIN, etc.) which can help operators to take better decisions [7]. Nevertheless, although both algorithms and computers are getting faster every day, in general still only mixed-integer linear approaches (MILP) are able to give solutions in reasonable time for large-scale problems (note that the problem complexity increases exponentially with the number of tasks) [8].

There exist several alternatives to formulate scheduling problems via mixed-integer and disjunctive programming [6]. Their choice will define the future structure, the solver to be used and the performance in obtaining a solution. If the number and type of tasks are known a priori, a formulation with **time-variable slots** is suitable [5]. However, for continuous processes where the total number of tasks to be accomplished within a time horizon cannot be defined in advance, this formulation is hard to be used. Another option is the so-called **precedence allocation**, where the algorithm has to order a finite number of tasks, but not all the tasks must be realized [12].

In addition, long-term effects which reduce performance are common in industrial processes (e.g., fouling in heat exchangers, catalyst deactivation, etc.). These effects force periodic stops to recover nominal performance, for instance, to clean the exchangers. Indeed, several people has devoted efforts to deal with such issue from the scheduling point of view: [18], [15] proposed a nonlinear MIP approach while [3] also proposed a time discretization to recast the problem as a MILP one. Here, we adapt the general precedence approach to deal with the scheduling of a continuous evaporation network with several plants and products to be processed.

Moreover, uncertainty is always present when facing real problems (mismodeling, failures, unplanned changes, disturbances, etc.). Therefore, considering uncertainty since the design phase to search for *robust* solutions is key. In general, robustness is understood as the ability of a system to tolerate unexpected perturbations without adapting its initial stable configuration. Hence, robustness can be provided by forcing a schedule to fulfill a bunch of scenarios, sampled according to expected realizations of the uncertainty. Searching for a single schedule for all scenarios is often used in the robust literature [9]. However, a less conservative option is using a multi-stage stochastic optimization [16], which benefits from the assumption that the uncertainty can be measured in the short future, so decisions could be adapted accordingly. Hence, we propose a two-step scheduling approach for the evaporation network considering uncertainty in the outdoor weather and production plan.

In consequence, several *conflicting* optimization criteria such as the economic cost, robustness, production capacity or resource efficiency, appear. Therefore, an offline multi-objective optimization problem (MOOP) [19] is stated as a first step. Then, the analysis of the Pareto front serves as a decision-support guidance to advise the operator about the expected performance of his/her decision [11].

The rest of the paper is as follows: next section describes the case study, Section III presents a model for the evaporators and the problem requirements, the problem formulation into predicate logic is given in Section IV, whereas Section V states the MOOP. Finally, an analysis of the obtained Pareto front is given in Section VI for a case example and a last section summarizes the conclusions.

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II. PROCESS DESCRIPTION

The scheduling problem to be approached takes place in a human-made cellulose fiber factory, which uses wood as raw material. The production process involves several mechanical and chemical procedures that aim to obtain the final product. In one part of the process, the spinning machines, a bath of water mixed with chemicals is used to increase the mechanical properties of the fibers. These chemicals have a sensible economic value. Consequently, they cannot be overlooked. In order to recover them, these mixtures go through an evaporation process to extract as many water as possible, and then enter into a crystallization process.

Each plant is composed by a series of heat exchangers, evaporation chambers, condensers and cooling systems (typically cooling tower), achieving a multi-effect evaporation. The reader is referred to [14] for a more detailed description of the process. There are several mixtures (called products on the following) to be concentrated. Each one may involve several evaporation plants at the same time. Each evaporation plant is able to be physically connected to different products, but it can only be processing one product at a time. Therefore, given a set of products and a set of plants, problems of plant assignment to products and load allocation appear (see Figure 1), where the production cost differs from one plant to other due to the different efficiency between equipment.

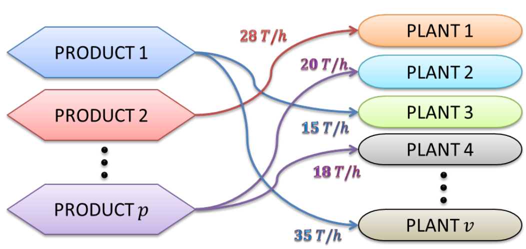

Fig. 1. Plant and load assignment.

Inside the heat exchangers a dirt layer grows during normal operation, caused by the deposition of organic material present in the products. This fouling reduces the efficiency of the equipment, decreasing thus the heat-transmission coefficient. Consequently, the heat exchangers have to be cleaned periodically. On the one hand, there are different options for such a task, each one with an associated cost of people and cleaning products, and each one achieving different recoveries too. On the other hand, because of personnel constraints, only one cleaning task can be performed at a time. Therefore, a scheduling problem appears in the whole network where, jointly with the plant-product assignment, we have to decide for all plants the best (according to any suitable objective) type and day to perform the cleaning.

The number of equipment that can be used for the evaporation operation is known, but the amount of tasks of any type that have to be performed within a time horizon is not fixed, as the process is continuous instead of batch.

III. SYSTEM MODELING

The optimal operation for a single plant was already analyzed in previous works from the authors [13], [14]. In these, a nonlinear grey-box model was developed and nonlinear programming (NLP) was used to identify optimal control policies for reducing the specific steam consumption. These policies were already implemented by a self-optimizing control concept [14] in all plants. Suggested cleaning policies for a plant operating in isolation were also given in [14] using a relaxed NLP. However, although such problem was still computationally tractable for one plant, it became intractable to address the scheduling of the whole interactive system via nonlinear MIP.

Therefore, as optimal operation is now ensured in each plant, here we decided to replace the nonlinear model by an approximated surrogate model [1] obtained in different operating conditions, either from simulation with the nonlinear model or directly from process measurements: these measurements allow to record a static map of the steam consumption as a function of the outdoor temperature and the evaporation flow (see Figure 2). Also, using experimental data recorded from the plant in reference conditions, a linear evolution of the fouling with the time the evaporator has been in operation can be assumed. In the end, the expression of the cost function for an evaporation plant v, processing a product p at time instant t, reads as follows:

$$Steam(v,t,p) = K_T \cdot T_{out}(t) + K_e(v) \cdot P_{vtp} + K_F(t) \quad (1)$$

Where K_T depends on the cooling towers, $K_e(v)$ represents the nominal efficiency of the evaporation plant v, and $K_F(t)$ is the increase of cost due to the current state of fouling. As illustrative example, Figure 2 shows three surfaces corresponding to three different fouling states.

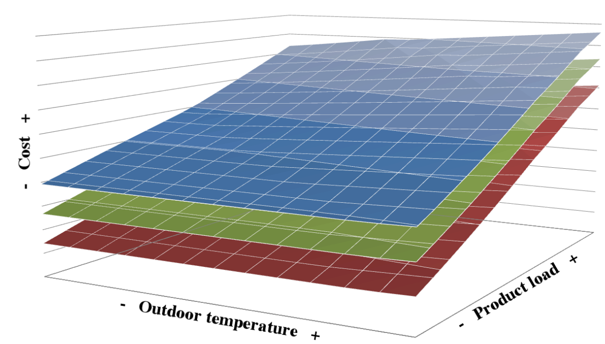

Fig. 2. Surrogate model for 3 different fouling states.

Remark 1: Note that this approach has not only the advantage of sensibly reducing the computational cost required to solve the optimization, but also allows an easier maintenance of models by the plant engineers.

The operation of an evaporation plant can be represented by three main stages: working, cleaning and standby. As there may be several types of cleaning tasks, there will be several cleaning stages too, one for each type. In addition, after analyzing experimental data taking into account prices for utilities, it was found that stopping a line for cleaning is not worthwhile during the first days of operation after a previous cleaning, because in such case the normalized cost per time unit is huge (fixed cost associated to a cleaning task is not amortized yet [14]).

The evaporation plants can be stopped because they have been already cleaned and are not needed, or because it is not profitable to keep working with them, but the cleaning resources are not available yet. The option of stopping the plant in the middle of an operation cycle to continue operating later on without cleaning is not considered.

IV. PROBLEM FORMULATION

The proposed approach discretizes the prediction horizon H in days (time to complete a cleaning task). This allows obtaining optimal solutions in acceptable time.

Fouling. The underlying ideas of general precedence approaches are used here to force the operation accordingly to the known time evolution of the fouling effects, which must be followed by a cleaning stage. This approach, allows an efficient formulation of scheduling problems for continuous processes. Hence, different working stages will be defined, related to the time that an evaporator has been in operation (i.e., one evaporator that has started operation today will be in a stage s_0, and one evaporator that has been working for two weeks will be in a stage s_{14}). Using these stages, we are able to indicate the performance degradation due to fouling, i.e., each stage s will get an associated value $K_F(s)$.

Uncertainty. The evaporation plants are affected by external factors: outdoor temperature and production demand, see (1). These are modelled by stochastic variables that generate an expected (probable up to some confidence level) convex region of uncertainty. Thus, a bunch of scenarios sampled from such region must be fulfilled by the schedule to provide robustness.

A two-step stochastic approach is used here to deal with uncertainty. The prediction horizon H is split in two: the first "robust horizon" H_R computes a *non-anticipative* solution for all expected uncertainty realizations, whereas the remaining horizon provides individual solutions for each scenario. Hence, assuming $H_R = H$ and a linear formulation, the whole region of uncertainty will be covered by considering only the vertex realizations. At the beginning, predictions are reliable, so only the nominal realization is considered for the first week. Then, two realizations for the ambient temperature (extreme values of an interval around the current prediction) are introduced. Finally, uncertainty in the production plan is also introduced from the day 14 onwards. Thus a new bunch of realizations appear with all possible combinations between the expected deviations in the demand for each product (see Figure 3). In the end, 2 realizations on the weather times 2^ρ realizations on the production (assuming ρ products) make a $2^{\rho+1}$ scenario tree.

Remark 2: Note that, as the weather forecast and production plans will be more precisely known as time advances, the two-step approach allows reducing conservativeness by providing individual schedules for each scenario within H_R.

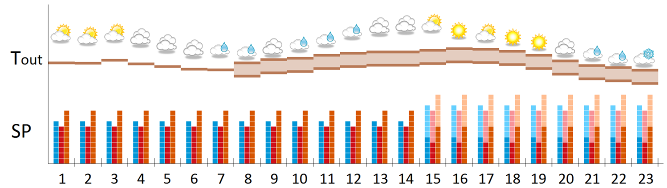

Fig. 3. Uncertainty introduced in the weather prediction (T_{out}) and in production set points for $\rho = 3$ (SP).

Five different sets have been defined for the problem:

- $\mathcal{V}$ denotes the set of all the evaporation plants.
- $\mathcal{S}$ is the set of possible stages where a plant can be. As subsets it includes:
  - $\mathcal{S}_I$ as initial stages, where a stop for cleaning is not worthwhile. In particular, s_0 will be the first stage.
  - $\mathcal{S}_X$ as stages where a decision between "keep working" or "make a cleaning task of type X" has to be made.
  - $\mathcal{S}_L$ as cleaning stages, where s_{LX} denotes a cleaning of type X.
  - $\mathcal{S}_P$ as the standby stages, where s_{PX} denotes an evaporator in standby before a cleaning of type X and s_{PL} the standby stage after being already cleaned.
- $\mathcal{M}$ is set of days in which H is discretized. In particular:
  - $\mathcal{M}_U$ is the set of days belonging to H_R.
  - t_F is the last day, i.e., the prediction horizon.
- $\mathcal{P}$ denotes the set of all products to be processed.
- Last, $\mathcal{E}$ denotes the set of the considered scenarios.

Three different types of variables will be used:

- E_{vtse}: boolean variable which states that, in scenario e, an evaporation plant v is in stage s at time t.
- A_{vtpe}: boolean variable which, in scenario e, links a product p to a plant v at time t.
- P_{vtpe}: real positive variable that assigns, in scenario e, the evaporation flow of product p in plant v at time t.

Thus, the problem formulation is formed by the following positive (i.e., true) logic statements for all $e \in \mathcal{E}$:

- An evaporator must be in one stage and only in one stage at each sample time.

$$\underline{\bigvee_{s\in\mathcal{S}}} E_{vtse} \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{M} \tag{2}$$

- An evaporator in a working stage must be necessarily processing a single product.

$$\underline{\bigvee_{p\in\mathcal{P}}} (A_{vtpe}) \underline{\bigvee_{s\in\mathcal{S}_L}} (E_{vtse}) \underline{\bigvee_{s\in\mathcal{S}_P}} (E_{vtse}) \quad \begin{matrix} \forall v \in \mathcal{V}, \\ \forall t \in \mathcal{M} \end{matrix} \tag{3}$$

- Only a single cleaning stage is allowed at a time.

$$\underline{\bigvee_{s\in\mathcal{S}_L, v\in\mathcal{V}}} E_{vtse} \quad \forall t \in \mathcal{M} \tag{4}$$

• Initial stages of operation (where stopping to clean is not worthwhile) imply themselves.

$$E_{vtse} \leftrightarrow E_{v(t+1)(s+1)e} \; \forall v \in \mathcal{V}, \forall t \in \mathcal{M}\backslash\{t_F\}, \forall s \in \mathcal{S}_I \tag{5}$$

• After a reasonable operation time, a choice can be made between continue operating, perform a cleaning of a suitable type, or go to standby until cleaning.

$$E_{vtse} \rightarrow E_{v(t+1)(s+1)e} \vee E_{v(t+1)s_{LX}e} \vee E_{v(t+1)s_{PX}e} \quad \forall v \in \mathcal{V},\ \forall t \in \mathcal{M}\backslash\{t_F\},\ \forall s \in \mathcal{S}_X \tag{6}$$

• A stopped evaporator which has not been already cleaned, must be cleaned or continue in standby.

$$E_{vts_{PX}e} \rightarrow E_{v(t+1)s_{PX}e} \vee E_{v(t+1)s_{LX}e} \; \forall v \in \mathcal{V}, \forall t \in \mathcal{M}\backslash\{t_F\} \tag{7}$$

• A clean evaporator in standby can continue in such state or begin to operate.

$$E_{vts_{PL}e} \rightarrow E_{v(t+1)s_{PL}e} \vee E_{v(t+1)s_0e} \;\; \forall v \in \mathcal{V},\ \forall t \in \mathcal{M}\backslash\{t_F\} \tag{8}$$

• After a cleaning task, an evaporator can start operation or go to standby.

$$E_{vtse} \rightarrow E_{v(t+1)s_{PL}e} \vee E_{v(t+1)s_0e} \quad \forall v \in \mathcal{V},\ \forall t \in \mathcal{M}\backslash\{t_F\},\ \forall s \in \mathcal{S}_L \tag{9}$$

• When an evaporator is associated to process a particular product, it must continue operating without product changes until it is cleaned.

$$A_{vtpe} \rightarrow A_{v(t+1)pe} \vee E_{v(t+1)se} \quad \forall v \in \mathcal{V},\ \forall t \in \mathcal{M}\backslash\{t_F\},\ \forall s \in \{\mathcal{S}_L \cup \mathcal{S}_P\}, \forall p \in \mathcal{P} \tag{10}$$

• The network situation at t_F cannot lead to infeasibility in the future, i.e., point of no return. This is avoided by forcing the plants to end up in: a) standby after cleaned, b) a cleaning stage, or c) an initial stage of operation S_I

$$\bigvee_{s \in \mathcal{S}_I} (E_{vt_Fse}) \bigvee_{s \in \mathcal{S}_L} (E_{vt_Fse}) \veebar E_{vt_Fs_{PL}e} \quad \forall v \in \mathcal{V} \tag{11}$$

Production demands and equipment constraints must be also accomplished:

• The evaporation flow in each plant must be between limits (or zero if stopped). Upper limits depend on T_{out}. Here **True**=1 and **False**=0 are assumed for A_{vtpe}.

$$P_{vtpe} \leq U_v(T_{out}) \cdot A_{vtpe}, \quad P_{vtpe} \geq L_v \cdot A_{vtpe} \quad \forall v \in \mathcal{V},\ \forall t \in \mathcal{M},\ \forall p \in \mathcal{P},\ \forall e \in \mathcal{E} \tag{12}$$

• A daily evaporation set point must be accomplished for each product and scenario.

$$\sum_{v \in \mathcal{V}} (P_{vtpe}) \geq SP_{pte} \quad \forall t \in \mathcal{M},\ \forall p \in \mathcal{P},\ \forall e \in \mathcal{E} \tag{13}$$

The problem is also constrained by the available physical conditions between products and plants, and by the current state of the evaporators. Moreover, the non-anticipativity requirement is enforced in H_R by:

$$E_{vtse} \equiv E_{vts},\ A_{vtpe} \equiv A_{vtp},\ P_{vtpe} \equiv P_{vtp}, \quad \forall t \in \mathcal{M}\backslash\mathcal{M}_U,\ \forall v \in \mathcal{V},\ \forall p \in \mathcal{P},\ \forall e \in \mathcal{E} \tag{14}$$

V. MULTI-OBJECTIVE SETUP

The objective function may consider three goals to improve: resource efficiency, productivity and robustness.

The two-step stochastic approach provides a tradeoff between performance and robustness by definition. However, as the scheduling involves binary discrete decisions in discretized time, there is a *risk* to assume: the suggested schedule may not be fully applied when the uncertainty realization is not considered in the scenario tree. A straightforward way to minimize such risk is either considering more scenarios (increases the computational burden considerably) or enlarging H_R. In this last option, a straightforward index to measure *robustness* could be $J_1 = H_R/H$. However, this way may become conservative, as the worst-case combination of uncertainty may happen in an intermediate day, so when H_R covers such day many advantages of the two-step approach vanish.

To overcome this issue, we introduce the concept of *similarity* between schedules as a way to measure robustness, without explicitly varying H_R. Thus, the similarity index (SI) will indicate schedules in between the more risky two-stage approach, to the risk averse single schedule. The idea is inspired in the concept of *minimum agreement index* for fuzzy duedate or fuzzy completion time [17] and is as follows. First, discrete binary decisions taken for a particular day are *fuzzified* along the surrounding days, e.g., the decision takes a value of 100 at the current day but it also influences the before and following days with a decreasing value, proportional to the distance from the current day. Then, the SI is defined as the intersection between the decisions of the schedules for all the scenarios, see Figure 4.

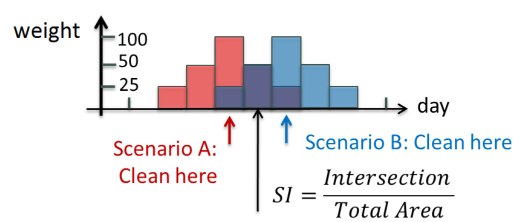

Fig. 4. Fuzzy discrete decisions and similarity.

Using just the two closest days to the current one ($t-1, t+1$), the SI index[1] to optimize is:

$$J_1 := \sum_{v \in \mathcal{V}} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{M}_U \backslash t_F} \min\big(100E_{vtse}, 50E_{v(t+1)se}, 50E_{v(t-1)se}\big) / \big(n_v(200(n_u-1)+150)\big) \quad \forall e \in \mathcal{E} \tag{15}$$

[1]The SI as defined in (15) is nonlinear in decision variables, but a lower bound for it can be computed introducing slack variables and additional linear constraints. Details omitted for brevity.

Where n_v is the number of evaporation plants and n_u is the number of days in $\mathcal{M}_U$. Hence, a $J_1 = 100\%$ means that the schedules coincide for all scenarios, so there is just a single schedule: the risk-averse solution.

In order to measure *efficiency* with resources of different nature (steam, manpower and cleaning products) with a single indicator, an economic aggregation of such resources using utility costs is used. Thus, the average normalized cost per day of operation, according to model (1), is defined for optimization:

$$J_2 := \sum_{e\in\mathcal{E}} \sum_{t\in\mathcal{M}} \sum_{v\in\mathcal{V}} \Big(\sum_{s\in\mathcal{S}} K(v,s) E_{vtse} + \sum_{s\in\mathcal{S}_W} K_T \cdot T_{out}(t) E_{vtse} + \sum_{p\in\mathcal{P}} K_e(v) P_{vtpe} \Big) / \big(t_F \cdot 2^{\rho+1}\big) \quad (16)$$

Where $\mathcal{S}_W := \mathcal{S} \backslash \{\mathcal{S}_L, \mathcal{S}_P\}$ and $K = [K_F, K_{s_P}, K_{s_L}]$ is a lookup table containing the costs associated to the fouling state, standby stages and cleaning tasks.

Last, the production plan of each product can be modified by parameters SP_{pte} in (13). So, the lowest demand δ for all scenarios, products and time instants is:

$$J_3 := \delta = \min\big(SP_{pte}\big) \quad \forall e \in \mathcal{E},\ \forall t \in \mathcal{M},\ \forall p \in \mathcal{P} \quad (17)$$

Hence, gaps $\Delta P_{pte} := SP_{pte} - \delta$ can be also computed. Now, if δ becomes decision variable, a way to uniformly vary the overall *productivity* via (13) is optimising J_3, adding constraints

$$SP_{pte} = \Delta P_{pte} + \delta \quad \forall e \in \mathcal{E},\ \forall t \in \mathcal{M},\ \forall p \in \mathcal{P} \quad (18)$$

to compute new set points with the already fixed ΔP_{pte}.

In the end, our MOOP is formulated as follows.

$$\begin{aligned} \text{optim } & J(E_{vtse}, A_{vtpe}, P_{vtpe}, \delta) = [J_1, J_2, J_3] \in \mathbb{R}^3 \\ \text{s.t.: } & (2)-(14), (18), (P_{vtpe}, \delta) \in \mathbb{R}^+ \\ & (E_{vtse}, A_{vtpe}) \in \{\text{True, False}\} \end{aligned} \quad (19)$$

To efficiently solve (19), we set additional constraints with bounds in J_1 and J_3, denoted by $\mathbf{J}_1$ and $\mathbf{J}_3$, so that only J_2 is in the objective function. In this way, the original MOOP is cat as a set of single-objective optimizations, able to be solved via MILP:

$$\begin{aligned} \min\ & J_2(E_{vtse}, A_{vtpe}, P_{vtpe}) \in \mathbb{R} \\ \text{s.t.: } & (P_{vtpe}, \delta) \in \mathbb{R}^+, (E_{vtse}, A_{vtpe}) \in \{1, 0\} \\ & (2)-(14), (18), J_1(E_{vtse}) \geq \mathbf{J}_1, J_3(\delta) \geq \mathbf{J}_3 \end{aligned} \quad (20)$$

VI. EXAMPLE & RESULTS

An analysis has been performed in simulation by processing three products (P_1, P_2 and P_3) in nine evaporators (V_1, V_2,..., V_9) during a prediction horizon of $H = 22$ days (H_R is set to 7). The possible physical connections between products and evaporators are listed in Table I.

The initial gaps to compute the evaporation set points per product, using (18), are randomly set to $\Delta P_1 = 5$, $\Delta P_2 = 9$ and $\Delta P_3 = 6$ T/h (stochastic values for each scenario are omitted for brevity). Each evaporator cannot operate under $L_v = 15$ T/h and gets a maximum capacity about $U_v = 30 + f(T_{out})$ T/h, where $f(\cdot)$ is a known function. Also, the evaporators get different efficiencies $K_e(v)$, depending on the type of equipment employed to build it. So, they have been named from high to low efficiency[2] as follows:

$$V_1 > V_2 > V_3 > V_4 > V_5 > V_6 > V_7 > V_8 > V_9$$

TABLE I

AVAILABLE LINKS PRODUCT-EVAPORATOR.

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9
P_1	✗	✓	✓	✓	✓	✓	✓	✓	✗
P_2	✓	✓	✗	✗	✓	✓	✓	✓	✓
P_3	✓	✓	✓	✓	✓	✓	✓	✗	✗

Two types of cleaning tasks have been defined, large (A) and small (B), with their corresponding associated costs $K_{s_{LA}}$ and $K_{s_{LB}}$ of manpower and chemical products. Also it has been estimated that an evaporator should not be operating more than 40 days without cleaning because it is clearly suboptimal. Marginal costs $K_{s_{PA}}$ and $K_{s_{PB}}$ have been added to the waiting stages before cleaning to avoid situations where evaporators are not used but remain unclean, which may lead to an overall loose of efficiency when they will be needed (for instance against unexpected production increments).

Expected largest deviations for the outdoor temperature and production predictions are $\sigma_{T_{out}} = 7$°C and $\sigma_p = 10$ T/h respectively. Hence, with 3 products and using max/min vertex values for the uncertainty, a 16-scenario tree arises.

Given these constraints, a solution is obtained by solving (20) in about 12 min[3] running CPLEX with GAMS in an Intel i3-2310M CPU. Now, defining a well distributed grid of points within the pertinency range for J_1 and J_3, optimal solutions in the Pareto sense can be computed by solving (20) offline. The found approximation of the Pareto front is shown in Figure 5. Some interesting conclusions can be extracted from its shape:

- Evidently, the absolute cost increases with the production. However, note that the sensitivity is higher for low productions, see Figure 6.
- Similarly happens with the sensitivity from robustness (SI) to cost. Indeed, the amount of different solutions reduces as production increases (see again Fig.6), tending to the single one with SI=100%, which leads to an important conclusion: the multi-stage stochastic approach is a waste of computational resources for high productions.
- Finally, if we look to the specific cost per amount of production (represented by the colormap) instead of the absolute cost, the lowest overall efficiency is achieved for low productions, which seems a kind of contradiction. However, this result is easily explained by the fact that all plants in operation must be cleaned after some time, despite of whether they are working at low load, so the fixed costs of cleaning tasks make the overall specific cost increase.

[2] Sensible values are not shown due to confidentiality agreements.

[3] Note that this value is just indicative, as it may vary depending on the initial state of the network.

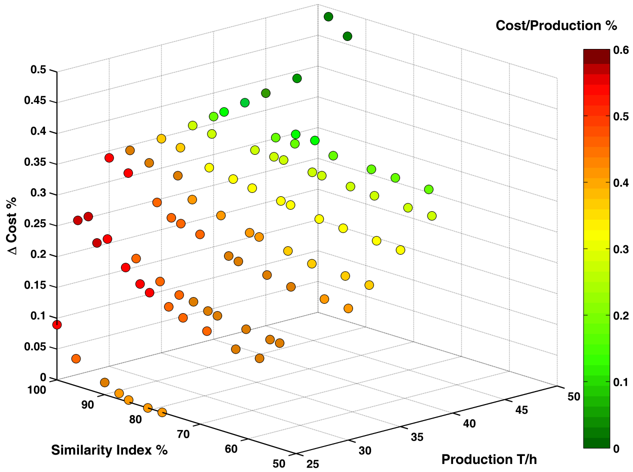

Fig. 5. Estimation of the Pareto front.

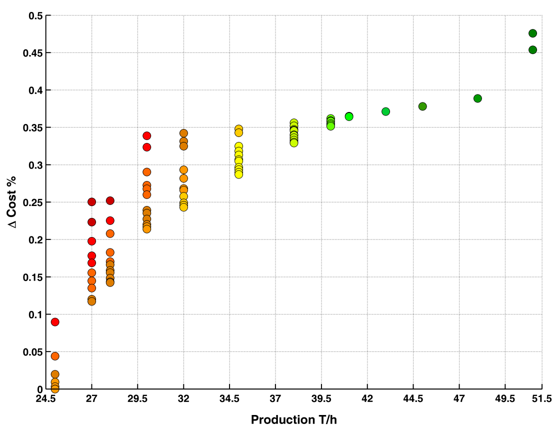

Fig. 6. 2D view from objectives J_2 and J_3.

For completeness, if (4) is relaxed to allow cleaning many plants at a day, the optimization elapses around 25 min and only a relative cost margin about 0.032% is achieved. So, hiring more personnel for cleaning does not seem worthwhile.

VII. CONCLUSION

This paper has addressed a scheduling problem for an industrial evaporation network under uncertainty. The main feature which makes the problem singular is that the production is continuous, so there is an infinite number of tasks to schedule, but equipment cannot operate efficiently forever without being stopped for maintenance. A modification of the general precedence allocation method has been proposed to efficiently tackle this problem.

Stochasticity has been introduced in the weather prediction and in the production plan via a two-step optimization approach. In this way, less conservative robust schedules are obtained thanks to the possibility of measuring the uncertainty and react. Also, a similarity index between scenario-based solutions has been used as a measure of robustness in order to give the scheduler the possibility of reducing the risk, at the price of increasing conservativeness.

Finally, a multi-objective analysis is given by adding other objectives of interest like maximizing the production or minimizing the specific cost of operation. Although the Pareto front depends on the current state of the system, interesting conclusions can be derived from the analysis of its shape, providing valuable information for decision support.

REFERENCES

[1] T. Bartz-Beielstein and M. Zaefferer, Model-based methods for continuous and discrete global optimization, Applied Soft Computing, vol. 55, pp. 154-167, 2017.

[2] G. Calleja and R. Pastor, A dispatching algorithm for flexible job-shop scheduling with transfer batches: an industrial application, Production Planning & Control, vol. 25, no. 2, pp. 93-109, 2014.

[3] J. Casas-Liza, J.M. Pinto and L.G. Papageorgiou, Mixed Integer Optimization for Cyclic Scheduling of Multiproduct Plants Under Exponential Performance Decay, Chemical Engineering Research and Design, vol. 83, no. 10, pp. 1208-1217, 2005.

[4] C.A. Floudas, Nonlinear and Mixed-Integer Optimization, Oxford University Press, 1995.

[5] C.A. Floudas and X. Lin, Continuous-time versus discrete-time approaches for scheduling of chemical processes: a review, Computers & Chemical Engineering, vol. 28, no. 11, pp. 2109-2129, 2004.

[6] I.E. Grossmann, Review of Nonlinear Mixed-Integer and Disjunctive Programming Techniques, Optimization and Engineering, vol. 3, no. 3, pp. 227-252, 2002.

[7] I. Harjunkoski, C.T. Maravelias, P. Bongers, P.M. Castro, S. Engell, I.E. Grossmann, J. Hooker, C.A. Méndez, G. Sand and J. Wassick, Scope for industrial applications of production scheduling models and solution methods, Computers & Chemical Engineering, vol. 62, pp. 161-193, 2014.

[8] U. Klanšek, A comparison between MILP and MINLP approaches to optimal solution of Nonlinear Discrete Transportation Problem, Transport, vol. 30, no. 2, pp. 135-144, 2015.

[9] P. Kouvelis, R.L. Daniels and G. Vairaktarakis, Robust scheduling of a two-machine flow shop with uncertain processing times, IIE Transactions, vol. 32, no. 5, pp. 421-432, 2000.

[10] T. Lastusilta, GAMS MINLP Solver Comparisons and Some Improvements to the AlphaECP Algorithm, Ph.D Thesis, Åbo Akademi University, Finland, 2011.

[11] D. Lei, Multi-objective production scheduling: a survey, Inter. Journal of Advanced Manufacturing Technology, vol. 43, pp. 926-938, 2009.

[12] C.A. Méndez, J. Cerdá, I.E. Grossmann, I. Harjunkoski and M. Fahl, State-of-the-art review of optimization methods for short-term scheduling of batch processes, Computers & Chemical Engineering, vol. 30, no. 6-7, pp. 913-946, 2006.

[13] C.G. Palacín, J.L. Pitarch and C. de Prada, Efficient Modelling and Real-Time Optimisation of Stationary Systems: Application to an Evaporation Process, in SIMUL 2015: The 7^{th} Intern. Conf. on Advances in System Simulation, IARIA XPS Press, pp. 6-11, 2015.

[14] J.L. Pitarch, C.G. Palacín, C. de Prada, B. Voglauer and G. Seyfriedsberger, Optimisation of the Resource Efficiency in an Industrial Evaporation System, Journal of Process Control, (In Press), DOI:10.1016/j.jprocont.2017.04.002, 2017.

[15] T.A. Pogiatzis, D.I. Wilson and V.S. Vassiliadis, Scheduling the cleaning actions for a fouled heat exchanger subject to ageing: MINLP formulation, Computers & Chemical Engineering, vol. 39, pp. 179-185, 2012.

[16] R. Ruiz-Femenia, G. Guillén-Gosálbez, L. Jiménez and J.A. Caballero, Multi-objective optimization of environmentally conscious chemical supply chains under demand uncertainty, Chemical Engineering Science, vol. 95, pp. 1-11, 2013.

[17] M. Sakawa and R. Kubota, Fuzzy programming for multiobjective job shop scheduling with fuzzy processing time and fuzzy duedate through genetic algorithms, European Journal of Operational Research, vol. 120, pp. 393-407, 2000.

[18] F. Smaïli, D.K. Angadi, C.M. Hatch, O. Herbert, V.S. Vassiliadis and D.I. Wilson, Optimization of Scheduling of Cleaning in Heat Exchanger Networks Subject to Fouling, Food and Bioproducts Processing, vol. 77, no. 2, pp. 159-164, 1999.

[19] M.M. Yenisey and B. Yagmahan, Multi-objective permutation flow shop scheduling problem: Literature review, classification and current trends, Omega, vol. 45, pp. 119-135, 2014.