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Analysis of the influence of fouling on the heat recovery in a heat exchanger network of a crude distillation unit

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Abstract

In the oil refining industry, fouling is one of the major problems since it reduces thermal and hydraulic performance of a heat exchanger network (HEN). As the performance of a HEN plays an important role in the energy consumption of a Crude Distillation Unit (CDU), it must be monitored in order to predict operational problems. The aim of this work is to elaborate a methodology to analyze the influence of fouling on the heat recovery in a pre-heat train and its operational and economic impact on the furnace inlet temperature. The procedure is based on a rigorous program developed in the Python Programming Language. The clean, dirty overall heat transfer coefficient and fouling factor of each heat exchanger have been calculated using this program and compared to a simulation using Aspen EDR from Aspen Technology. Results of the mentioned methodology applied to a pre-heat train of the main CDU at La Pampilla Refinery, Peru, are presented.

1. Introduction

The issue of fouling in pre-heat train represents an increase in operating costs since more energy must be provided by the fired heater. Extensive fouling may cause an unscheduled plant shutdown, incurring in production losses and higher maintenance costs. In addition, the burning of additional fuel increase the emission of greenhouse gases and other pollutants. Data from oil refineries suggest that crude oil fouling accounts for about 10% of the total CO2 emission of these plants [1].

The main objective of this work is to develop and implement a methodology to monitor the thermal efficiency of each heat exchanger (measured by the fouling factor, for instance) as well as of the whole pre-heat train with the minimum user interaction. This program developed using Python can help to select which heat exchanger of the pre-heat train should be removed for cleaning and also to program a heat exchanger cleaning schedule.

2. Data processing

The first step is to collect the HEN operational data and identify stable periods. The information was collected every 15 minutes from the Plant Information System and the period of steadiness was defined as 3 hours. The stability of a period was defined using the coefficient of variation (CV) for every particular variable (CV < 1%). The average values of each instrument during the stable period are calculated and used for the heat balance calculation in the pre-heat train.

The second step is to close heat and mass balances for each exchanger of the HEN. This is achieved using SLSQP (sequential least squares programming) for the whole pre-heat train. It performs a data conciliation to account for the errors expected on both flow-meters and thermocouples, as well as calculating remaining variables that do not have direct measurement [2].

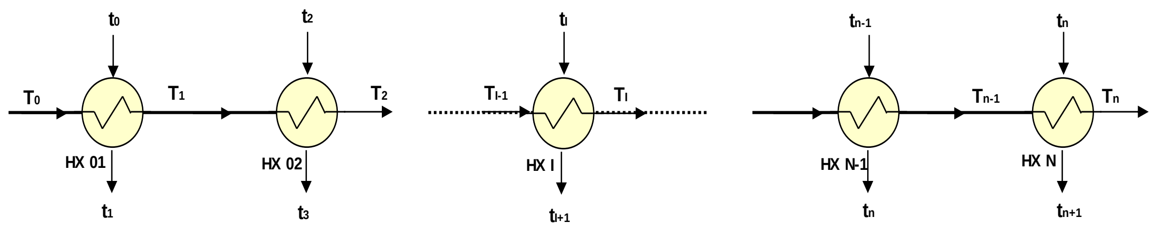

Figure 1: General scheme of operative data of a HEN

Here, the measured temperature is denoted by T_i and the reconciled temperature (after closing heat and mass balances) is denoted as:

$$\overline{T_\iota} = T_i + \varepsilon \quad \text{[Eq. 1]}$$

where ε_i is the random error in measurement.

The heat balances around the each exchanger of the HEN can be written as:

$$Duty_{shell} HX_i = Duty_{tubes}\ HX_i \text{ [Eq. 2]}$$

$$m_{shell} * cp_{shell} * (t_i - t_{i+1}) = m_{tubes} * cp_{tubes} * (T_{i-1} - T_i) \text{ [Eq. 3]}$$

Since the measured values do not satisfy the above equations, it can be assumed that the differences between the measured and estimated temperatures, also referred to as adjustments, should be as small as possible.

This objective can be represented by:

$$Min_{\bar{T},\bar{t}}(\textstyle\sum_{i=0}^{n}(\bar{T}_i - T_i)^2 + (\bar{t}_i - t_i)^2) \quad \text{[Eq. 4]}$$

where

$$\bar{T} = [\overline{T_\iota}, \overline{T_2}, \ldots, \overline{T_n}] \text{ [Eq. 5]}$$

$$\bar{t} = [\overline{t_\iota}, \overline{t_2}, \ldots, \overline{t_n}] \text{ [Eq. 6]}$$

In addition, the laboratory data available for the petroleum fractions is retrieved from the Laboratory Management System and oil crude physical properties (density, viscosity and thermal conductivity) are calculated using a Python subroutine and correlations from API Technical Databook [3].

3. Calculation Methodology

The AspenTech Hysys and EDR programs allow for the rigorous rating of heat exchangers. However, the calculation must be done manually, since it is difficult to automate the process using the standard extensions provided for regular users. This alternative is cumbersome and difficult to apply when there is a need to analyze extended periods of time. As an alternative to the calculation using Hysys+EDR, a model was developed to implement the heat transfer equations used by EDR and correlations from the API Technical Databook.

The reconciled data generated in the previous step is manually exported to a Hysys simulation file that contains both simple Heat Exchanger Models to calculate the dirty overall heat transfer coefficient (U_d) and Aspen EDR models to calculate the clean overall heat transfer coefficient (U_c), and those are used to calculate the fouling factor for each heat exchanger. Finally, the normalized furnace inlet temperature (NFIT) for each stable period is calculated using Uc and the inlet conditions of a base case and the fouling factor calculated before. The NFIT is a measurement of the HEN global fouling. During the monitoring of a HEN, most the operating such as crude inlet flows, temperatures, etc, change every day. These changes can hide the real effect of the fouling in the furnace inlet temperature. If the operating conditions were always the same, there would be no need to normalized the furnace inlet temperature.

A program written in Python was developed to calculate the NFIT values with minimum user interaction, instead of the extensive procedure using a process simulator. The Uc coefficient was calculated using the rigorous Delaware method (to calculate the shell side heat transfer coefficient, h_o) and the Sieder and Tate correlation (to calculate the tube side heat transfer coefficient, h_i). The Ud value was calculated directly using the reconciled duty of a heat exchanger and the corrected mean logarithmic difference of temperatures:

$$U_d = \frac{Q}{A*\Delta T} \quad \text{[Eq. 7]}$$

The fouling factor (R_f) for each heat exchanger was calculated as:

$$R_f = \frac{1}{U_d} - \frac{1}{U_c} \text{ [Eq. 8]}$$

Equivalent results were obtained using Aspen Hysys simulation and Python program.

As Uc and Ud are known for each heat exchanger, a final Python subroutine can be performed in order to analyze and evaluate what would be the improvement on the NFIT if a specific heat exchanger is removed and returned cleaned.

4. Case Study: CDU, La Pampilla Refinery

The methodology was applied to a pre-heat train of the main CDU at La Pampilla Refinery, located in Callao, Perú. Figure 2 shows the pre-heat train scheme. First, the crude is heated up before entry to the desalter (02 D1) where salt, sediments and water are removed. Then, it is pumped and heated up through a pre-heat train (11 heat exchangers) before entry to the fired heater (02 H1).

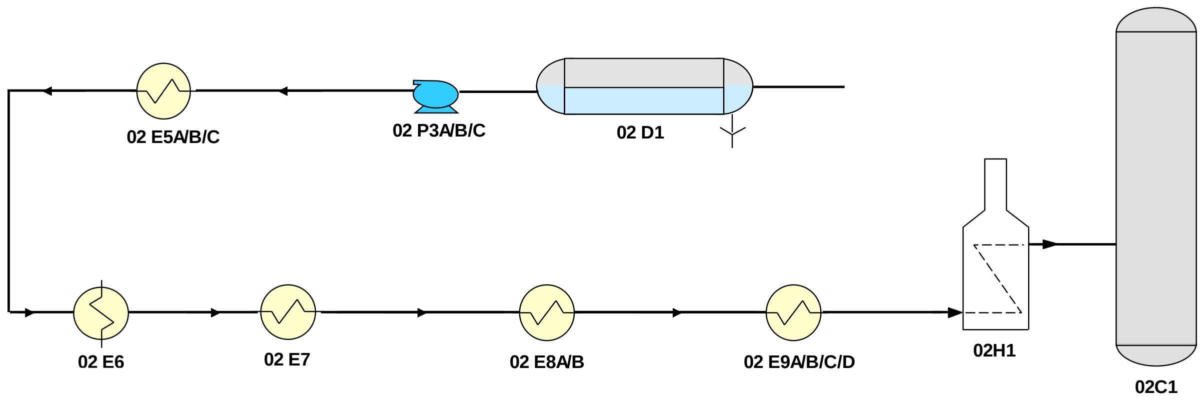

Figure 2: Pre-heat train scheme

Raw data from Plan Information System (measured temperatures, volumetric flowrates and API°) was collected since October 2015 up to August 2016.

Table 1. Heat Exchanger Data Sheet

Heat Exchanger	**Units**	**HX 02E5C/B/A**	**HX 02E6**	**HX 02E7**	**HX 02E8B/A**	**HX 02E9C/B/D/A**
Tubes						
Tube OD	in	0.75	0.75	0.75	0.75	0.75
Tube ID	in	0.584	0.584	0.584	0.584	0.584
Length	ft	20	20	20	20	20
Tubes passes	#	2	6	6	2	2
Tube N°	#	940	290	901	860	986
Pitch (Pt)	in	1	1	1	1	1
Tube Pattern	%	45	45	45	45	45
Baffles						
Type	Single Segmental					
Number	#	10	10	10	8	16
Cut	%	22.13%	45.78%	19.42%	29.30%	18.41%
Baffle pitch	in	17.323	18.580	13.701	22.205	10.709
Shell						
Shell ID	in	39.331	25.039	39.016	37.008	39.173
Shell passes	#	1	1	1	1	1

The construction information for the HEN showed in Table 1 was introduced to both the EDR model and as variables to the Python sub-routine.

4.1 Data retrieval

Data from the Plant Information System was retrieved every 15 minutes since the unit-startup after general maintenance. This information included the inlet and outlet temperatures for each heat exchanger, the standard volumetric flow of most the products that enter the HEN and the specific gravities from the last laboratory measurement. From

36 values needed to close the mass and energy balance in the HEN, three were not know, and had to be calculated in the reconciliation step.

4.2 Steady-state detection

Before closing the mass and energy balance across the HEN, it is important to feed the model data as accurate as possible. It has been suggested to only calculate the fouling factors in periods when the plant has been stable [4]. For this application, the program calculated the average values of the most stable period in each day and save those to a file for later reference and use. Figure 3 shows a stable period selected by algorithm. In the actual application, the program considered 41 variables but only six are showed for demonstration purposes.

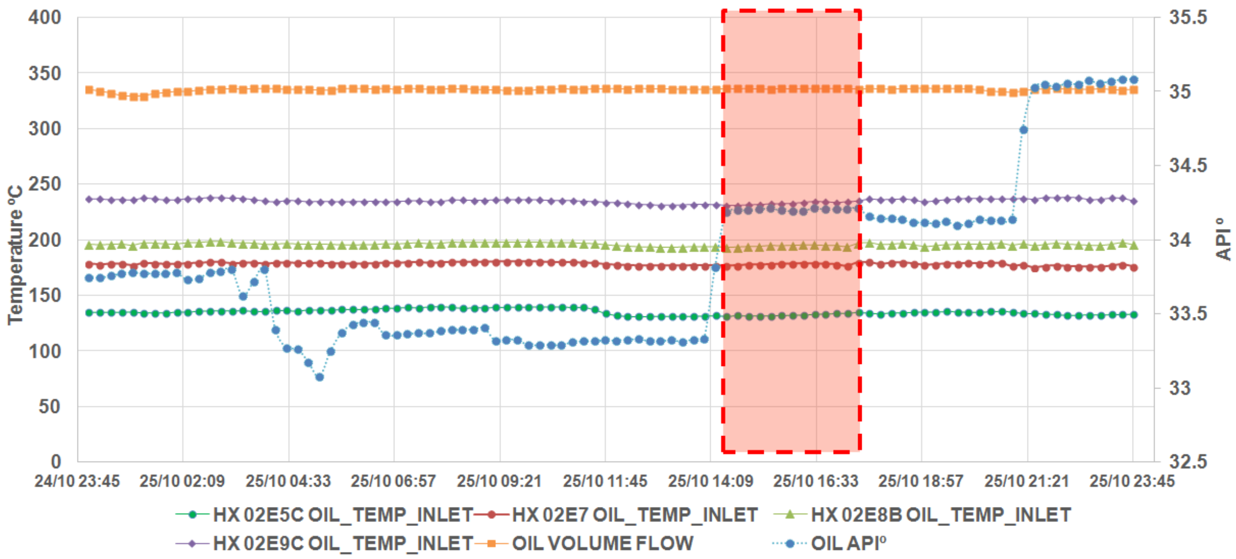

Figure 3: Steady state selected by program

4.3 Data Reconciliation

The data reconciliation was performed since the energy balances can be off by more of 25% given the typical inaccuracies of thermocouples and flow meters. Figure 4 shows the average values for a given heat exchanger, and how the reconciliation change them in order to close the energy balance. In addition, the reconciliation was used to calculate the fraction of the total diesel and kerosene pump that exchange heat with the crude since only the total pump around was measured.

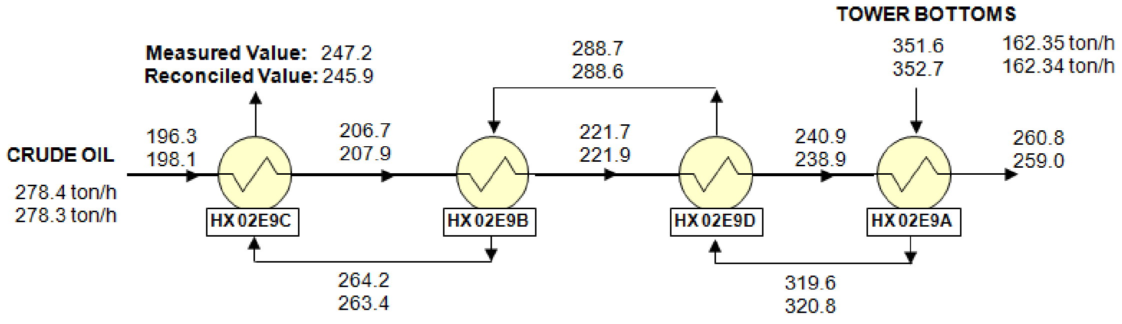

Figure 4: Measured and reconciled values for a portion of the HEN

4.4 Fouling and NFIT calculation using Hysys EDR and Python

Fouling calculation for each heat exchanger was manually calculated using a procedure similar to the one showed in [**4**]. It required a manual input from the reconciled data into a Hysys file that had the EDR models for each heat exchanger. After that, the calculated fouling for each heat exchanger and the NFIT value was copied to an Excel spreadsheet for record keeping and monitoring. This whole procedure took about 2 hours for each day and it was not feasible to apply it to the historic data of the plant from the period 2010 - 2015.

The Python subroutines implemented allowed for an automatic calculation of the fouling and NFIT values for each day. It took approximately 30 minutes to run all the calculation for 270 days. Figure 4 shows the comparison of the NFIT values calculated using both EDR and Hysys and Figure 5 the comparison of fouling factors for the E5C heat exchanger. It is showed that after 210 days of operation the fouling decreases. This behavior is expected when the flow to the exchanger increases and helps to clean the unit by removing deposits.

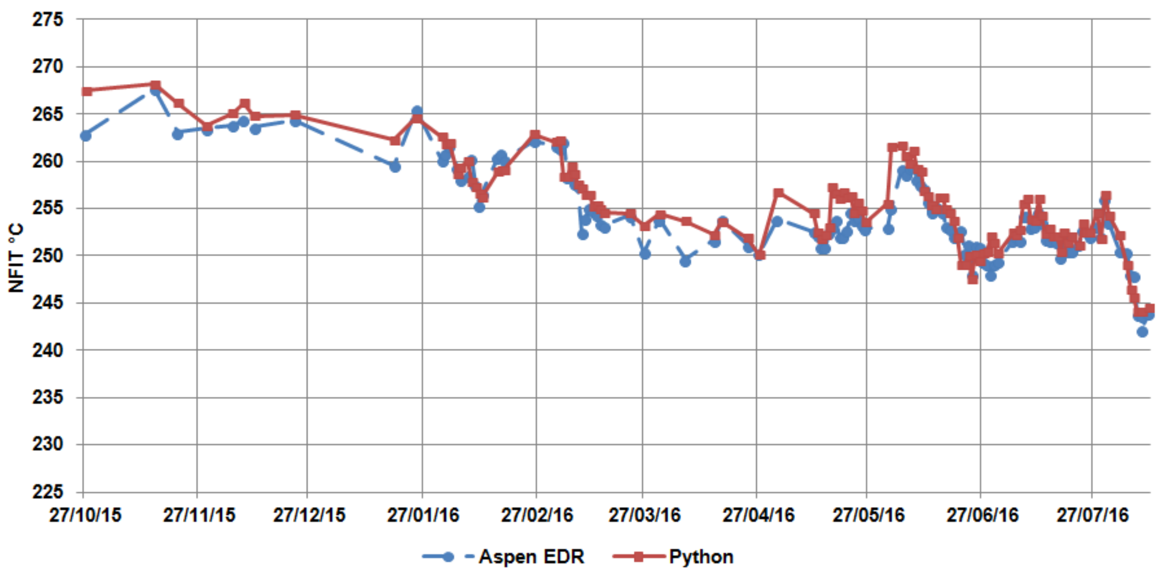

Figure 4: Comparison of NFIT values calculated using Aspen EDR and Python

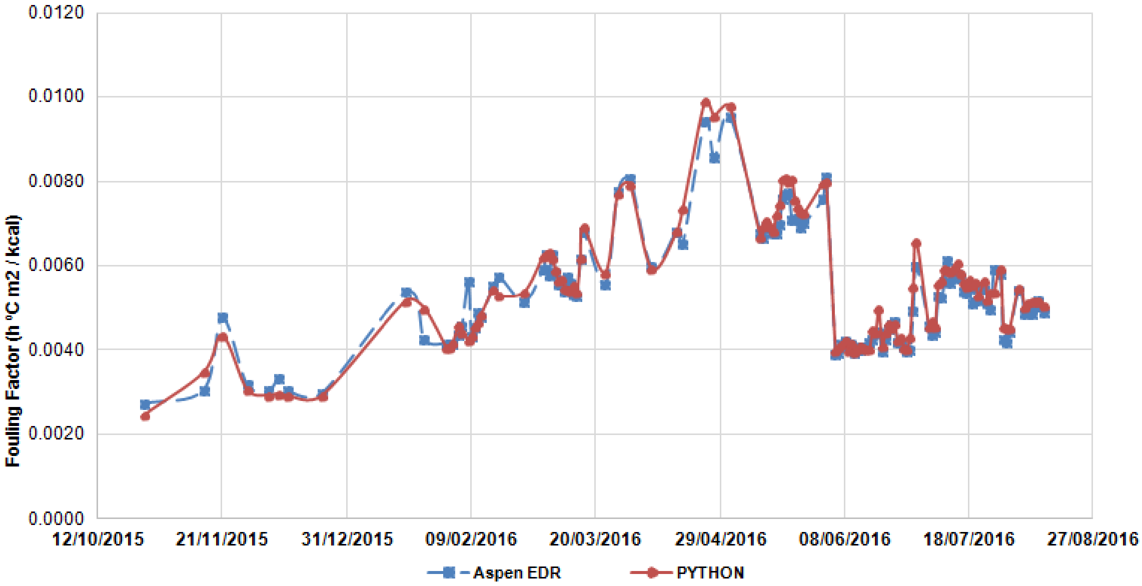

Figure 5: Comparison of fouling values for the HX E5C

4.5 Economic impact of cleaning a group of Heat Exchangers

The overall fouling of the HEN increases over time. However, not all heat exchangers are equally important for the heat recovery in the train since most of the heat is recovered in the last four exchangers (crude oil versus column fractionator bottoms). In addition, even though cleaning a heat exchanger will always increase the overall performance and, as a result, increase the NFIT value, it may not be obvious how to choose the heat exchanger that return the best return on investment.

For this case, an additional subroutine in Python was written to determine which clean heat exchanger provided the greatest increase in the NFIT. The fouling considered for the clean case was not zero, since a mechanical cleaning cannot achieve such value. Instead, an average value of the fouling for the first 15 days of operation since the last cleaning was used. The fouling value was used to calculate the expected increase in NFIT value as a result of the cleaning.

In addition, the program calculated the economic savings in fuel oil not burned in the fired heater over a month period after the cleaning. It also took into account the cost of the cleaning service (12 KUS$ per heat exchanger) and the additional fuel burned in the fired heater during 15 days period that the heat exchanger is out of service. The expected savings when cleaning the HX E9C/B were 6.8 KUS$ after the first month. For the next three months the expected savings were 194 KUS$.

5. Conclusion

The present work showed that the monitoring of the overall fouling of a Heat Exchange Network can be done with a procedure written in the Python Programming Language since it returns similar results to the values calculated by commercial software (Aspen Hysys + EDR). This approach has also advantages over commercial fouling monitor software since it can accommodate the particular configuration of a given plant, automatically retrieve data from the Plant Information System and can be implemented using Open Source software without cost to the end user. In addition, the proposed methodology helps to select the heat exchanger with the greatest effect in the HEN and to timely propose a cleaning schedule that can provide a significant return of investment and help to reduce CO_2 emissions.

6. References

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