HEATTRAX: A NEW APPROACH TO EXCHANGER FOULING MANAGEMENT

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ABSTRACT

HeatTrax is a software solution, used in combination with engineering support, that runs a scheduler devoted to determining optimal cleaning actions within the operational horizon. A nonlinear mathematical model, containing continuous and binary variables is used. We consider different cleaning types (mechanical, chemical, and equipment replacement), consider fouling rate changes with throughput and crude density (blends), and calculate needed throughput reduction during cleanings when furnace load is compromised. The scheduler can incorporate logistic constraints, such as limiting the number of cleanings during any period, forbidding cleanings for individual exchangers, limiting the number of certain cleanings over the time horizon for all or any particular exchanger, etc. The scheduler also needs to be fed by the current fouled status of each exchanger and the fouling growth parameters. The fouled status and the fouling growth parameters are obtained from plant data by using a pseudo-steady-state nonlinear reconciler followed by regression tools. We illustrate all these capabilities and discuss practical implementation details.

INTRODUCTION

The energy cost to process crude oil into useable products is substantial and steadily increasing due to increased environmental standards, societal, and financial pressures from Environmental, Social, and Governance (ESG) mandates. A large portion of the energy a refinery consumes is used to preheat crude oil in distillation units. If not maintained properly, crude preheating exchangers can foul at a large rate, raising the consumption of energy, and eventually reducing the unit's feed rate. The fouling is not limited to crude units; it reaches virtually every process unit. Refiners typically sub-optimize their heat transfer systems for several reasons:

- Heat exchanger fouling is often set aside for other process concerns and is difficult to continuously model and forecast.
- Engineering resources needed to monitor exchanger fouling rates are limited due to competing priorities and high turnover.
- Economic trade-offs of different cleaning methods (e.g. traditional hydro-blasting vs. ultrasonics vs in-situ chemical cleaning) and the effectiveness of each method are either poorly understood or not modeled comprehensively into the economic decision-making tools.

To manage the cleaning of pre-heating trains with many exchangers prone to foul an optimization of the cleaning schedule is needed. In turn, this scheduler needs to look into the future and make fouling rate predictions using fouling growth models. Finally, to obtain the parameters of the fouling model, reliable data are needed. However, plant data is many times not reliable: it contains random errors and biases. To handle this situation, our service relies on three pieces of software:

- Reconciler: It obtains reliable estimators of the flows and temperatures using measurement data. The Reliability of the estimators is achieved using bias detection techniques. The final set of consistent data is then used to obtain the overall heat transfer coefficients (*U*) of each exchanger and the fouling factors (*Rf*).
- Regression: We plot all the daily values of the fouling factor (*Rf*) for each exchanger and we use this data to obtain the fouling model parameters.
- Scheduler: This software obtains the optimal cleaning decisions: what exchange to clean when to clean it and what cleaning method (ultrasonic, hydro blasting, chemical, etc.) is to be used.

CLEANING PROGRAM ECONOMICS

Historically, heat exchanger cleaning programs have been predominantly reactive or time-based. A reactive, scheme triggers a cleaning event based on the presence of a condition such as high exchanger pressure drop and/or heat transfer performance that has deteriorated below an acceptable value. Alternatively, time-based cleaning, also known as cyclic, involves cleaning heat exchangers at a given interval to maintain the furnace inlet temperature (FIT) at or above the desired minimum value. The cleaning interval may be fixed based on operator experience, historical fouling performance, and other operational constraints, or it may be synchronized with other opportunistic events such as unit pit-stops or plant turnarounds. Due to practical considerations, most operators employ cleaning practices that are a combination of these two methods rather than purely

ISBN: 978-0-9984188-2-7; Published online www.heatexchanger-fouling.com

reactive or time-based. These methods do not produce the optimal economic outcome.

The economics of cleaning includes a trade-off of competing forces. The more often cleanings occur, the greater the cleaning cost and because cleaning while the plant is functioning (by using exchangers bypasses to isolate and clean them) reduces energy recovery, the energy expenditure in the furnaces increases in those cleaning periods. By contrast, less frequent cleaning reduces energy recovery and increases energy cost and environmental impact.

It is well-known that there exists an optimal cleaning schedule that resolves the above-described tradeoffs. These have been studied by several initiatives [1-16]. Many of these initiatives are based on cyclic schedules, i.e., cleaning certain exchangers at a certain frequency. Others are more elaborate and allow the determination of the cleaning of each exchanger at the right time. These are called acyclic schedules. Some simpler approaches rely on determining the impact of the cleaning of an individual exchanger on the overall energy expenditure and calculating the payoff. Those exchangers with a larger payoff would have the cleaning implemented.

The underlying mathematical problem for scheduling decisions is optimization. One wants to minimize cost over a horizon. Binary variables are used to model cleaning-non cleaning decisions (zero or one). Each set of binaries selected represents one solution to the problem, which is associated with an overall cost (Energy expenditure +Cleaning costs). These costs are calculated by solving the energy balances around all exchangers. These balances are known to be nonlinear. Hence, the problem is Mixed-Integer Nonlinear. While some attempts have been made to use metaheuristic methods (simulated annealing, genetic algorithms), mathematical programming has been emerging as the solution procedure of choice [1-16], where some attempts to circumvent nonlinearity exists [11-13]. Later, the uncertainty of the parameters of these models has been added [17-22].

SCHEDULING

We refer to the example in Figure 1.

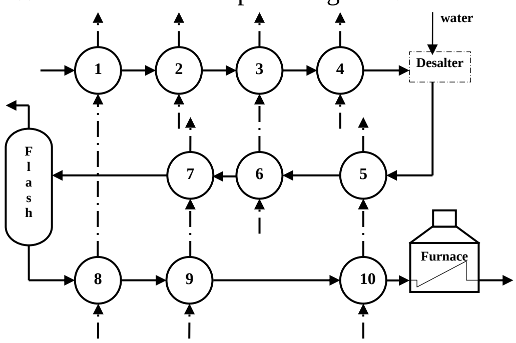

Fig. 1. Classical example from the literature [6].

A typical cleaning schedule is shown in Figure 2. It is showing only the first 9 periods (typically months) and what exchanger is cleaned and in what period, but the periods usually covered are a horizon of around 20-25 months. In this example, there is little cleaning at the beginning, because the exchangers are not yet dirty.

The complexity of multiple cleanings at the same time, that is, the choice among multiple cleaning modes (mechanical or chemical), is enriched in our models by bundle replacements and bundle swaps. Worth mentioning is also the fact that among these different cleaning modes there is synergy for cleaning efficiency and cost. Concerning logistics, concentrating cleanings in one period may provide logistical advantages. This is shown in Figure 3. One can force this upfront by determining the periods where cleaning will take place, or asking the algorithm to pick a given number of periods to use. Alternatively, the logistics costs can be modeled into the algorithm. We use the first option.

Period/HEX	1	2	3	4	5	6	7	8	9	....	....
#1									X	....	....
#2							X			....	....
#3								X		....	....
#4				X						....	....
#5						X				....	....
#6				X			X			....	....
#7				X				X		....	....
#8					X		X		X	....	....
#9				X		X		X		....	....
#10			X		X		X	X		....	....

Fig. 2. Typical schedule obtained using Mathematical Programming.

Period/HEX	1	2	3	4	5	6	7	8	9	....	....
#1									X	....	....
#2							X			....	....
#3									X	....	....
#4				X						....	....
#5							X			....	....
#6				X			X			....	....
#7				X					X	....	....
#8							X		X	....	....
#9				X			X		X	....	....
#10				X			X		X	....	....

Fig. 3. Schedule rearranged to concentrate cleanings in 3 periods.

The scheduling optimization models consist of the minimization of the overall cost over a horizon.

$$Cost = \begin{Bmatrix} Energy \\ Costs \end{Bmatrix} + \begin{Bmatrix} Production \\ Impact\ Costs \end{Bmatrix} + \begin{Bmatrix} Cleaning \\ Costs \end{Bmatrix} \quad (1)$$

Energy costs are related to the furnace inlet temperature (FIT) drop because of the loss of the ability of the network to perform heat recovery due to fouling. This is often made up by increasing fired or steam heater loads. The more cleaning is performed the smaller these costs are.

Production impact refers to the point when exchanger network performance is reduced beyond the heater's capacity to compensate for those losses. The result is a decrease in throughput or product properties affected by heat integration with the pre-heat network. If system performance has degraded significantly enough to impact this category, the value of lost opportunity typically increases dramatically.

Cleaning costs are composed of the cost of the cleaning materials and labor, as well as the temporary increase of the FIT during the time the exchanger being cleaned is bypassed. Thus, the cleaning time plays a role.

These models are solved using a variety of methods (we use mathematical programming). In this article, we do not discuss these issues, even though they are of importance. Aside from the methods that are used to obtain the optimal schedule at a given time, there are a few issues that need to be highlighted:

- The schedule is rerun at the beginning of every period. This is called, a "rolling horizon".
- Any schedule obtained at any given time is only implemented in the period when it is run. For example, the schedule in Figure 2 states that no action ought to be taken in the first period because it is advisable to wait.
- Before any run of the scheduler optimizer, an assessment of the starting value of the heat transfer coefficient (*Uo*) is needed. The scheduler tracks the changes in the heat transfer coefficient (*U*) in future periods. For this fouling prediction models are needed. Two types are used (see below).
- Only one cleaning type is assumed by the existing published literature. The richness of options is nonetheless large (see below).
- In the literature, it is often assumed that each cleaning restores the exchanger to a fully clean or close to fully clean exchanger, even though issues like aging, the efficiency of cleaning procedures, etc.
- No distinction is usually made by the published models regarding which side is cleaned.
- Usually, throughput and density changes are not incorporated into the published models, although there are exceptions [12].
- Usually, the capacity of the fired heaters to deliver the crude at the desired final temperature is not modeled in the literature. Models that do not consider revenue losses, tend to increase the number of cleanings to be able to maintain the throughput.

Refined Technologies (RTI) uses a scheduler that considers

- Periods of flexible duration
- Throughput and density changes are anticipated for future periods.
- Fouling prediction models that are sensitive to flowrate and density changes.
- Different types of cleaning: mechanical and chemical (see below), as well as bundle replacement or swap that are customized to each exchanger by considering cost, duration, and availability
- Restoration after cleaning is different for different cleanings, even among mechanical cleanings. The age of the deposits plays a role in the efficiency of cleaning. This modeling is a work in progress.
- Throughput changes when the FIT is too low. This includes computing the production losses (in the form of USD per barrel not processed). Increased cleanings to maintain throughput are usually favored, but sometimes, several cleanings end up being limited by logistical constraints, manpower, etc. This requires an amended objective where the scheduler minimizes the costs plus the lost revenue.
- Forcing and forbidding cleanings at given periods are considered.

While the scheduler is run to obtain the minimum of the overall costs, the reports are based on a KPI that refers to savings in USD, as follows:

$$Savings = \left\{ \begin{matrix} Costs\ corresponding\ to\ the \\ optimal\ cleaning\ Schedule \end{matrix} \right\} - \\ - \left\{ \begin{matrix} Costs\ if\ no\ cleanings \\ are\ performed.* \end{matrix} \right\} \qquad (2)$$

*Any base case cleaning scenario can be used.

CLEANING MODES

We start by discussing the complexity of the different cleaning modes. They can be classified broadly as mechanical cleaning and chemical cleaning. For mechanical cleanings, the most common are hydro blasting and ultrasonic methods. For chemical cleanings, one can broadly classify them as vapor-based and liquid-based.

Hydroblasting cleanings can be applied to both the shell and the tube side or one of the sides only. Ultrasonic cleanings are applied to the tube side only.

- Mechanical options can be applied in real-time by classifying cleaning type
- Additional mechanical options can be included based on applicability – bundle replacement or bundle swap
- Bundle replacement involves purchasing new exchanger internals. This is typically done if an exchanger has reached the end of life, and restoring capability reliably cannot be done for cheaper than purchasing a new bundle.
- Bundle swap means a spare bundle is available that has been previously cleaned after being removed from the unit – done at the facility's discretion as resources are available. This results in lower cleaning costs through cheaper maintenance and smaller energy expenditure impacts through a shorter duration of exchanger maintenance.

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Chemical cleanings work by injecting a chemical that acts as a solvent to dissolve foulant material in existing equipment. This can be done in the liquid or vapor phase, typically in the presence of a carrier fluid such as a cutter stock or steam, respectively. This cleaning method can be done in conjunction with mechanical cleaning to expedite the mechanical cleaning process, or as a stand-alone method done in place, removing the need to physically move the equipment.

Different cleaning modes have different efficacy rates. The effectiveness of different cleaning methods is dependent on several factors, so these values can be individually defined in the software to best reflect reality. Generally, greater cleaning effectiveness is directly proportional to higher cleaning costs.

FOULING MODELS

Fouling models that are typically used are linear.

$$Rf = a\,\tau \tag{3}$$

and asymptotic

$$Rf = Rf_{\infty}\,(1 - e^{-b\tau}) \tag{4}$$

The type of model is determined from observations by parameter estimation (see below).

At any period, the scheduler determines if the exchanger under analysis is to be cleaned. If it is, the value of Rf is changed to the corresponding restored value at the beginning of the period. Irrespective of whether an exchanger is cleaned or not, the value of the fouling for the end of the corresponding period is updated. Restoration values are hard to predict theoretically, and they are obtained from observations after each cleaning.

OVERALL TECHNICAL STRUCTURE OF THE HEATTRAX SERVICE

The core of the HeatTrax service is the scheduler. RTI runs a schedule as described above and shares cleaning recommendations with the client regularly. RTI periodically receives the measurement data from the plant, corrects and calculates pertinent exchanger performance indicators, and then uses the historical behavior of those properties to project their change over time. The first task consists of obtaining the overall heat transfer coefficient change through time.

To obtain heat transfer coefficients (U_i) daily, one needs to use the following expression

$$U_i = \frac{Q_i}{A_i\, F_i LMTD_i} \tag{5}$$

where Q_i is the heat transferred in each exchanger, A_i is its area, and F_i as well as $LMTD_i$ are the correction factor and logarithmic mean temperature differences, respectively.

To use the equation, one needs to know all 4 temperatures around the exchanger and at least one flow. However, these are often not available, because only some variables are measured, not all. The simpler approach is to use material and energy balances around different equipment to infer the values needed for measurements elsewhere. The exercise is problematic because different routes render different values. Fortunately, a technique known as Data Reconciliation formalizes the task. While data reconciliation is mostly used for flows, RTI uses a procedure of nonlinear data reconciliation that uses energy balances to obtain temperatures. Because the values of physical properties (density, and heat capacity) depend on temperature, the procedure involves determining these properties for each stream involved in an exchanger.

Once the reconciliation is performed for each day, the values of the fouling factors are regressed to obtain the parameters of equations (3) or (4).

Thus the overall structure of the service is defined by three modules

a. The Reconciler module is run first to correct instruments and perform heat transfer calculations
b. The Regression module then uses historical data from the Reconciler to project and predict future fouling performance.
c. Lastly, the Scheduler module is run, using outputs from the Reconciler and Regression, along with other inputs required to evaluate the economics of different cleaning practices.

We review the first two now.

DATA RECONCILIATION

Because not all the temperatures and flows around each exchanger are measured, there is a need to infer them from other measurements, using material and energy balances. Data reconciliation is used to obtain the estimators of the unmeasured values and to resolve discrepancies that arise from redundancy. In a nutshell, the Data Reconciliation model is the following

$$Minimum\ \sum_i \left(\frac{F_i - F_i^M}{\sigma_{F,i}^M}\right)^2 + \sum_j \left(\frac{T_i - T_i^M}{\sigma_{T,i}^M}\right)^2 \tag{6}$$

that is, obtain the closest estimator possible of the flows and temperatures by minimizing the difference between the estimators (F_i and T_i) and the measured values (F_i^M and T_i^M), weighted by the inverse of the corresponding standard deviation of the measurements $\sigma_{F,i}^M$ and $\sigma_{T,i}^M$.

Posed as above, the solution is a trivial answer: $F_i = F_i^M$ and $T_i = T_i^M$. However, the estimators (F_i and T_i) have to satisfy the plant material balances.

BIAS HANDLING

It is a very well-known fact that instrument maintenance (i.e. calibration) is costly and as a consequence, plants have often settled on a reactive policy, consisting of calibrating when a sensor creates an operational problem, compromises safety, etc. Policies that promote a healthy set of measurement data, mostly exempt from biases are rare.

Data reconciliation technology has the means to detect measurements that stand out as biased, by presenting unacceptably high mismatches. RTI uses the well-known measurement test (MT) to detect these biases.

When the number of biases is small, the MT is fairly accurate. However, when the number of biases is large, corrupted data are not easily identifiable. Techniques to deal with these situations exist. We use the simplest one: serial elimination.

We also recognize that in large plants, cross corruption between biased flows and biased temperatures creates problems for serial elimination, calling for more powerful methods to be implemented. As a first approximation, RTI has been successful using a two-step procedure: reconciling the mass balances first, simultaneously eliminating all possible flow measurements that are biased. Subsequently, we assume the flowrates known and reconcile the temperatures. Future work will incorporate more powerful methods.

FOULING MODEL PARAMETER REGRESSION

Once the fouling factors $R_{f,i}$ are obtained for every day, that information is plotted as a function of time and the parameters of the fouling models (equations 3 or 4). are determined using regression. The parameters of these models are later used in the scheduler.

SERVICE ORGANIZATION

Once service has been initiated, the process below is followed to build the client's model in HeatTrax and begin optimizing future cleaning activities:

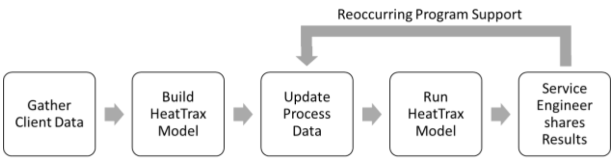

Fig. 4. HeatTrax Workflow Overview

1. The service engineer works with the client to gather the necessary model data
   a. Exchanger specs
   b. Plant data – instruments and lab
   c. Plant mechanics – constraints, available bypasses, cleaning costs, durations, etc.
2. The software team creates the HeatTrax model of the equipment network.
3. The service engineer begins routinely engaging with the client and runs HeatTrax to support technical recommendations for exchanger maintenance.

Ultimately, the deliverable is a report that outlines both current exchanger system performance and different cleaning schedules for future maintenance activities with comprehensive economic value. This provides the client with all the information necessary to decide and take action as needed to work towards improving their heat network and maximizing the unit's profitability.

EXAMPLES AND USER STORIES

HeatTrax and the included HXM service can be scaled to match the complexity of the heat exchanger network. Small systems with only a few exchangers with no online cleaning capability and large systems with parallel trains and complex operating practices can all capture the order of magnitude of millions of USD over a typical turnaround interval.

A current HXM client with a 150MBPD crude capacity typically saves about $500K over an 18-month horizon in purely fuel gas savings. These savings can increase dramatically if fouling is significant enough to impact unit throughput.

Typical plant practices, such as mid-cycle outages or "pit stops" to address various unit issues can also be incorporated into the Scheduler inputs. Another HXM client that typically has bi-annual decoking windows often reviews multiple Scheduler scenarios – some runs where maintenance is constrained within the existing decoke windows, and others where cleanings are unconstrained to be performed at any time. Maintenance during these existing decoking windows is often discounted due to logistical synergies between other work. The ability to accurately reflect these nuisances in plant practices leads to more realistic and tangible predictions that lead to achievable savings.

Another success story seen recently was when reconciled values around an exchanger began showing unrealistic and problematic numbers, while the instruments were not. This issue was raised with the client, and upon a field survey, the data irregularities were confirmed. The exchanger was taken online promptly so the issue could be addressed. The exchanger performance since then has returned to normal and the plant.

CONCLUSIONS

In this paper, we have presented the organization and rationale of HeatTrax, our new service. We remark that the service makes use of three pieces of software: reconciliation, fouling prediction model regression, and a scheduler. The scheduler RTI uses is based on a Mixed-Integer Nonlinear Model, which considers different cleanings at different times.

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ISBN: 978-0-9984188-2-7; Published online www.heatexchanger-fouling.com