Benefits of optimizing the cleaning schedule in crude preheat trains

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Abstract

Crude oil fouling in refinery preheat trains can impact throughput and result in higher energy use. Significant savings can be achieved by optimizing the cleaning schedule of heat exchangers in the crude preheat train. Effective monitoring of operating data (temperatures, flow rates, and pressures when available) requires detailed heat exchanger and network models. The data can then be used to determine the parameters of a dynamic predictive fouling model representative of the refinery operation and crudes being processed. After the current fouling behavior is established, the model can predict future fouling behavior and network performance, including the impact of various heat exchanger cleaning schedules. The paper discusses a study showing the benefits and improvements in energy management KPIs [key performance indicators] from using simulation of heat exchanger networks combined with economic analysis in an oil refinery.

Introduction

Crude preheat trains are networks of heat exchangers that preheat the crude oil from atmospheric conditions to furnace inlet temperature before it enters the furnace and then flows to the separation columns. Due to the complex nature of the crude oil and the severe operating conditions of the preheat trains, the crudes are subject to fouling. These unwanted deposits on heat transfer surfaces can result in undesired operation, such as reduction in overall heat transfer, reduction in production, increase in furnace fuel consumptions and emissions, and possible plant shutdowns.

ENAP (Empresa Nacional del Petroleo) is a state-owned Chilean oil company. A study in 2007 for the Topping 1 unit at ENAP Refinerias S.A. in Concón, Chile, revealed that during every plant shutdown, the plant loses approximately US$ 14 million based on an equivalent loss of throughput (Padilla, 2007). The loss was calculated as a result of a reactive strategy carried out to mitigate fouling. This paper includes analysis of two of their crude preheat trains, the first (Topping 1) with a throughput of ~54,000 bbl day\(^{-1}\) and the second (Topping 2) with a throughput of ~36,000 bbl day\(^{-1}\). No systematic method is currently used to monitor and analyze the performance of the heat exchangers, and instrumentation is sparse.

Fouling in preheat trains is, in normal operation, a chronic event, and it would be important to quantify the losses caused by fouling on a daily basis. Effective techno-economic decisions in the refinery require monitoring and analysis of data, as well as an improved understanding of fouling dynamics for accurate performance prediction. Examples of this informed decision-making include desalter temperature control through fouling prediction and heuristic cleaning scheduling in an Argentinian refinery (Ishiyama et al., 2010), crude preheat train operation subject to furnace firing capacity in a UK refinery (Ishiyama et al., 2013) and quantification of deposit ageing in a Swedish refinery (Ishiyama et al., 2017). In this paper, we quantify the approximate daily penalty caused by fouling (quantified as the daily penalty cost) and propose a cleaning schedule to be performed while the plant is in operation. The analysis was performed with SmartPM, a thermohydraulic heat exchanger network tool that monitors performance and analyzes predictive maintenance scenarios for heat exchanger networks subject to fouling. This paper refers to SmartPM as the simulator. The KPIs highlighted in this manuscript are the daily energy penalty (due to fouling), furnace duty savings, and CO\(_2\) emission savings.
Model construction

Detailed heat exchanger specification sheets, P&ID, stream thermophysical properties, and monitoring data are entered in the simulator for the construction of preheat train models (Figure 1 and Figure 2) of the preheat train downstream of the desalter. Shells in series are modeled as separate shells because the fouling behavior of each shell is different. The simulator uses the stream analysis method to perform detailed heat transfer and pressure drop calculations for each shell, and the results can be viewed for each exchanger over the simulated period.

Figure 1: Topping 1 preheat train model (post desalter).

Figure 2: Topping 2 preheat train model (post desalter).

The monitoring data include temperature and flow measurements over four years (from January 2014 to January 2018). The simulator reconciles the data, fitting the measurements to a heat and mass balance while simultaneously generating heat exchanger performance information. During the data reconciliation process, any missing stream flows or temperatures is generated, enabling performance analysis even with sparse monitoring data.

During the data reconciliation process, the simulator also compares the energy economic losses due to fouling with representative ‘base case’ conditions. For this example, the base case uses operating conditions on 01/04/2014 for Topping 1 and 03/09/2016 for Topping 2, with dates given in DD/MM/YYYY format. Figure 3 illustrates that Topping 1 has an average daily energy penalty of
approximately US$ 5000 and Topping 2 has an average daily energy penalty of approximately US$ 1000 (assuming an energy cost of US$ 6.25 per GJ).

(i)  

![Daily Energy Penalty for (i) Topping 1](image1)

(ii)  

![Daily Energy Penalty for (ii) Topping 2](image2)

Figure 3: Daily Energy Penalty for (i) Topping 1 and (ii) Topping 2. Dashed horizontal lines show average daily energy penalty over the historical period.

After the data reconciliation process is complete, the simulator plots heat exchanger performance with the fouling behavior. For example, Figure 4 shows performance parameters such as heat duty, shear stress, and film temperature plotted above the fouling resistance.

Following data reconciliation, the simulator uses dynamic fouling models to fit the fouling behavior of each shell to its operating conditions. A dynamic fouling model is a model that describes the rate of fouling for a given fluid and surface as a function of operating temperature (e.g. bulk, surface, or film temperature) and operating shear stress. An example of such dynamic fouling model (Wilson et al., 2015) is

\[
\frac{dR_f}{dt} = \frac{FPF}{h} \exp\left(-\frac{E}{RT}\right)P
\]  

(1)
Here, \( \frac{dR}{dt} \) is the rate of fouling, \( FPF \) is the fouling propensity factor, \( h \) is the film transfer coefficient, \( E \) is the activation energy, \( R \) is the gas constant, \( T \) is the film temperature, and \( P \) is the probability of attachment.

Figure 4: An example exchanger overview plot showing exchanger duty, crude-side surface shear stress, crude-side film temperature, and fouling resistance.

Formulation of cleaning scheduling

Using the dynamic fouling model described in Equation (1) together with a cleaning cost of US$ 20000 per shell and an energy cost of US$ 6.25 per GJ, the simulator generates heuristic cleaning schedules representing (i) which exchangers to clean on a specific date and (ii) which unit to clean when. This section describes the cleaning schedule generated for Topping 1 only.

Figure 5 shows the generated list of top exchangers to clean (or not to clean) on a specific date (in this case, 01 January 2018). The cost of cleaning incorporates the labor cost and the additional energy required by the furnace when the exchanger is offline. The network duty increase is usually less than the individual shell duty increase due to the network interactions. An example is highlighted in Figure 6.
Cleaning is considered an investment. Cleaning events are based on an economic analysis of the return on investment over a specified period of time. Any specified practical operational or safety constraints could dominate this economic decision-making. Figure 7 shows the generated cleaning schedule for two years, with the predicted cleaning budget required during each period of the proposed schedule. Figure 8 summarizes economic performance. The total energy savings in that period is approximately US$ 2.69 million (US$ 1.04 + 1.65 million). The energy savings in the second year is higher than the energy savings in the first year because some of the benefits of cleaning in the first year are realized in the second year.
Conclusions

ENAP implemented a performance monitoring and predictive maintenance system for two preheat trains. A simulator, SmartPM, used exchanger geometry and operational data to simulate detailed exchanger performance, enabling the generation of any missing or incorrect flow and temperature measurements.

Analysis of the existing plant performance identified a dynamic fouling model linking the individual shell operating conditions with the fouling rate. The resulting techno-economic analysis identified exchangers to clean on a specific date in the descending order of benefit. The software also generated a heuristic cleaning schedule identifying which units to clean and when.

The simulation analysis of Topping 1 presented in this paper shows a potential energy savings of approximately US$ 2.7 million over the next two years based on the generated heuristic cleaning schedule. The analysis illustrates the benefit for ENAP of using a performance monitoring and predictive maintenance tool to quantify techno-economics of the preheat train.

Reference


Figure 8: Summaries of cleaning economics: (a) annual total net energy savings, (b) average furnace duty saving and annual CO₂ emission savings in metric tons.
Nomenclature

\[ E \] activation energy, J mol\(^{-1}\)
\[ FPF \] fouling propensity factor, h\(^{-1}\)
\[ h \] film transfer coefficient, W m\(^{-2}\) K\(^{-1}\)
\[ P \] probability of attachment
\[ R \] gas constant, J mol\(^{-1}\) K\(^{-1}\)
\[ R_f \] fouling resistance, m\(^2\) K W\(^{-1}\)
\[ T \] film temperature, K
\[ t \] time, h

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