DEVELOPMENTS IN OPTIMAL SCHEDULING OF CLEANING ACTIONS FOR HEAT EXCHANGER NETWORKS SUBJECT TO FOULING

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ABSTRACT

Scheduling cleaning actions in a heat exchanger network subject to fouling and operating continuously over a long time period (*e.g*. a crude oil distillation preheat train) is a challenging optimisation task. A further complication is that there is often considerable uncertainty over the values of key operating parameters, particularly fouling rates. This paper reports a new approach to the scheduling problem. It exploits the recent finding that the problem exists characteristics of an optimal control problem which can be solved using ‘bang bang’ control methods. This allows uncertainty in fouling model parameters, clean overall heat transfer coefficients and cost parameters to be included within the scheduling calculations. Results are presented for a network consisting of 10 exchangers. The sensitivity to each parameter is considered for both linear and asymptotic fouling scenarios.

INTRODUCTION

The occurrence of fouling in heat transfer systems which operate continuously results in the need to clean some units on a regular basis. This can determine the operating time for a process, as in the dairy sector, where units operate for a period and are then subject to cleaning-in-place for a given cleaning time. The overall productivity of the process is determined by the balance between manufacturing and cleaning operations, and mathematical models for optimizing this have existed for some time, *e.g*. [1]. Developments in this area have included consideration of the effect of ageing on cleaning, via the formation of deposits which are harder to remove [2-6], and the linked scenario where management of cleaning involves a selection of cleaning method [7]. The mathematical methods used to solve the associated optimisation problem range from standard gradient techniques to multiple integer non-linear programming (MINLP) ones.

The optimisation problem associated with management of cleaning for a continuous process which must continue operating is more complex. This can either be managed by (i) having duplicate exchangers available to take up the duty, *e.g*. standby units which operate in parallel, as considered in [8], or (ii) accepting a period of reduced overall performance of a heat exchanger network consisting of many exchangers where the absence of units for cleaning are partially compensated by the change in duties on other units as a result of changes in temperature driving forces. The latter scenario is the one regularly encountered with oil refinery crude distillation preheat trains, where the hot products from the atmospheric and vacuum distillation columns are used to preheat the incoming crude oil stream in order to reduce the duty required in the furnace upstream of the atmospheric distillation column. The preheat trains are required to operate continuously between refinery shut-downs, for periods lasting several years, and intermediate cleaning actions are required in order to counter the effect of fouling on the temperature of the crude entering the furnace (reducing it, so that a furnace firing limit may be reached) or pressure drop across the network (increasing it, possibly resulting in hot crude vapourising in exchangers and/or leading to a reduction in throughput). With an extended operating period, the question associated with cleaning management is ‘When to clean which exchanger?’, first posed in [9].

The associated optimisation problem is complex because cleaning actions reset the state of the network and there are therefore many potential solutions. Furthermore, the full problem model may be highly nonlinear, involving both difficult to linearise fouling resistance kinetic forms, and also bilinearities in the material balances if variable flow rates are considered. There has been a steady research effort into mathematical methods for solving the type of optimisation problem generated by the above cleaning schedule question. Discretising the time horizon into discrete periods (often quantized in terms of the length of time taken to remove, clean and reconnect an exchanger

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from a network, e.g. one week) yields an MINLP problem which has been considered by standard and new methods (e.g. [8, 10-15]: a comprehensive review of the literature is not provided here, but can be obtained by a citation search on these papers). The underlying problem is non-convex, which means that guaranteeing that the results obtained include the globally optimal result require considerable computational effort.

The desire to incorporate more detailed fouling model dynamics, pressure drop considerations and control actions prompted the use of simpler optimisation techniques such as the greedy algorithm [11] which, while not generating globally optimal solutions, are relatively fast and robust. These have proved capable of generating feasible cleaning schedules for refinery operations (e.g. [16, 17] and have been incorporated in commercial software tools for managing refinery preheat train cleaning operations.

A fundamental feature of fouling in refinery preheat trains is uncertainty in fouling rates. This is linked to the variation in crude feed composition on a unit operating for periods lasting several years, changes in product slate, and changes in equipment. The effect of uncertainty in costing factors (energy, cleaning, crude price) has been considered by Bagajevic and co-workers [18, 19] but there has been little work on the effect of fouling rates. An important exception is the work by Zubair and co-workers on scheduling cleaning in individual heat exchangers [20, 21]. With networks, the methods referred to above often involve running complex simulations many times and selecting the most favourable result: to do this with a distribution of possible fouling rates to generate statistically significant results is anticipated to require excessive computational effort.

Vassiliadis and co-workers [22, 23] recently showed that the form of the optimisation problem involved in scheduling cleaning operations in heat exchanger networks (HENs) can be expressed as a multistage optimal control problem, whose solutions are found on surfaces defined by the constraint set. This feature, known as 'bang-bang' control, can be exploited to generate solutions requiring considerably less computational effort. It also removes the need to impose a set of allowed times at which cleaning is performed. This work has been followed by a paper [24] that exploits this feature in considering uncertainty in fouling rate parameters directly. Uncertainty in model parameters for HEN models plays a paramount role in basing decisions on them, and that work demonstrated for the first time an efficient way for its inclusion in general nonlinear HEN models.

This paper presents a summary of this development, reporting the key points. One of the case studies in the paper is presented. The reader can find a second case study, and the mathematical details, in the original paper.

PROBLEM FORMULATION

The heat exchanger scheduling problem can be written as an optimal control problem (OCP) where the property to be optimized (usually the total operating cost including energy consumption, cleaning and lost production) is subject to control and differential algebraic equations. The problem features differential and algebraic state variables as well as binary control variables, and belongs to the class of multiple integer OCPs, or MIOCPs. To solve the problem, the time horizon is split into a number of periods in which cleaning decisions are made. The length of each period is not specified: this is calculated as part of the solution procedure. When the control actions in the relaxed multistage MIOCP are linearly related to the process variables, the optimal control for the relaxed MIOCP exhibits bang-bang behaviour [25] and the control action exists at either bound of the feasible region. This is described in detail in [22, 23].

The objective function is defined in terms of total operating cost over the time horizon t_F:

$$Obj = \frac{\left(\sum_{s=1}^{S}\int_0^{t_F}\frac{C_{E,s}Q_{F,s}(t)}{\eta_F}dt\right)}{S} + \sum_{p=1}^{NP}\sum_{n=1}^{NE} C_{cl}\left(1-y_{n,p}\right) \quad (1)$$

The first term is the cost of energy consumed in the furnace and the second term is the cost of cleaning actions: setting $y_{n,p} = 0$ results in exchanger n being cleaned in period p. The symbols are defined in the Nomenclature. Calculating the furnace firing duty requires a simulation of the network thermal performance: this work employs the set of linear equations linking heat exchanger inlet and outlet temperatures presented previously (e.g. [11]), where the performance of an individual exchanger is modelled using the NTU-effectiveness method with overall heat transfer coefficient U and fouling behaviour is quantified using a single lumped thermal resistance, R_f:

$$R_f = \frac{1}{U} - \frac{1}{U_{clean}} \quad (2)$$

Here, U_{clean} refers to the clean state. Both linear (constant rate) and asymptotic fouling behaviours are considered, *viz*.

$$\frac{dR_f}{dt} = a \quad (3)$$

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$$R_{\mathrm{f}} = R_{\mathrm{f},\infty}\left(1 - e^{-t'/\tau}\right) \quad (4)$$

with parameters $\{a\}$ and $\{R_{\mathrm{f},\infty},\ \tau\}$, respectively. In Eqn. (4), t' is the time elapsed since the last cleaning action and τ is the characteristic timescale for fouling.

The first term in *Obj* is where the uncertainty in the fouling model(s) and other operating parameters is incorporated in the formulation. A series of scenarios (labelled *s*, total number *S*) is considered in which the value of the uncertain parameters $\{a$ or $R_{\mathrm{f},\infty}$, τ, U_{clean} and $C_{\mathrm{E}}\}$ is assigned a random value, normally distributed about the mean of that property. The normrnd function in MATLAB® was used for this. The sensitivity of the solutions to an individual parameter is considered by setting the value of the other parameters to their mean. This approach to incorporating uncertainty has advantages in the size of the optimisation problem, outlined in [24], including the feature that the approach is highly parallelisable.

The calculations were peformed in MATLAB® with its Optimisation Tool-box™ and Parallel Computing Tool-box™ on a 4 GHz Intel Core i7 16GB RAM iMac running macOS Sierra. Further details of the implementation are given in [24].

CASE STUDY

Scheduling of cleaning is considered for the crude oil preheat train network involving 10 exchangers presented in Fig. 1. The case study employs constant flow rates over a period of 18 months, a furnace efficiency of 85% and a common clean overall heat transfer coefficient value of 88.1 Btu/ft^2/°F/h (500 W/m^{2}K). The crude (cold stream) temperature dropped by 18°F (10 K) over the desalter.

Costing parameters were C_{E} = 2.93 £/MM Btu and C_{cl} = £4000, with a cleaning time of 0.2 month (6 days), taken from [11]. One cleaning episode (of potentially more than one exchanger) was allowed each month. Only one of exchangers 1-4 was allowed to be cleaned in any one month, and only one of exchangers 5-7 could be cleaned in any one month.

The thermal performance parameters are summarised in Table 1 while the average value of the fouling model parameters is summarised in Table 2.

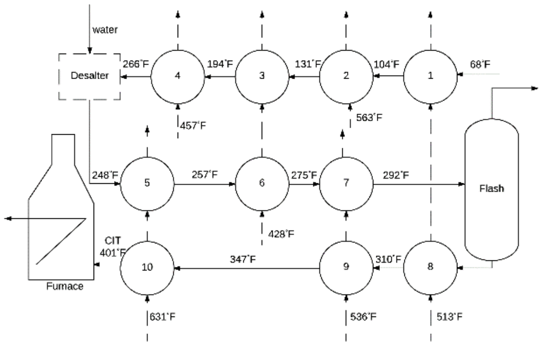

Fig. 1 Schematic of crude oil preheat train HEN. Circles indicate heat exchangers; solid line – crude oil path; dashed lines –hot streams; CIT is the coil inlet temperature in the furnace. The temperatures shown are for the start of the simulation, when all the heat exchangers are clean. Reproduced from [24], with permission.

Table 1. Case study network parameters (see Fig. 1). Symbols defined in the Nomenclature.

HEX	F_{h}	F_{c}	C_{h}	C_{c}	A
	klb/h		Btu/ft^2/°F		ft^2
1	141	721	0.67	0.46	465
2	738	721	0.70	0.46	287
3	423	721	0.62	0.46	1192
4	429	721	0.62	0.46	1488
5	208	721	0.67	0.55	183
6	423	721	0.62	0.55	546
7	210	721	0.69	0.55	492
8	141	649	0.67	0.57	437
9	283	649	0.69	0.57	885
10	208	649	0.67	0.57	1257

Table 2. Fouling parameters. Bar indicates that these are average quantities, subject to variation.

HEX	$\bar{a}$	$\overline{R_{\mathrm{f}}^{\infty}}$	$\bar{\tau}$
	ft^2°F/Btu	ft^{2}h°F/Btu	month
1	1.23	1.61	4
2	1.84	2.41	4
3	1.23	1.61	4
4	1.64	2.14	4
5	3.07	4.02	4
6	2.25	2.95	4
7	3.07	4.02	4
8	3.27	4.29	4
9	3.68	4.82	4
10	3.88	5.09	4

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Linear fouling

The optimised cleaning schedule for the case where no uncertainty was considered, *i.e.* the deterministic result, incurred a cost of £260k. The effect of the number of samples, S, considered in the uncertainty calculation was tested with a set relative standard deviation (RSD) of 10% in the four process parameters. Each test used a fresh set of parameter values (*i.e.* data for S = 20 were calculated from scratch, not by adding 10 tests to the S = 10 result). The results are summarised in Table 3.

Table 3 Effect of number of samples on scheduling results: linear fouling, RSD for a, U_{clean} and C_{E} was set at 10%

S	10	20	30	40	50
Mean cost /£k	234	274	276	296	288
RSD /%	53.7	34.3	31.1	34.6	36.0
Min. cost /£k	40.8	94.0	87.1	98.9	43.7
Max. cost /£k	523	519	408	546	544
No. cleanings	9	10	10	11	10

With the exception of the S = 10 result, the mean cost exceeds the deterministic value. The S = 10 result also differs noticeably in the number of cleanings (lower than others), and the minimum cost. This demonstrates the need to include uncertainty in these scheduling calculations.

Sensitivity analyses for the process parameters subsequently employed S = 30 and four different RSD values for the parameter under consideration. The results are presented in Table 4. The number of cleaning actions for all three parameters remains similar, at 10 or 11. There is noticeably greater impact of U_{cl} and C_{E} (determining the overall thermal performance and cost, respectively) than the fouling rate, a, with strong sensitivity to U_{cl}. The latter could be interpreted in terms of the effectiveness of the cleaning action.

Fig. 2 present the distribution of results where the uncertainty in a, U_{clean} and C_{E} was considered simultaneously, with RSD = 10% and S = 30. The distribution in Fig. 2 is approximately normal with no skew, and the salient parameters are reported in Table 5

Table 4 Effect of process parameter uncertainty for the linear fouling case. S = 30.

(a) a varied

RSD	5%	10%	15%	20%
Mean cost /£k	262	266	265	266
RSD /%	1.1	2.2	3.2	4.0
Min. cost /£k	257	254	247	247
Max. cost /£k	267	275	279	293
No. cleanings	10	10	11	11

(b) U_{clean} varied

RSD	5%	10%	15%	20%
Mean cost /£k	252	269	299	303
RSD /%	17.2	38.2	43.0	60.7
Min. cost /£k	157	67.4	109	50.2
Max. cost /£k	338	483	620	836
No. cleanings	10	10	10	11

(c) C_{E} varied

RSD	5%	10%	15%	20%
Mean cost /£k	261	266	265	273
RSD /%	4.7	8.7	13.5	15.5
Min. cost £k	235	215	180	196
Max. cost /£k	283	311	338	355
No. cleanings	10	10	10	10

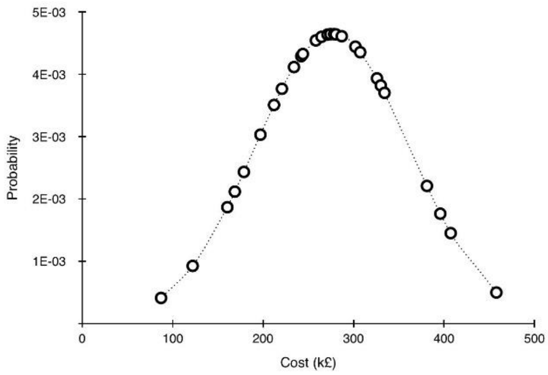

Fig. 2. Parametric sensitivity plot for linear fouling with RSD of 10% in a, U_{clean} and C_{E}. S = 30. Reproduced from [24], with permission.

The RSD of 31.1% is less than the sum of the individual components in Table 4, i.e. 2.2% + 38.2% + 8.7% = 49.1%, illustrating the need to consider the uncertainties together. The weighted average cost is the sum of all outcomes × their probability, and is similar to the median (P50) as the distribution is close to normal.

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Table 5. Summary of parametric sensitivity study results, linear fouling (see Fig. 2). P90% is the cleaning cost is the value where 10% of the runs gave a greater cost than, and 90% less than or equal to, the value.

Mean cost	276 £k
RSD	31.1%
Full width at half maximum	202 £k
Standard deviation	86 £k
Minimum cost	87.1 £k
Maxium cost	458 £k
P90%	397 £k
P50% = median cost	276 £k
P10%	168 £k
Weighted average cost	277 £k

The Table shows that the expected cost of the optimised cleaning when uncertainty is considered is 277±86 k£, which is larger than that for the deterministic case, of 260 k£. The deterministic schedule is compared with one of the schedules obtained with a cost close to P50 in Table 6. Both schedules show the absence of cleaning actions at the start and end of the time horizon reported in other studies where the exchangers start in the clean state and there no penalty associated with the state of the exchanger at t_F. The same exchangers are selected for cleaning, with the exception of 2. Exchangers 9 and 10, located at the hot end of the train, are cleaned more frequently.

Table 6. Comparison of optimised cleaning schedules for linear fouling scenario. #i indicates unit i is to be cleaned (see Fig. 2)

month	deterministic	P50
1-5	-	-
6	#10	#9
7	#9	
8	#2, #7	#10
9	#3, #5	#4, #6, #9
10	#4, #6	#3, #7
11	#8	#5, #9
12	#9, #10	#10
13-18	-	-
Total	11	10

The deterministic problem required 446 CPU s in which the HEN was simulated 2269 times. The uncertainty problem in Fig. 2 required 16 160 CPU s and 2921 simulations. The increase in CPU time (approximately 36×) is slightly larger than the value of S used (30 in this case). The extra effort is considered acceptable in order to capture the impact of uncertainty.

Asymptotic fouling

Tables 7-9 summarise the results for the case where the increase in R_f is described by Equation (4). Using 10 samples (Table 7) again gives results which differ noticeably from S > 10.Table 8 shows that the impact of uncertainty in both fouling parameters and U_{clean} is similar, and smaller than C_E. The importance of C_E in these calculations mirrors the linear fouling result. This is not unexpected as this parameter appears within the objective function, and it has been considered previously [19], albeit as a single varying parameter.

Comparing Table 8 with Table 4, asymptotic fouling gives rise to larger costs but less impact of uncertainty. This is due to the difference in fouling kinetics: the asymptotic model gives initially high fouling rates, followed by prolonged periods where the overall heat transfer coefficient is low and heat recovery is poor. Cleaning would have to be repeated many times in order to restore thermal efficiency. This is reflected in the cleaning schedules in Table 10, where both approaches require units 9 and 10 to be cleaned, but the deterministic approach requires one early clean of unit 9.

The deterministic problem required 461 CPU s and 2055 simulation runs, which is comparable to the resource for the asymptotic fouling scenario. The parametric uncertainty case, however, only required 8722 CPU s and 1370 simulations, which is attributed to the smaller number of cleaning actions being scheduled.

Table 7 Effect of number of samples, S, on scheduling results: asymptotic fouling, RSD for R_f^{∞}, τ, U_{clean} and C_E was set at 10%

S	10	20	30	40	50
Mean cost /£k	476	524	507	552	534
RSD /%	18.2	16.9	20.6	17.2	21.8
Min. cost /£k	316	352	310	360	327
Max. cost /£k	635	718	732	795	769
No. cleanings	4	3	3	3	4

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Table 8 Effect of process parameter uncertainty for the asymptotic fouling case. *S* = 30.

(a) R_f^∞ varied

RSD	5%	10%	15%	20%
Mean cost /£k	508	499	511	512
RSD /%	1.2	2.5	4.3	4.9
Min. cost /£k	493	475	454	457
Max. cost /£k	519	528	543	568
No. cleanings	3	6	4	3

(b) τ varied

RSD	5%	10%	15%	20%
Mean cost /£k	508	518	501	508
RSD /%	1.5	3.0	5.4	7.0
Min. cost /£k	495	490	424	428
Max. cost /£k	522	546	552	581
No. cleanings	4	3	4	3

(c) U_{clean} varied

RSD	5%	10%	15%	20%
Mean cost /£k	504	518	501	508
RSD /%	1.5	3.0	5.4	7.0
Min. cost /£k	493	490	424	428
Max. cost /£k	522	546	552	581
No. cleanings	4	3	4	3

(d) C_E varied

RSD	5%	10%	15%	20%
Mean cost /£k	504	503	498	499
RSD /%	4.3	9.7	13.9	17.7
Min. cost /£k	466	404	307	302
Max. cost /£k	545	590	641	620
No. cleanings	4	4	3	4

Table 9. Summary of parametric sensitivity study results, asymptotic fouling.

Mean cost	507 £k
RSD	20.6%
Minimum cost	310 £k
Maxium cost	732 £k
P90%	666 £k
P50%	502 £k
P10%	401 £k
Weighted average cost	502 £k

Table 10 Comparison of optimised cleaning schedules for asymptotic fouling scenario. #i indicates unit i is to be cleaned (see Fig. 2)

month	deterministic	P50
1-3	-	-
4	#4	-
5-6	-	-
7	#10	#10
8	#9	#9
9-10	-	-
11	#10	-
12	-	#10
13-18	-	-
Total	4	3

Discussion

The parametric uncertainty calculations ran automatically and did not encounter any convergence problems. This indicates that the methodology can be applied to larger networks operating over longer operating horizons. Application of the approach to a more complex network featuring 25 heat exchangers, initially reported in [11], is reported in [24]. The numerical calculations converged in acceptable times, certainly compared to the timescales of months involved in refinery crude preheat train fouling. This suggests that the method could be implemented in an adaptive mode, wherein data collected from the refinery could be used to update the fouling models (reducing the uncertainty) and the schedule recalculated.

One shortcoming of the network simulations here is that they do not incorporate pressure drop and the possible impact on crude throughput (see [16]). This can be implemented in the simulation, as long as the relationship between thermal fouling resistance and hydraulic impact is known. Ishiyama *et al*. [16] achieved this by treating the fouling layer as a thin layer with uniform properties (thermal conductivity, density, roughness). These properties will be subject to uncertainty - related to their composition and structure – and extension of the approach to this more complex modelling task is under consideration.

The multistage optimal control based approach proposed in this work has the ability to include all the complexities of a real-world model for HEN dynamic operation under fouling. This paper considered variability in fouling rates: in a similar vein, the effectiveness of the cleaning operation could be allowed to vary.

Due to its nature, it can both incorporate on-off binary decisions as to when and what to clean, handled efficiently by the 'bang-bang' optimal control property, and also continuous control decisions such as flow rates. Furthermore, due to the way that it is solved, *i.e*. the feasible path approach for optimal control problems [26, 27], it can be used very efficiently - and using parallelisation very effectively - for robust decision making, *i.e*. considering model parametric uncertainty.

Finally, again due to the feasible path approach solution methodology, the bulk of the model is handled by totally matured solvers, such as dynamic simulation software and robust ODE/DAE integrators. This property is by far completely unprecedented so far in any type of maintenance models in the open literature, and allows for future implementations considering not only the HEN network in isolation, but also a more extensive model integrating upstream and downstream processes as well their associated decision making. Overall, the proposed methodology constitutes a truly unique and radical solution approach for this very challenging and important maintenance problem, and gives rise to promising research and application opportunities in a number of fields.

CONCLUSIONS

A new approach to the heat exchanger scheduling problem, incorporating uncertainty in the process and cost parameters, is presented. Treating it as an optimal control problem and solving it using ‘bang bang’ methods allows uncertainty considerations to be incorporated and solved in feasible times using mature calculation methods, *i.e*. it is robust.

Both linear and asymptotic fouling behaviours were considered. The case study taken from the literature representing a small oil refinery preheat train network, exhibits the following features: (i) the variation in operating costs is approximately normally distributed when the uncertainty in the parameters is based on a random distribution; (ii) the width of the distribution is not related to the uncertainty in each parameter in a simple way as the network sensitivity to each parameter can differ; (iii) uncertainties in costing parameters are more significant than in fouling parameters, for the case study considered here.

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NOMENCLATURE

Roman

A Area, m^2
a Linear fouling rate, ft^2°F/Btu
C_c Specific heat, cold stream, Btu/lb/°F
C_{cl} Cleaning cost, £
C_E Cost of thermal energy, £/MM Btu
C_h Specific heat, hot stream, Btu/lb/°F
F_c Mass flow rate, cold stream, lb/h
F_h Mass flow rate, hot stream, lb/h
NE Number of exchangers, -
NP Number of periods, -
Q_F Furnace firing duty, Btu/h
R_f Fouling resistance, ft^{2}h°F/Btu
R_f^∞ Asymptotic fouling resistance, ft^{2}h°F/Btu
S Number of sample tests
t time, s
t' elapsed time, s
t_F Length of operating horizon, s
U Overall heat transfer coefficient, ft^{2}h°F/Btu
$y_{n,p}$ Cleaning decision variable, -

Greek

η_F Furnace firing efficiency, -
τ Asymptotic fouling time constant, h

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