INTEGRATION OF OPTIMAL CLEANING SCHEDULING AND CONTROL FOR FOULING MITIGATION IN HEAT EXCHANGER NETWORKS: A RECEDING HORIZON APPROACH

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ABSTRACT

Fouling mitigation is paramount to maintain a reliable, efficient, and economic operation of heat exchanger networks in the food, water, chemicals and refining industries. Two common mitigation strategies are controlling the flow distribution in the network, and optimizing the periodic cleaning of units. Due to high complexity, these are currently addressed separately (sequentially). This paper presents for the first time an online solution that i) exploits the strong synergy between the two strategies by optimizing them simultaneously and ii) corrects for dynamic process changes, plant disturbances and model mismatch by using a nonlinear model predictive control scheme.

A network-wide estimation model exploits measured and soft-sensed past data to generate an accurate estimation of the current state and reliable performance predictions over a long range. The prediction model is then solved to optimize both control and cleaning schedules. Estimation and prediction models are continuously updated in a receding horizon scheme. The significant economic benefits achieved with this online solution are demonstrated via a case study that captures all the relevant elements of a refinery preheat train.

INTRODUCTION

Fouling in refining applications has been a problem of major concern through the years. It has a big impact in the operation, safety, and economics of the process. Fouling is especially important in the preheat train, where all the crude processed in a refinery is heated up from atmospheric conditions to the high temperature (~ 360°C) required in the crude distillation unit (CDU). At these conditions crude oil has a high fouling propensity, and a small decay in the efficiency of the heat exchangers incurs large costs. Eliminating or reducing fouling has economic benefits for the operation as it leads to significant energy savings. Fouling mitigation strategies include design options (the use of antifouling agents, surface coatings, heat exchanger inserts, network retrofits), and operational options, discussed below [1], [2]. So far, no single design approach has proved capable of eliminating fouling completely in the preheat train of a refinery, so that operational mitigation alternatives still play an important role. The most common operational options are control of the flow distribution in the network (bypasses, flow splits in parallel branches, e.g. Fig 1), and the periodic cleaning of units. Flow control can reduce fouling rates or partially remove the deposit by increasing the sheer rate in certain units. Cleaning a unit (offline or online) removes the deposit and restores its thermal and hydraulic performance, but takes it out of service for a period. Both generate complex and hard to predict thermal and hydraulic interactions in the network.

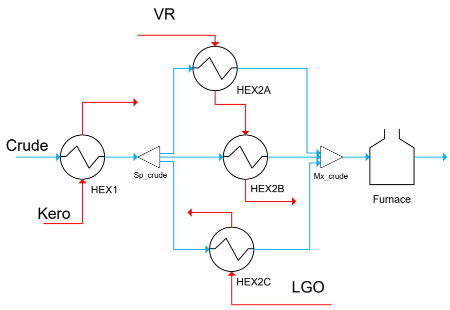

Fig 1. Small refinery heat exchanger network.

Several studies in the literature have looked at the optimal cleaning scheduling problem on its own (e.g. [3], [4]), while some analyzed the flow distribution problem alone (e.g. [5], [6]). Only more recently the integration of both at the same decision level has been tackled [7], highlighting their strong synergy and large benefits arising. The above approaches differ in the way of modelling the heat exchangers (e.g. lumped parameter models, cell models) [8], in the fouling model used (e.g. semi-empirical, empirical) [9], in the solution strategy (e.g. deterministic optimization, stochastic optimization) [10], or in the problem simplifications adopted (e.g. linear approximation, cyclic operation) [11], [12]. However, all cases assume that: i) the

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operating conditions in the process remain constant or are known a-priori over long-time horizons (> 1 year), and ii) the model can predict the operation perfectly for such horizon. In actual refinery operations, the first condition does not hold, as process conditions change frequently (for instance, crude blends change every few days). The second condition is very unlikely to hold for such long-horizons in the presence of disturbances, and no model is ever perfect. For these reasons, an offline fouling mitigation solution developed at any one time will not capture future variability in the process, will soon get out of date and will lead to suboptimal, possible even unfeasible operation. Considering process variability in the decision making would result in better fouling mitigation actions. Acknowledging that any prediction model has limitation and its prediction capabilities may extend until certain point, one approach is to update models periodically.

In this paper a new scheme and solution for online fouling mitigation are presented, following the principles of model predictive control (MPC) used in control engineering. This approach uses past primary measurements of the plant to regularly update a prediction model of the plant performance, and that model is used in the decision-making process. Here, the prediction model is used to optimally define an operation plan comprising a schedule of cleaning actions (which exchanger to clean and when) and time profiles for the flow split distribution. The operation plan is implemented, and then periodically updated online in a closed loop.

OPTIMIZATION COMPONENTS

This section briefly describes the key concepts of model based receding horizon control. A formulation of three optimization problems for fouling mitigation is then introduced. The performance of the on-line implementation depends strongly on the update of these models from plant data, their efficient solution, and implementation of their predictions.

The on-line fouling mitigation methodology proposed is based on two key concepts from process control: 1) a nonlinear predictive controller (NMPC) that predicts the future behavior of the plant and defines the actions to take (manipulated variables) [15], [16], and 2) a moving horizon estimator (MHE) that updates the model parameters using past data to ensure a good quality of prediction [17]. Fig 2 shows how these two elements work and interact. Here we use an economic oriented NMPC instead of the classic NMPC with a tracking objective function. At each sampling time t^* a solution of the MHE problem defines the model parameters and gives an estimation of the actual conditions of the process at time t^*. These initial conditions are not the current measured values from the plant because they have noise or are not even measured (e.g. the deposit thickness). The MHE problem is defined over a past estimation horizon, PEH, that contains a number N of measurement points. Next, the NMPC problem is solved, the solution of which is the optimal future actions (u) over a future prediction horizon (FPH), and corresponding prediction of the future states (x) of the plant. Although the predictions are available for a long horizon, only the first control action is implemented, and the rest are discarded. At the next sampling time $(t + \Delta t)$, with Δt much shorter than the prediction horizon, the process is repeated. New measurements are available to update the model by solving the MHE problem, and new control actions are determined and implemented by solving the NMPC problem. Note that both the MHE and the NMPC operate in a receding horizon scheme.

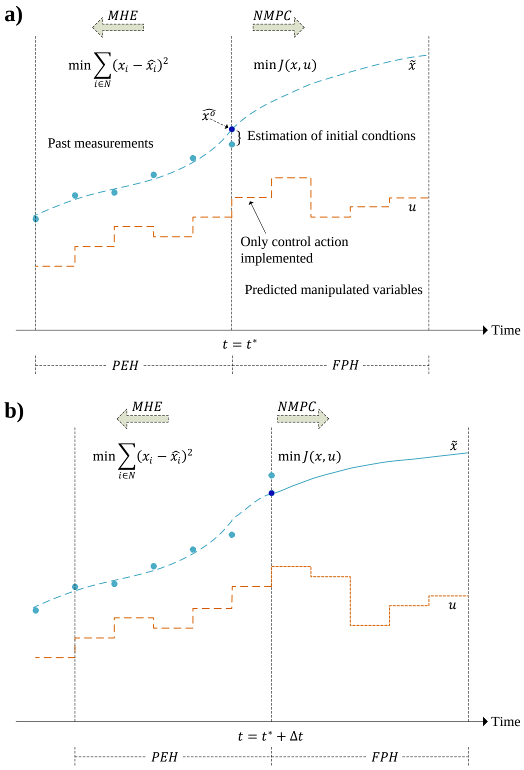

Fig 2. NMPC and MHE schematic description. a) Past measurements and predictions at $t = t^*$, b) Past measurements and predictions at $t = t^* + \Delta t$

These two elements are the key ideas used in the online approach for fouling mitigation. While the MHE estimates the fouling model parameters and current fouling state, the NMPC defines the actions to take in order to minimize the effects of fouling and maximize energy recovery. The fouling mitigation problem is divided in two layers based on the time scale of the process: 1) a scheduling layer, and 2) a control layer. The scheduling layer captures the operation over long time (~months). The decisions involved in this layer have a low frequency (which units to clean and when). On the other hand, the control layer capture more rapid variation of the process (~daily) and decisions in this

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layer are taken at high frequency (setpoints to flow control valves). For each of these layers an optimization problem that aims to minimize the total operation cost over a future horizon is formulated. Although models in the two layers share the same objective and are similar in structure, the decision variables, length of the prediction time, and mathematical complexity of each are different.

The main building blocks for an accurate model of heat exchanger networks under fouling are:

- A heat exchanger model to predict its performance (heat duty, outlet streams temperature, and pressure drop).
- A fouling model to predict the deposit time evolution and how it is affected by the operational conditions.
- A network model that defines dynamically the connectivity between different units (including stream mixers and splitters).
- An objective function that quantifies the performance of the whole network to evaluate the effectiveness of fouling mitigation alternatives.

Optimization problems at the scheduling layer and control layer share these building blocks. A lumped parameter model, the P-NTU model, is used to describe the operation of each heat exchanger. This model calculates the heat duty and streams temperature as a function of the inlet conditions and design specifications of the unit (e.g. number of passes, number of tubes) [13]. The semi-empirical Ebert-Panchal model [14] is used to model the crude oil fouling in each unit. This model predicts the fouling thermal resistance as a function of the operating conditions of the unit, and its parameters can be tuned to match plant observations. The hydraulic effects of fouling (pressure drop) are calculated from the deposit thickness, taking into account the curvature effects of the surface in the deposit formed. The heat exchanger network is modelled as a multigraph in which each stream type (e.g. crude oil, LGO) defines a graph that connects the nodes, and two graphs interact only at the heat exchanger nodes. This formulation allows defining the mass flow rate through the network, and setting split ratios and inlet flow rates of different streams, as detailed in [7].

The final element of the optimization model is the objective function (OF), which in this case is the minimization of the total operating cost due to fouling over the time horizon (Eq. 1). The first term in OF represents the energy cost, which is proportional to the furnace duty. Fouling in the exchangers requires more fuel to be used in the furnace to maintain a desired inlet temperature to the crude distillation unit. The second term accounts for the cost of carbon emissions, assumed proportional to the furnace duty. The final term is the cost associated with all the cleanings performed on all units.

$$J_{op} = \int_{t_0}^{t_f} \left[P_Q Q_f + P_{CO_2} m_{CO_2} Q_f\right] dt + \sum_{t \in Time} \sum_{i \in HEX} P_{cl,t,i} y_{t,i} \qquad (1)$$

The optimization problem solved in the NMPC at the scheduling layer is defined by Eq. 2. The decision variables are the starting time of cleanings $\left(t_{s,p,i} \forall p \in Periods, i \in HEX\right)$, the assignments of cleanings to units $\left(y_{t,i} \forall t \in Time, i \in HEX\right)$, and the flow rates in the network $(m_{t,a} \forall t \in Time, a \in Arcs)$. Flow rate decisions are considered together with the cleaning scheduling variables because of their strong interaction [18]. Although flow control is implemented at a different level, flow rates influence scheduling decisions in the upper layer, and cannot be omitted. Constraints include: the network connectivity equations (mass and energy balance at each node), the heat exchanger model and the fouling model for all units, operational constraints (e.g. firing limit of the furnace), a continuous time representation of time, any scheduling constraints (e.g. “clean certain exchangers simultaneously”, “do not clean a specific unit in a specific period”), and the formulation of disjunctions. The latter are used to model logical OR decisions, for example that an exchanger can be either in a “cleaning” or “operating” state at a specific time. This is an MINLP problem with a large number of binary decision variables and nonlinear terms, over long prediction horizons (0.5 – 4 years). The reader is referred to [7] for more information about the continuous time formulation and the solution strategy.

$$\begin{aligned} &\min_{t_s, y, m} J_S = Eq.3 \\ &s.t. \\ &Network\ connectivity \\ &Heat\ exchangers\ model \\ &Fouling\ model \\ &Operational\ constraints \\ &Time\ discretization\ constraints \\ &Bounds\ on\ operating\ time \\ &Scheduling\ constraints \\ &Disjunctions\ of\ operating\ mode \end{aligned} \qquad (2)$$

The optimization problem solved in the NMPC at the control layer is defined by Eq. 3. The decision variables here are the mass flows in the network $\left(m_{t,a} \forall t \in Time, a \in Arcs\right)$. At this level, the future cleanings are known and set as parameters (from the upper layer), i.e. the future operating modes of each exchanger is known a-priori. Constraints include the network connectivity constraints, the heat exchanger model and the fouling model for all units, and the operational constraints. Some common operational constraints

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in this layer are: bounds on the split fraction of parallel branches, pressure drop limits, and furnace duty limits. This problem has significantly fewer constraints than the optimal scheduling problem, Eq. 2, and no discrete variables, as the cleanings in this layer are set. This is a dynamic optimization problem, that after discretization of the differential equations become a large-scale NLP with many constraints and nonlinear terms, defined over short prediction horizons (~days). In this case time is represented using a discrete approach.

$$\begin{aligned}&\min_{m} J_C = Eq. 3\\&s.t.\\&Network\ connectivity\\&Heat\ exchangers\ model\\&Fouling\ model\\&Operational\ constraitns\end{aligned} \tag{3}$$

The previous two optimization problems are parametric problems, i.e. their solution depends on a set of parameters P_S and P_C for the scheduling and control problem, respectively. Set P_S includes the initial model conditions (initial fouling resistance of each exchanger), the fouling model parameters, and the prediction horizon. Set P_C includes the same elements plus the definition of all cleanings within the prediction horizon. The values of parameters in these two sets are updated online according to the plant measurements at a specific time, and become inputs to the corresponding optimization problem. However, the fouling model parameters are not updated directly as they are obtained by solving a parameter estimation problem with past measurements.

The fouling model parameters for each exchanger of the network are calculated by solving the network-wide *parameter estimation problem* defined by Eq. 4. This problem corresponds to the MHE problem, and it is defined for each of the layers, so there is a MHE for the scheduling layer, and a MHE for the control layer. Here the objective function is the minimization of the quadratic error (difference between model and plant data) for the primary measurements in the network. These include tube side streams outlet temperature, shell side streams outlet temperature, and tube side outlet pressure, each weighted depending on their relative importance. The problem is subject to the same constraints as the previous optimization problems in their respective layer. The solution of this single problem defines the fouling parameters for each exchanger in the network, which may vary from one unit to the other. To avoid correlation-related numerical difficulties, the activation energy is assumed fixed and only the deposition constant (α), the removal constant (γ), and the deposit roughness (ϵ) are considered as degrees of freedom (fitting parameters). The solution of this problem also provides an estimation of the initial conditions (initial fouling resistance) at the beginning of the prediction horizon, for the scheduling, Eq. 2, and control, Eq. 3, optimisations. The parameter estimation problem includes the number (N) of data points collected in the past estimation horizon (PEH). The PEH for the control layer is shorter than that of the scheduling layer, but both should be proportional to the future prediction horizon (FPH) of the corresponding problem. This ensures that enough data is used to fit a model, so as to provide accurate predictions over the future horizon.

$$\begin{aligned}\min_{\alpha_i,\gamma_i,\epsilon_i \forall i \in HEX} J = \sum_{k\in N}\sum_{i\in HEX} & w_{Tt}\left(T_{t,i,k} - \hat{T}_{t,i,k}\right)\\ &+ w_{Ts}\left(T_{s,i,k} - \hat{T}_{s,i,k}\right)^2\\ &+ w_P\left(P_{t,i,k} - \hat{P}_{t,i,k}\right)^2\end{aligned} \tag{4}$$

$$\begin{aligned}&s.t.\\&Network\ connectivity\\&Heat\ exchangers\ model\\&Fouling\ model\end{aligned}$$

ONLINE FOULING MITIGATION

The three problems formulated in the previous section are used together in an on-line fouling mitigation strategy that, by updating the models using the past measurements from the process, is able to handle disturbances and operational changes. The diagram in Fig 3 summarizes data flows and major functional activities in the overall scheme. It is composed by the equivalent of two control loops: an inner, fast one that defines the flow rate distribution in the network every time new information is available, and an outer, slow one that defines the cleaning schedule over a future horizon. The two loops address different time scales of the process and allows responding efficiently to unknown process changes and disturbances. The inner loop responds faster and uses a shorter PEH and FPH than the outer loop. Each loop corresponds to one layer of decisions and solves recurrently a NMPC and a MHE problem. Also, the PEH for the MHE, and the FPH for the NMPC are different for each loop. The MHE of the inner loop (control) looks at data over just the past few days (short PEH) to capture the current variability of the process, so that the corresponding NMPC can quickly define the flow distribution accordingly. On the other hand, the MHE of the outer loop (scheduling) has a much larger PEH and FPH, usually of the order of months, because of the slow fouling rates of most units. Also, a large FPH allows including future cleaning actions, their interactions and trade-offs. As noted, the control decision variables are also considered at the outer loop as that NMPC problem can predict optimal flow rates simultaneously with the optimal cleaning scheduling, which has been demonstrated to have a strong synergetic effect on fouling mitigation [18]. However, these updates are much slower than the variability of the process, and

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therefore flow distribution variables are handled in the inner loop. Only the optimal cleaning schedule for the first prediction period, calculated by the outer loop NMPC, is sent to the plant and inner loop NMPC controller for implementation.

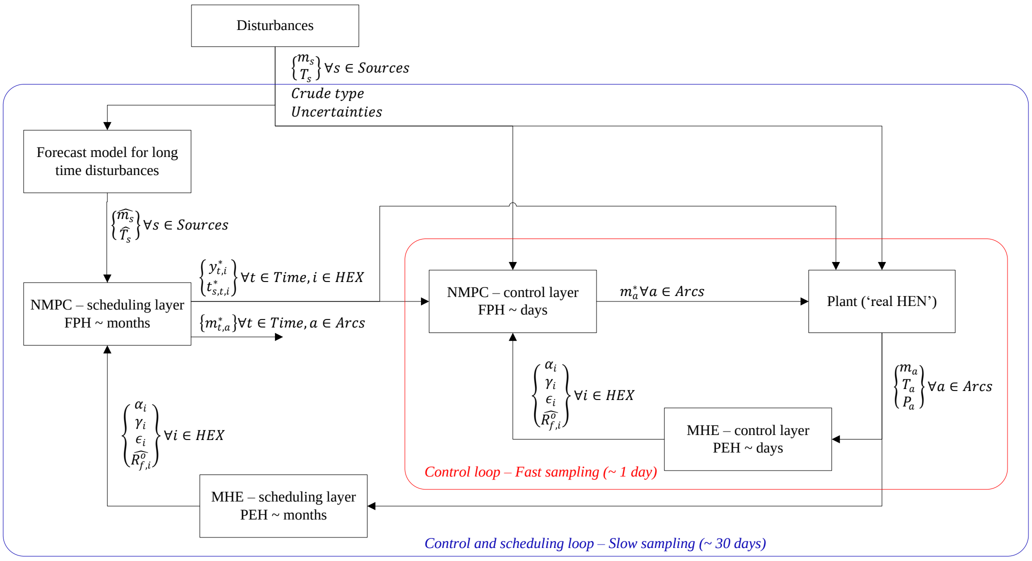

Fig 3. Control and scheduling diagram representing the receding horizon approach for online fouling mitigation.

The process is considered to be subject to disturbances such as changes in the inlet flow rates, inlet streams temperature, type of crude processed, etc. Some of these disturbances can be measured, and are included directly in the inner loop controller. For the outer loop it is necessary to forecast disturbances over long periods (~months). If forecast functions are available, they can be used directly in the NMPC algorithm for this layer. Alternatively, a suitable disturbance model may be used, for example a disturbance can be fixed at its average or worst-case value over a past horizon, or expected value over a future window, in the optimization of future cleaning schedules. However, known future events are readily incorporated.

In summary, this scheme updates the model online, and defines cleaning schedules and the flow distribution profiles over the entire network using a receding horizon approach. For a successful implementation of this methodology, the optimization problems must solved in a much shorter time than the sampling times, so no delay is introduced.

All algorithms are implemented in Python, using Pyomo 5.2 [19] as a modelling environment to formulate and solve the optimization problems. For more information about the formulation of the optimization problems, and specially the solution strategy of the integrated optimal scheduling and control problem using complementarity constraints the reader is referred to [7], [18].

CASE STUDY, RESULTS AND DISCUSSION

This online fouling mitigation methodology is demonstrated for the case study depicted in Fig 1, a heat exchanger network with four exchangers and three parallel branches. Although small, it captures the important features of industrial size ones: multiple hot streams with different properties, flow splits on the crude side, interaction between the exchangers through the hot streams, a furnace to supply the additional energy, and different design specifications for the units. Only mechanical cleanings and flow split control are considered. It is assumed that the flow split can be freely manipulated within a lower bound of 10% and an upper bound of 50% to each branch. The case where the flow split is defined by the pressure drop in the branches can be included in the model and the implementation. However, this reduces the degrees of freedom associated with the flow distribution of the network and is not considered here. Other operational constraints are bounds on pressure drop (hydraulic limit), maximum furnace duty, and the number of units that can be simultaneously cleaned (maximum 2). It is assumed that all the measurements from the plant are available. Here, the "real" plant is represented using the same prediction model but with different parameters for the fouling model. Also, these parameters can be changed dynamically to mimic the variability of a real operation.

Two scenarios are analyzed. Scenario 1 has constant inputs and step changes in the inlet flow rate of crude, with model-plant mismatch. Scenario 2 is more realistic, with dynamic inputs (variable inlet flow rate and streams temperature) and again model-plant mismatch. Both scenarios start with clean conditions. Key operating conditions and algorithm settings are summarized in Table 1.

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Table 1. Key settings for the case study

Frequency of plant measurements	1 day
Duration of a cleaning	10 days
Cost of cleanings	$30,000
Price of energy	$ 27 / MW-h
Coil outlet temperature	350°C
Control layer	
Future prediction horizon (FPH)	30 days
Past estimation horizon (PEH)	30 days
Sampling time	1 day
Scheduling and control layer	
Future prediction horizon (FPH)	180 days
Past estimation horizon (PEH)	90 days
Sampling time	30 days

Scenario 1. Step disturbances in flow rate, and model-plant mismatch.

The closed-loop performance of the network is analyzed over 600 days of operation. The crude inlet flow rate is set to 90 kg/s for the first 200 days, decreased to 70kg/s for 200 days, and finally increased to 110 kg/s for another 200 days. To test for model mismatch, the deposition constant of the fouling model (α) of the plant is 10% larger than that of the control model at the start of the operation.

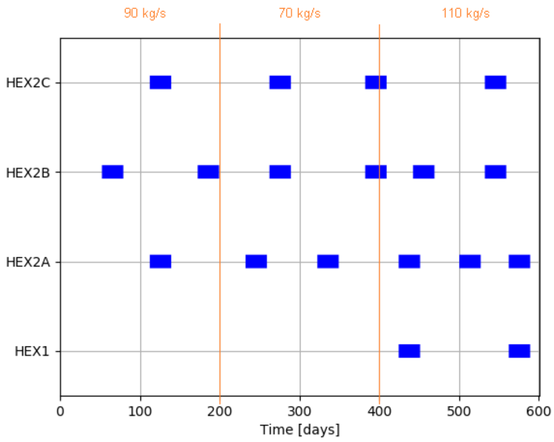

Fig 4. Cleaning scheduling for case study - scenario 1. Step changes in the crude inlet flow rate

Fig 4 shows the cleaning schedule as implemented, at the end of the 600 day period. During execution, the number and assignment of cleanings changes significantly when the crude flow rate changes. Crude throughput changes the trade-off between the cost of cleaning and benefit of future energy recovery. High inlet crude rates favor more frequent cleanings, while for low throughput operations, cleanings are not favorable as their higher cost is not offset by the future benefits from higher energy recovery. Nonetheless there are more cleanings during the period at a crude flow rate of 70 kg/s than at crude flow of 90 kg/s. This is because after 200 days of operation there is already a built-up deposit, and cleanings become advantageous. The overall operating cost of the network over 600 days is $ 16.81 Millions, distributed as follows: 32.26 % for the initial 200 days operating at 90 kg/s, 25.86 % for 200 days at 70 kg/s, and 41.88 % for the final 200 days at 110 kg/s.

Scenario 2. High variability input data.

This scenario mimics more closely the operation of a heat exchanger network where the type of crude processed and operating conditions change frequently. Inlet flow rates and inlet streams temperature are assumed to change daily. In the prediction step, their variability is modelled as normal or uniform distributions around the nominal operating point. To simulate the effect of changing the crude being processed, it is assumed that different crudes have different fouling propensities. These are represented as random changes in the deposition constants of the fouling model in the "real" plant simulation.

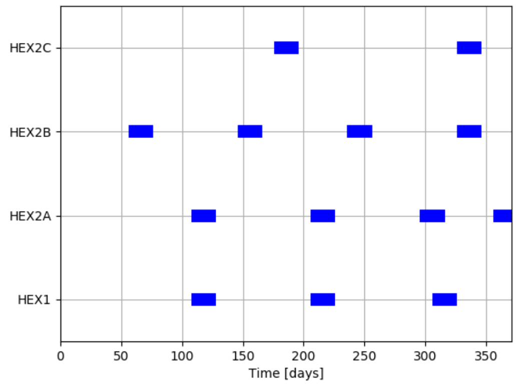

Fig 5. Cleaning scheduling for case study - scenario 2. Dynamic inputs

This is a much more challenging scenario as the input dynamics make it more difficult to achieve an accurate prediction of the network future performance. However, the feedback loop, the data sampling, and the online estimation of model parameters handle this effectively. Fig 5 shows the cleaning schedule achieved after 370 days of operation. Despite the variability in the process, the cleanings are regular, and the algorithms are able to predict simultaneous or consecutive cleanings that are advantageous to mitigate fouling. For example, at time 100 days HEX1 and HEX2A are cleaned simultaneously, and at time 300 those two exchangers are cleaned sequentially starting with HEX2A. Other methods that define the cleaning schedule offline tend to agglomerate all the cleanings towards the middle of the operation, with no cleanings at the beginning nor at the end. This online implementation reflects the current state of the network, assumes a continuous operation and distributes the cleanings better along the operating time.

Regarding the optimal flow distribution in the network, Fig 6 shows the split fraction between the three parallel branches. At the beginning of the

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operation, when there is no fouling, the branches are balanced and the optimal split fraction is 0.33 to each one. This changes with time as material starts to deposit and the operating conditions change. The algorithm interacts with the predicted cleanings by modifying the split fraction, so that the minimum flow is sent to a branch of an exchanger being cleaned, and the rest is distributed optimally to maximize energy recovery (or by passed in some cases to meet the flow constraints). Operating constraints such as the bounds on the split ratio are satisfied at all times, in spite of the cleanings and disturbances in the inlet streams.

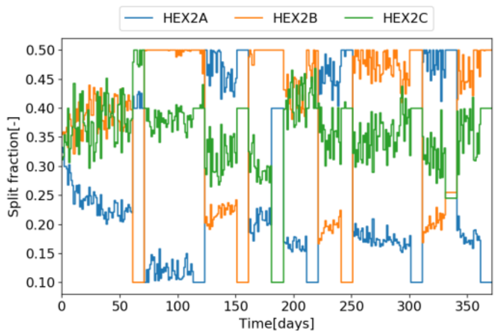

Fig 6. Optimal flow split to parallel branches for the case study - scenario 2

To illustrate the benefits of the proposed approach, scenario 2 is simulated with the same inputs variability and disturbances, but without any fouling mitigation action. The split ratios are fixed at 33.33% for each branch, and there are no cleanings. Fig 7 shows a comparison between the no mitigation case (NM) and the simultaneous online optimal cleaning scheduling and control (O-SC) for the CIT This figure clearly shows that the dynamic inputs and changes in the crude oil introduce large variability in the process and have a strong effect on the network performance. In spite of disturbances, in the NM case the CIT has a clear underlying decreasing trend. By the end of the year the overall decay in performance due to fouling results in a loss of about 40°C in the CIT. On the other hand, the online optimal solution maintains the CIT at significantly higher levels for most of the operation.

Until the first cleaning (of HEX2B starting on day 61) the CIT for the two approaches is very similar. Afterwards, the optimal cleanings and flow distribution reduce significantly the performance decay caused by fouling, with a loss of about 15°C in the CIT by the end of the year. During the cleaning periods, the CIT reaches lower levels because of the lack of units in the network, but this is compensated in the future by the restoration of the heat transfer capabilities of the unit. In economic terms, the total cost due to fouling for the NM operating mode is $ 11.20 Millions. For the optimal O-CS operation it is reduced to $ 10.83 Millions (including furnace fuel saving of $ 0.8 Millions against a cleaning cost of $0.39 Millions, a 100% return on the cleaning investment). As operations are assumed to continue after 365 days, the economic benefits of the cleanings close to the final time of the analysis (5 cleanings carried out after day 300) are not yet been accounted for.

CONCLUSION

A method and implementation for online fouling mitigation in heat exchanger networks has been presented, and a case study for a representative refining application has demonstrated its applicability and benefits. The method calculates the optimal flow distribution in the network and the optimal cleaning schedule simultaneously. The optimal decision policies are updated online by solving optimization problems at appropriate frequencies. The prediction models used in the optimizations are updated frequently, based on past plant measurements.

The main conclusions of this study are:

1. the online operations optimization is very effective in countering process variability.
2. the periodic update of prediction models in a closed loop scheme ensures their validity.
3. the optimization formulation is very powerful and flexible. It allows for the simultaneous optimization of flow distribution and cleaning schedules, with a variety of constraints.
4. The proposed scheme reduces the total operating cost of fouling significantly.

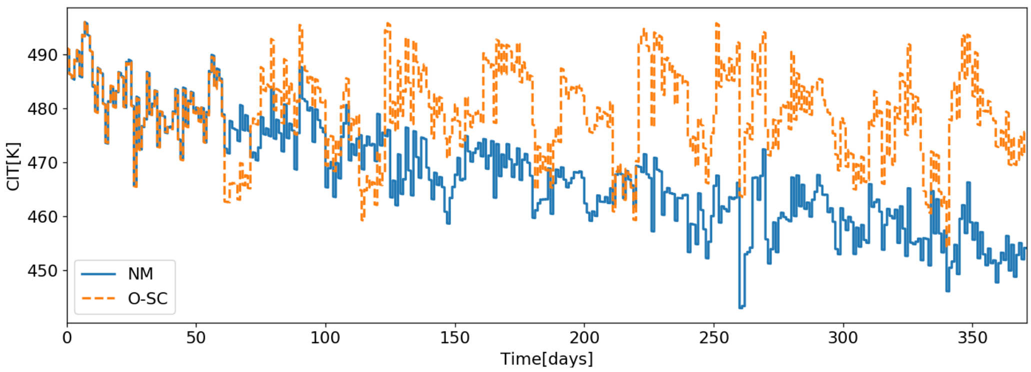

Fig 7. CIT for case study – scenario 2. Comparison of the no mitigation case (NM) and the optimal online cleaning scheduling and control case (O-CS).

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NOMENCLATURE

$Kero$ Kerosene
VR Vacuum residue
LGO Light gas oil
NLP Nonlinear program
$MINLP$ Mixed integer nonlinear program
CIT Coil inlet temperature

HEX Set representing all exchangers in a network
m Mass flow rate, kg/s
m_{CO_2} Ratio of carbon emissions per energy, kg /W
P Unitary price
P_t Tube side outlet pressure, bar
Q_f Furnace duty, MW
t Time, days
u Manipulated variables
w Relative weights in objective function
x General representation of the plant states
y Binary variable for cleanings definition

α Fouling deposition constant, m^{2}K/W day
γ Fouling removal constant, m^{4}K/W N day
δ Deposit thickness, mm
λ_d Deposit thermal conductivity, W/m K

Subscript

0 Initial condition
C Optimal control problem
f Final condition
s Starting time
S Optimal cleaning scheduling problem

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