CHEMICAL ENGINEERING TRANSACTIONS

VOL. 94, 2022

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Yee Van Fan, Jiří J. Klemeš, Sandro Nižetić

ISBN 978-88-95608-93-8; **ISSN** 2283-9216

DOI: 10.3303/CET2294156

Fouling Management in Crude Oil Heat Exchangers using Plant Data

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It has been reported that about 50% of the total amount of fuel in an oil refinery plant is consumed in crude oil and vacuum distillations. Thus, the heat exchanger networks of crude oil distillation units significantly affect the overall energy efficiency and CO_2 emissions of refinery plants. Crude oil fouling in heat exchanger networks is one of the most troublesome problems in crude oil refineries. It reduces heat transfer amount or blocks the flows in tubes, leading to requiring additional fuel for the furnace following heat exchanger networks. Therefore, many cleaning methods have been developed. Mechanical cleaning of heat exchangers is the most effective method to mitigate the fouling in heat exchangers. However, it is necessary to open heat exchangers for cleaning. So, the timing of mechanical cleaning is limited because the normal refinery operation must be stopped. Therefore, to keep the good energy and economic performance of the refinery, it is necessary to predict the appropriate maintenance timing and to conduct a suitable cleaning. To find a suitable cleaning schedule or timing, the authors proposed a method for predicting fouling resistance in near future for crude oil fouling from actual online plant data in this research. The prediction results are in good agreement with the measured results, which demonstrate that the proposed method is effective for predicting the cleaning timing for the industry in the future.

1. Introduction

Oil refinery plants are very important plants for our daily lives because we owed many petroleum products such as fuels and chemicals. It is often heard that oil refinery plants still consume plenty of energy. Although many heat integration or recovery technologies have been installed in oil refineries since the 1970s, it is reported that about 5% of treated crude oil is still used as fuel in an oil refinery. By analysing the total energy consumption of oil refinery, it has been reported that about 50% of the total amount of fuel in an oil refinery plant is consumed in the crude oil and vacuum distillation units (Kansha et al., 2012). Therefore, it is natural to have designed heat exchanger networks for crude oil distillation and to have developed optimization methods for the heat exchanger networks of crude oil distillation units (Promvitak et al., 2009).
Crude oil fouling in the heat exchanger networks for crude oil distillation units is one of the most crucial issues in the operation of oil refineries because it strongly affects the operation and utility costs (Smith et al. 2017). Generally, oil refinery plants have a regular maintenance period. During this period, all regular operations of the refinery are stopped. Needless to say that the heat exchanger networks are also cleaned during the period to maintain high heat transfer amounts. In this case, heat exchangers are opened and foulants that cause fouling in heat exchangers are mechanically removed by water flow or jets. However, it must be costly and difficult to often conduct a mechanical cleaning in actual plants (Coletti and Hewitt, 2015). Therefore, a chemical cleaning such as mixing chemical solvents or treated oils into the inlet streams of heat exchangers is often conducted instead of mechanical cleaning. However, foulants are normally mixed substances of organic and inorganic materials (Speight, 2015). Therefore, it sometimes does not match the suitable material to prevent fouling, leading to no or less heat transfer improvement.
To overcome the issue, many researchers have investigated the dynamic behaviour of physical and chemical properties (Deshannavar et al., 2010), and an overall heat transfer coefficient or a thermal fouling resistance of the heat exchanger (Ishiyama et al., 2017) and developed several fouling models based on chemical (Watkinson and Wilson, 1997) or empirical characteristics (Loyola-Fuentes and Smith, 2018). Furthermore, some

Paper Received: 15 April 2022; Revised: 19 May 2022; Accepted: 25 May 2022
Please cite this article as: Kansha Y., Horikoshi S., Kiyomoto H., Kato S., Mei X., 2022, Fouling Management in Crude Oil Heat Exchangers using Plant Data, Chemical Engineering Transactions, 94, 937-942 DOI:10.3303/CET2294156

researchers conducted the optimization of cleaning schedules (Wang et al., 2021), retrofitting under consideration of cleaning (Yanyongsak and Siemanond, 2018), or fault detection based on these models (Loyola-Fuentes and Smith, 2019), or developed new chemical solvents for fouling prevention.
In this research, to find the suitable cleaning timing, a simple method for predicting a thermal fouling resistance in near future for crude oil fouling in the heat exchanger networks from actual plant data was proposed. Initially, available data from oil refineries were stochastically analysed to capture the relationship between the thermal fouling resistance and the other data. Then, a data-driven linear model to predict the future fouling resistance was constructed by following the analysis.

2. Methodology

The actual data related to the heat exchanger networks such as inlet/outlet temperatures, flow rate, and so on were obtained from four Japanese oil companies; Cosmo Oil Co., Ltd., ENEOS Corporation, Idemitsu Kosan Co., Ltd., and Taiyo Oil Company, Limited. All targeted heat exchangers are categorized into a shell and tube type. The available data from four different refinery plants (A, B, C, and D) located in Japan were stochastically analysed by interquartile range to get rid of outliers at the first step and measured Pearson correlation coefficients as measuring collinearity among overall heat transfer coefficients and other values around heat exchangers to identify data significances to the fouling in heat exchangers. Normally, crude oil fouling strongly occurs at higher temperature heat exchangers. Therefore, correlation coefficients of data sets around heat exchangers just before the furnace (last heat exchangers of heat exchanger networks for crude oil distillation units) in each refinery were examined as targets for fouling in this research. It is noted that these four refineries equip different processes and treat different types of crude oils as shown in Table 1. Therefore, we cannot apply the same fouling models. After examining all correlation coefficients, it was founded that overall heat transfer coefficients (U) have a strong linear relationship with processed flow amounts from the previous cleaning. The correlation coefficients between U and processed flow amounts are summarized in Table 1. It can be seen that most of the cases have strong negative linearity (correlation coefficients > 0.7). This means that the heat transfer rate decreases with the processed flow.

Table 1: Correlation coefficients between U and processed flow amounts and data characteristics

Refinery	negative value of correlation coefficients	Number of data sets	Maximum Crude Oil Temp. [K]
A	0.776-0.953	14	565
B	0.692-0.950	12	562
C	0.723-0.848	3	533
D	0.856-0.903	2	515

In theory, an overall heat transfer coefficient (U) of the heat exchanger [J m^{-2} s^{-1} K^{-1}] can be determined by

$$U = \frac{Q}{A(\Delta T)_{\mathrm{lm}}} \tag{1}$$

where Q is a heat transfer amount in the targeted heat exchanger [J s^{-1}], A is a heat transfer surface area [m^2], and $(\Delta T)_{\mathrm{lm}}$ [K] is a logarithmic mean temperature difference in the heat exchanger.

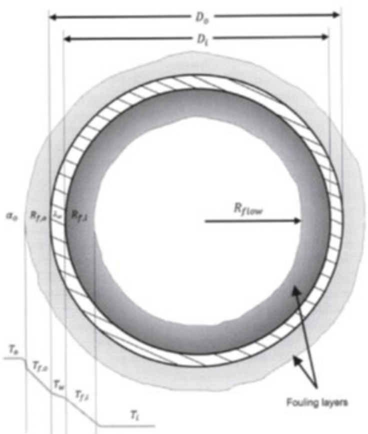

Figure 1: Temperature profiles on a heat transfer surface and fouling image of a tube (Coletti and Hewitt, 2015)

Coletti and Hewitt (2015) reported the overall heat transfer coefficient during fouling developing periods considering a tube in a heat exchanger as shown in Figure 1 can be represented by the following equation:

$$U = 1/\left[1/\alpha_o + D_o/(\alpha_i D_i) + R_{f,o} + D_o R_{f,i}/D_i + D_o/2\lambda_w \ln(D_o/D_i)\right] \tag{2}$$

where α is a heat transfer coefficient [J m^{-2} s^{-1} K^{-1}], D is tube diameter [m], R_f is a fouling resistance [m^2 s K J^{-1}], and λ_w is the thermal conductivity of the tube [J m^{-1} s-^{1} K^{-1}]. Furthermore, a subscript o denotes an outer and a subscript i denotes an inner the tube.
The targeted heat exchangers are shell and tube types and the current thermal fouling resistance of tube side (R_f) can be simply examined using the difference of U as follows:

$$R_f = \frac{1}{U} - \frac{1}{U_0} \tag{3}$$

where U_0 is a cleaned overall heat transfer coefficient during induction periods.
Bayat et al. (2012) reported the fouling two periods, induction and developing periods, as shown in Figure 2.

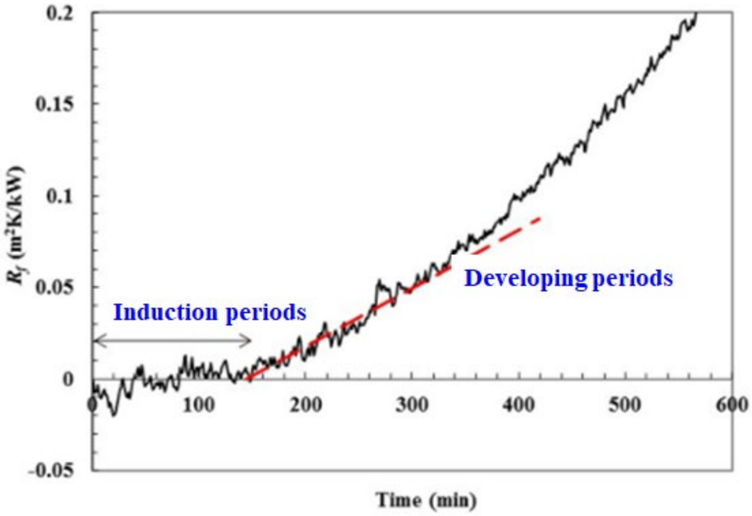

Figure 2: Fouling induction and developing periods (Bayat et al., 2012)

Wang et al. (2015) reported the developing periods can be divided into two; exponential deposition, and asymptotic fouling in a typical idealized fouling curve. However, asymptotic fouling is short or cannot be observed in many of the data sets obtained from refineries. This might be because all refineries in Japan often have conducted the cleaning before showing severe effects on the normal operation. In fact, according to our collinearity analysis, thermal fouling resistance (R_f) during developing periods proportionally increases with the processed flow amount in many cases.
Therefore, the linear model to predict R_f will be created as follows:

$$R_f = aP_{\mathrm{sum,x}} + b \tag{4}$$

where P_{sum} denotes a total processed flow amount [m^3] at a certain period (x) and a and b are linear parameters. Considering induction periods, it is difficult to determine the exact U_0 due to unstable characteristics, and U_0 itself must be constant. Furthermore, the length of the induction period cannot be determined due to differences of cleaning ways and the processed crude oils. Therefore, we modify the definition of R_f represented by Eq(3) to the following equation in this paper.

$$R_f \cong \frac{1}{U} \tag{5}$$

Then, R_f becomes independent value from $U_{0,}$ and a threshold of thermal fouling resistance for cleaning, R_{fmax}, can be defined without considering any other parameters as shown by a red line in Figure 3.
a and b in Eq(4) are examined by the obtained data until a certain period (x) as the training data and the suitable cleaning timing represented by processed flow amount ($P_{\mathrm{sum,max}}$) can be determined by

$$P_{\mathrm{sum,max}} = 1/a\left(R_{f,max} - b\right) \tag{6}$$

The red line in Figure 3 can be perfectly fitted when $b = 1/U_0$. However, the suitable cleaning timing would shift to later than the real cleaning timing in the case of a long induction period as shown in Figure 3. To avoid such a situation, the other option to predict future R_{fmax} and the suitable cleaning timing was proposed. In this option, b in Eq. (6) will be updated until R_f has a minimum value as shown by a blue line in Figure 3. In this case, the exact induction period is still unknown, the prediction becomes better. This idea follows the characteristics of the thermal fouling resistance increase with processed flow amount.

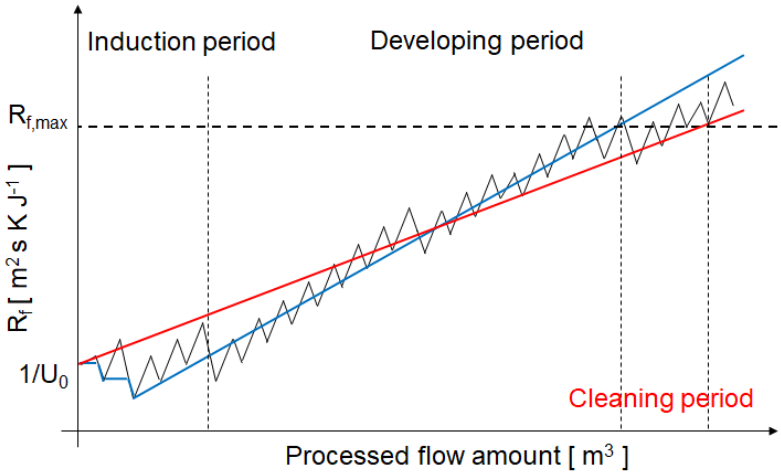

Figure 3: A schematic image of the proposed prediction of thermal fouling resistance

The series of actions to predict future R_f and to predict the suitable cleaning timing are summarized;

(1) Online data, thermal fouling resistance (R_f), and total processed flow amount (P_{sum}), at this moment is prepared as training data.
(2) From the data, the coefficient (a) is obtained by linear regression. The other parameter (b) is fixed as $1/U_0$ (option 1) or updated as the minimum R_f (option 2). Furthermore, the prediction model of R_f is created.
(3) $R_{f,max}$ which determines a cleaning is set as a threshold.
(4) From the prediction model of R_f, $P_{\text{sum,max}}$ would be obtained following Eq(6)
(5) New online data is obtained, go to (1).

3. Case studies

The prediction validation was conducted in data sets of refinery A. $R_{f,max}$ was determined at 0.01 [m^2 h K kcal^{-1}] (≒8.6 [m^2 s K kJ^{-1}]). The results are shown in Figure 4. Figure 4 a) shows the change of cleaning timing. The red line shows the prediction results of option 1 associated with the processed flow amount. The blue line shows those of option 2. Figure 4 b) shows the change of actual R_f vs the processed flow amount.

It can be understood from Figure 4 that option 1 predicts the cleaning timing later than the actual predicting timing. This is simply because the initial value of R_f=$1/U_0$ is too large. It must be an outlier. Furthermore, the induction period continues at around 1000×10^3 [m^3] as processed flow amount. When the induction period is long, the prediction of the cleaning timing of option 1 becomes later. On the contrary, it can be seen from Figure 4 that option 2 predicts the cleaning timing well around the intersectional points at $R_{f,max} = 0.01$ [m^2 h K kcal^{-1}]. Among 14 data sets of refinery A, seven data sets have conditions that R_f is larger than 0.01. Considering these seven data sets, option 1 around the intersectional points at $R_{f,max} = 0.01$ [m^2 h K kcal^{-1}] predicted the cleaning timings were three cases predicted with less than $\pm 10\%$ errors. However, in the other four cases, the prediction by option 1 has large errors (larger than $\pm 20\%$). These are simply because the reason same as the above mentioned. On the contrary, option 2 around the intersectional points at $R_{f,max} = 0.01$ [m^2 h K kcal^{-1}] predicted the cleaning timings were six cases predicted with less than $\pm 10\%$ errors. The large prediction errors take place in only one sets (larger than $\pm 20\%$). These prediction error distribution was summarized in Table 2.

R_f, which caused large prediction errors in option 2, gradually increases initially.

However, the value of R_f suddenly decreases at once during processing as shown in Figure 5. Therefore, the prediction errors were large. In this data set, option 1 also has the large prediction errors categorized as larger than $\pm 20\%$.

Although the prediction accuracy of option 1 is less than that of option 2 in this case study, option 1 is much simpler than option 1. Furthermore, the prediction might be improved when the outlier should be got rid of the data sets by the appropriate method. When the threshold to determine outlier makes smaller, the initial R_f as shown Figure 4b) will be removed. Then, the R_f increasing following with processed flow amount. Therefore, the initial prediction becomes much better. Therefore, it must be significant for creating appropriate method for outlier removal.

Table 2: Summary of prediction errors distribution among seven data sets

Option	±5% errors	±10% errors	±20% errors	±30% errors	others
1	2	1	0	3	1
2	3	3	0	1	0

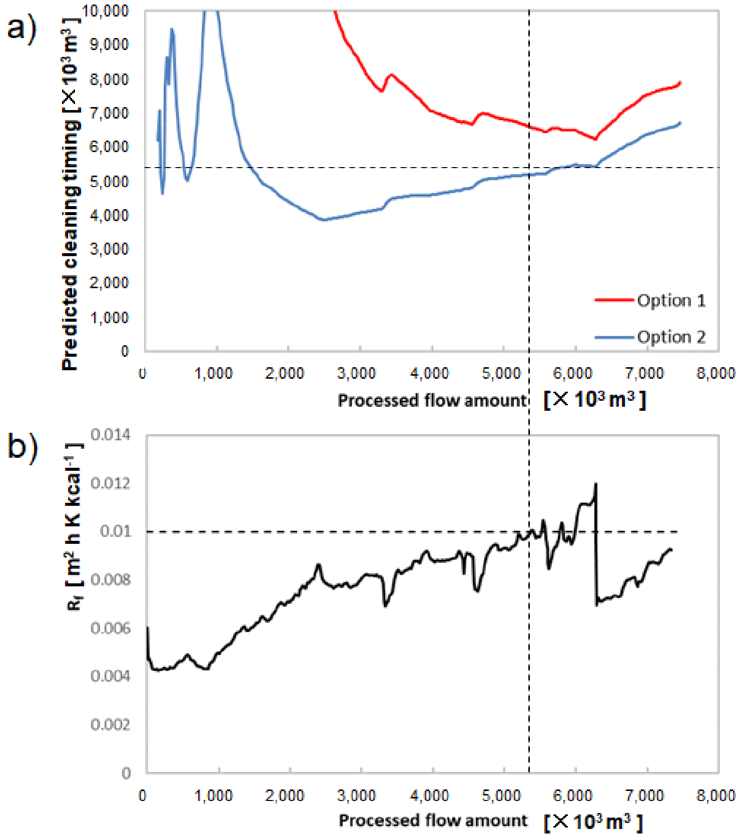

Figure 4: Prediction validations; a) the change of predicted cleaning timing, b) actual R_f vs processed flow amount

4. Conclusions

In this research, a simple linear model for predicting a future thermal fouling resistance was developed through stochastic analysis of actual plant data. Furthermore, the suitable cleaning timing was estimated by the proposed linear model with two options for thermal fouling resistance in the heat exchanger networks.

The data sets obtained from four different refineries were analysed to catch the common characteristics of crude oil fouling. According to our analysis, thermal fouling resistance proportionally changes with the processed flow amount. From this result, a simple linear model was proposed. Using this linear model, the suitable cleaning timing was estimated. The estimation results are well-matched with the actual data in many cases. From these results, the proposed linear thermal fouling model can be used for the prediction of suitable cleaning timing.

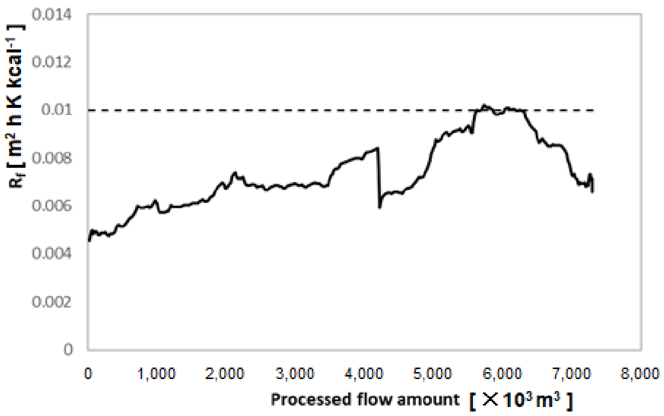

Figure 5: Prediction validations; actual R_f vs processed flow amount

Acknowledgments

The authors gratefully acknowledge the historical dataset provided by member companies (Cosmo Oil Co., Ltd., ENEOS Corporation, Idemitsu Kosan Co., Ltd., and Taiyo Oil Company, Limited) of the fouling prevention committee in the Society of Chemical Engineering, Japan.

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