applied sciences

MDPI

Article

Cleaning Schedule Optimization of Heat Exchanger Network Using Moving Window Decision-Making Algorithm

Simegnsh Bekele Dekebo, Gi-Taek Oh and Min-Woo Lee *

Department of Chemical Engineering, Keimyung University, Daegu 42601, Republic of Korea
* Correspondence: mwlee@kmu.ac.kr

Abstract: A moving window decision-making algorithm is proposed for the cleaning schedule optimization of heat exchanger network system subject to fouling in refinery crude preheat train. This algorithm is designed by incorporating the moving window scheme into a conventional multi-period optimal control problem (OCP) framework and has a distinct feature that it can efficiently handle a complex problem where a long-time horizon is considered. When compared with the conventional multi-period OCP method using fixed time horizon, our algorithm always shows an excellent performance regarding the computational time, still finding a compatible optimal solution. In our moving window decision-making algorithm, it is important to determine the optimal moving window size for the given time horizon as it significantly influences the optimization performance.

Keywords: crude preheat train; heat exchanger network; fouling; mixed-integer nonlinear programming; optimal control problem; bang-bang control

check for updates

Citation: Dekebo, S.B.; Oh, G.-T.; Lee, M.-W. Cleaning Schedule Optimization of Heat Exchanger Network Using Moving Window Decision-Making Algorithm. *Appl. Sci.* **2023**, *13*, 604. https://doi.org/10.3390/app13010604

Academic Editor: Nicholas Vassiliou Sarlis

Received: 5 December 2022
Revised: 26 December 2022
Accepted: 29 December 2022
Published: 1 January 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Crude oil distillation process is one of the largest consumers of thermal energy in industrial section [1,2]. To address this energy consumption issue, the distillation process usually adopts a complex heat exchanger network (HEN) system, so called preheat train, which is designed to recover thermal energy as much as possible [3–5]. When HEN is operated for a long time, however, its overall performance can be seriously deteriorated by the fouling of individual heat exchangers. Complex constituents of the crude oil and their involved high-temperature reactions can stimulate the deposition and accumulation of undesirable insulating materials on the internal surface of heat exchanger (i.e., fouling), resulting in increase of heat transfer resistance [6–8].

Several mitigation methods are currently employed to resolve the fouling problem. Antifouling additives such as polyphosphate, chlorine, hypochlorite, etc. are effective to delay the fouling proceeding, but some heavy metals can be released into the environment if corrosion is the dominant fouling mechanism [9–11]. The use of more robust heat transfer equipments in the preheat train can be another choice, but this usually increases the overall system's operating costs [12–14]. Among others, direct cleaning of the fouling deposits has been considered as the most common and effective method to cope with the fouling issue since the early 1980s [15–17]. The cleaning of the HEN system, however, should be performed in a way of taking turns without the whole system shutdown, hence inevitably encounters an optimization problem of cleaning schedule.

The HEN cleaning schedule optimization can be defined as a discrete decision-making problem that determines when and which heat exchanger unit(s) should be cleaned during the HEN operation [18,19]. Many researchers have proposed varied mathematical programming techniques to address this optimization problem. Due to the coexistence of discrete and continuous variables in the mathematical model to simulate the HEN performance under fouling, and the nonlinearity of the model as well, mixed-integer nonlinear programming (MINLP) approaches have been mainly investigated [20–23]. Smaïli et al. [21]

presented a MINLP framework with a multi-period time discretization, which was widely adopted in the optimization studies of the preheat train afterwards. They used a lumped parameter model and compared two optimization methods, i.e., a commercial deterministic MINLP solver and a simple heuristic greedy algorithm (GrA), concluding that both methods could not guarantee a global optimum because the problem itself was highly nonconvex. Although stochastic techniques such as outer approximation-extended relaxation algorithm [22] and backtracking threshold accepting algorithm [23] were explored, they all found only local minimum and even suffered from failure in convergence with a large-scale problem [21]. To find a global solution, mixed-integer linear programming (MILP) approaches have also been employed [15,24–26]. Georgiadis and Papageorgiou [27] presented a MINLP model considering cyclic cleaning actions and attempted to find a global solution after reformulating it into a MILP model. Lavaja and Bagajewicz [15] also presented a rigorous MILP model based on the multi-period time discretization and proposed a decomposition procedure to obtain a global solution. The MILP approach, however, has a critical drawback that the problem scale becomes much larger by the linearization [1,17]. In addition, the linearization itself has been argued in the real situations. More recently, several advanced stochastic optimization techniques such as imperialist competitive algorithm [6,28], genetic algorithm [4,11], particle swarm optimization [11], duelist algorithm [11], etc. have also received great attention along with the advances in computer hardware technology. However, it seems that the global optimality of the solutions obtained by these stochastic methods should be further confirmed because their performance could be varied depending on parameter tuning [17]. Moreover, they still require too much computational resources to make a rapid decision in the actual fields.

The difficulty in identifying a global solution has made the researchers rather focus on more robust optimization techniques capable of handling a large-scale HEN cleaning schedule problem. This practical need has been emphasized as the mathematical model has become more complex with the deepened understandings about the effects of varied operating conditions on the fouling and the different types of fouling mechanisms/cleaning actions. For example, the effect of wall temperature and flow velocity [29], controlling the desalter inlet temperature [2], distinguishing the foulant deposit into two layers, i.e., soft (fresh) and hard (aged) layers [3], cleaning-in-place methods and off-line mechanical cleaning [30], etc. were successfully incorporated into the model. It is noteworthy, however, there has been any significant improvement for the optimization techniques in these studies. Most of them still adopted heuristic approaches such as GrA or its modifications.

In recent, Ismaili et al. [18] proposed a simple but robust algorithm for the HEN cleaning schedule optimization problem, which is quite different from the previous approaches. They defined the optimization problem as a multi-period optimal control problem (OCP), where a nearly bang-bang optimum solution could be obtained for the non-discretized control (decision) variables simply by using a traditional gradient-based optimization algorithm. In this method, however, the optimization was conducted based on the simulation results for the entire time horizon, so thus sometimes failed in obtaining a bang-bang solution as the problem scale became larger with a long-time horizon.

As reviewed above, most precedent optimization approaches dealing with the HEN cleaning scheduling problems have undergone some limitations, mainly originating from the complexity and nonlinearity of the models [1,17]. Moreover, these limitations become critical as the problem scale increases due to a long-time horizon. In this case, moving window algorithm can be a good supplementary method because it can efficiently handle such complicated large-scale problems. Kashani et al. [31] used the moving window method to predict crude oil fouling in a preheat train and successfully proved its robustness. Lavaja and Bagajewicz [15] also compared a moving window decision-making algorithm with other methods, but rather criticized the moving window scheme only identifying local minimums inferior to other solutions. Their study, however, did not consider the effect of moving window size, which could be critical in an extremely complicated HEN cleaning scheduling problem. According to our literature survey, there has been no research

applying the moving window algorithm over such a long-time horizon to make an issue of scale problem.

In this study, we propose a moving window decision-making algorithm based on the multi-period OCP framework presented by Ismaili et al. [18]. The primary distinction of our method is that a small size of window continuously slides over the entire time horizon making decisions sequentially at each moving step, so the complexity of the optimization problem could be greatly reduced. We compare the performance of our approach with the method using a fixed time horizon with respect to the optimality of solution and the computational time required as well.

2. Moving Window Decision-Making Algorithm

Our moving window decision-making algorithm is indeed a modified version of the multi-period OCP approach proposed by Ismaili et al. [18]. So, herein, we first describe the multi-period OCP framework for the HEN cleaning schedule optimization as simply as possible since its details can be found in [18].

The heat transfer rate (Q) in each heat exchanger unit can be calculated by using the overall heat transfer coefficient (U) with the heat transfer area (A) and the logarithmic mean temperature difference (ΔT_{lm}). Q is also related with the inlet and outlet temperatures of hot and cold streams (T_h^{in}, T_h^{out}, T_C^{in}, and T_C^{out}) through the simple mass balances as shown in Equation (1), where F and C_p represents the mass flow rate and the specific heat, respectively, together with relevant subscripts for the cold and hot streams.

$$Q = UA\Delta T_{lm} = F_h C_{ph}\left(T_h^{in} - T_h^{out}\right) = F_c C_{pc}\left(T_C^{out} - T_C^{in}\right) \tag{1}$$

Along with the fouling proceeding, Q is decreased by the increase of the fouling resistance (R_f) because U is inversely corelated with R_f in a sense of overall heat transfer resistance as given by Equation (2), where subscript c denotes the clean condition. The fouling kinetics can be described by several models [10,18,19], but here we just considered a simple linear model with the fouling constant a as shown in Equation (3).

$$\frac{1}{U} = \frac{1}{U_c} + R_f \tag{2}$$

$$\frac{dR_f}{dt} = a \tag{3}$$

The fouling proceeding is simulated for a fixed time horizon (from 0 to t_F), which is discretized into time periods of equal length (one month in usual). Each period can be further divided into a cleaning and operating sub-period, of which length is represented by Δt^{CL} and Δt^{OP}, respectively. With this discretization, the cleaning actions can be incorporated into the model by using binary control (decision) variable y_{np} shown in Equation (4). It should be noted that at this moment the problem becomes a mixed integer optimal control problem (MIOCP), which is more difficult to solve in general. However, Ismaili et al. [18] treated y_{np} as a continuous variable that is bounded for the range of 0 to 1, so that the problem could still remain in the OCP framework. They also proved that the cleaning actions are indeed the controls which occur linearly in the system (model) equations, and in this case a bang-bang solution (0 or 1) could be obtained for the control variable.

$$y_{np} = \begin{Bmatrix} 0 & if\ the\ n\text{-}th\ heat\ exchager\ is\ cleaned\ in\ period\ p \\ 1 & other\ wise \end{Bmatrix} \quad \forall n, p \tag{4}$$

By incorporating the control variable y_{np}, Equations (1) and (3) can be rewritten into Equations (5)–(9). The actual system equations incorporating the control variable are Equations (2) and (5)–(9), which is an index-1 differential-algebraic system of equations (DAEs).

$$\alpha = \frac{UA}{F_h C_{ph}} \tag{5}$$

$$P = \frac{F_h\, C_{ph}}{F_c\, C_{pc}} \tag{6}$$

$$T_C^{out} = T_C^{in} + P\left(T_C^{in} - T_h^{out}\right) \tag{7}$$

$$T_h^{out} = y_{n,p}\left[\frac{(1-P)T_h^{in}e^{-\alpha(1-P)} + T_C^{in}\left(1-e^{-\alpha(1-P)}\right)}{1-P\,e^{-\alpha(1-P)}}\right] + \left(1-y_{n,p}\right)T_h^{in} \quad \forall n,p \tag{8}$$

$$\frac{dR_f}{dt} = y_{np}a \qquad \forall n,p \tag{9}$$

The objective function to be minimized for the cleaning schedule optimization is given by Equation (10), which is the additional operating cost to resolve the fouling problem. This additional operating cost can be represented as the sum of the fuel and cleaning costs. The fuel cost is the extra energy cost in the furnace of preheat train which is needed to compensate the temperature drop of the crude oil due to the fouling. This extra cost term can be calculated by integrating $Q_F(t)$, which is the extra energy consumption depending on the difference between the actual and the target temperature of the crude oil entering the furnace, together with the cost of fuel (C_E) and the furnace efficiency (η_f). The cleaning cost term, in the meantime, can be calculated from the control actions y_{np} with the cleaning cost (C_C). Here, N_P is the number of the discretized time periods and N_E is the number of heat exchangers.

$$Obj = \int_0^{t_F} \frac{C_E Q_F(t)}{\eta_f}\, dt + \sum_{p=1}^{N_P}\sum_{n=1}^{N_E} C_C\left(1-y_{np}\right) \tag{10}$$

The moving window decision-making algorithm presented in this study basically adopts the multi-period OCP framework described above. However, we have combined the moving window method with the OCP framework in the context of its extension, which is the distinct feature of our decision-making algorithm. Figure 1 shows the scheme of our moving window algorithm. On the contrary to the previous method where an optimal cleaning schedule is determined in a single lump based on the simulation results obtained for the whole time periods of 0 to N_P, our algorithm sequentially determines cleaning decision only for the very first time period within the moving window. With this scheme, the complexity of the optimization problem can be greatly reduced because the number of control variables to be optimized is decreased from $(N_P - 1) \times N_E$ to N_E. Moreover, the simulations can be conducted only for the time periods corresponding to the moving window size (S_{MW}), which makes it possible that the OCP is solved very fast at each moving step. After the moving window reaches the final step $(N_P - S_{MW})$, the optimal cleaning schedule is constructed by combining each decision in a whole.

It should be noted that the presented moving window decision-making algorithm is different from the GrA [21] or its modified versions [32], although they are very similar in that they use a sliding time horizon. While the GrAs makes the cleaning decisions based on a "threshold heuristic" or "greedy threshold", our moving window method makes decisions simply using the gradient-descent algorithm within the OCP framework, which is not a heuristic approach.

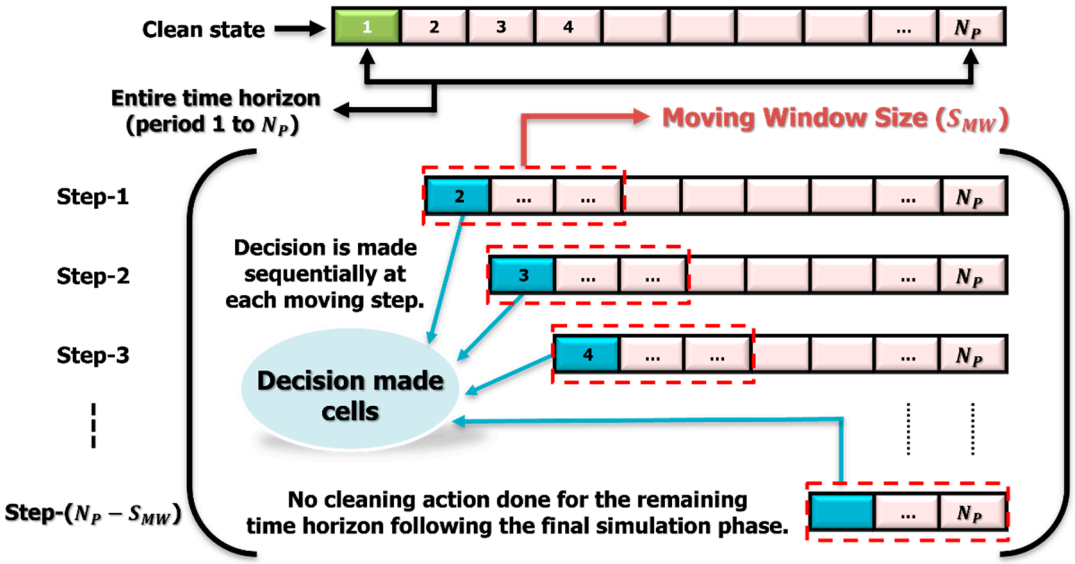


Figure 1. Scheme of HEN cleaning schedule decision-making algorithm using the moving window method.

3. Case Study

In this study, the performance of our moving window decision-making algorithm was compared with the previous method using a fixed time horizon. Figure 2 shows the 10-unit HEN system chosen for this purpose, which was adopted from the work of Lavaja and Bagajewicz [15]. This HEN system uses 6 different heat sources and some heat exchanger units share the same heat source interconnectedly. While the crude oil passes through a series of heat exchangers, its temperature increases up to the crude inlet temperature, CIT. The effect of fouling in the heat exchangers results in the decrease of CIT, which requires extra energy consumption in the furnace after all.

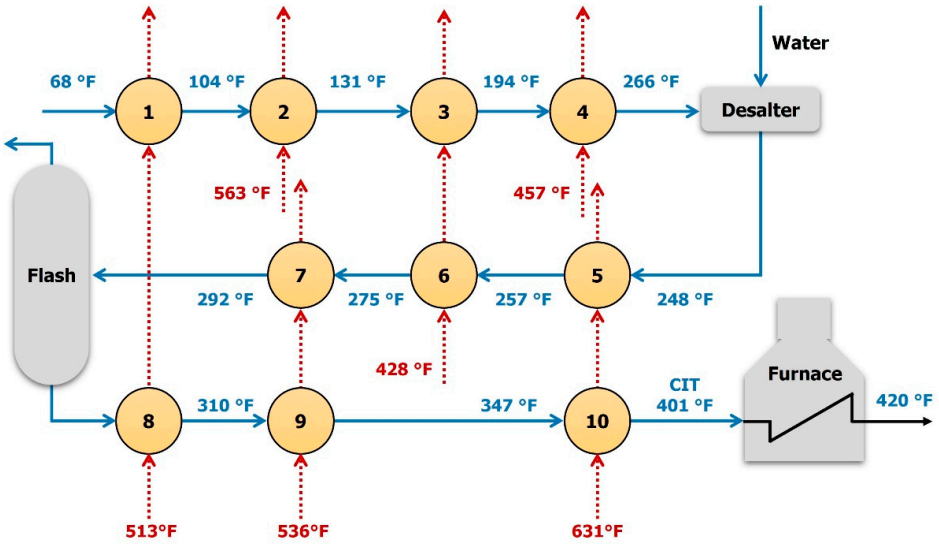


Figure 2. Schematic diagram of 10-unit HEN system; solid lines, cold (crude) streams; dashed lines, hot streams; CIT, crude inlet temperature to furnace; the temperature given in each stream represents the value at initial cleaned condition; adopted from [15].

The model parameter values of each heat exchanger used in the simulation studies are summarized in Table 1. Other common parameters are: $U_c = 88.1$ BTU/ft^2 h °F, $\Delta t^{CL} = 0.2$ month, $\Delta t^{OP} = 0.8$ month, $\eta_f = 0.75$, $C_E = 2.93$ £/MM BTU, and $C_C = 4000$ £/cleaning action, which was also adopted from the work of Ismaili et al. [18]. In our study the

target temperature entering the furnace was 420 °F. The following operational constraints were also considered during the simulation studies: only one unit of exchangers 1–4 can be cleaned in each period; only one unit of exchangers 5–7 can be cleaned in each period; there is a temperature drop (18 °F) across desalter.

Table 1. Model parameters used in cleaning schedule optimization of 10-unit HEN system. Adapted from Ismaili et al. [18].

Parameter	Heat Exchanger									
	1	2	3	4	5	6	7	8	9	10
$F_h \times 10^{-5}$ [lb/h]	1.41	0.74	4.23	4.29	2.08	4.23	2.10	1.41	2.83	2.08
$F_c \times 10^{-5}$ [lb/h]	7.21	7.21	7.21	7.21	7.21	7.21	7.21	6.49	6.49	6.49
C_{ph} [BTU/lb °F]	0.67	0.70	0.62	0.62	0.67	0.62	0.69	0.67	0.69	0.67
C_{pc} [BTU/lb °F]	0.46	0.46	0.46	0.46	0.55	0.55	0.55	0.57	0.57	0.57
A [ft^2]	465	287	1192	1488	183	546	492	437	885	1257
$a \times 10^7$ [ft^2 °F/BTU]	1.23	1.84	1.23	1.64	3.07	2.25	3.07	3.27	3.68	3.88

All simulation studies were conducted using the MATLAB software (MATLAB® R2016b) together with Optimization Toolbox™ and Parallel Computing Toolbox™ (The MathWorks Inc., Natick, MA, USA, 2016). We used the 'ode15s' for the solver of DAEs and the 'fmincon' for the optimizer with the option of Sequential Quadratic Programming (SQP) algorithm. To compare the computational time for optimization, all simulations were conducted on a single desktop PC of which spec is rather outdated (3GHz Intel Core i5, 8 GB RAM).

4. Result and Discussion

In the presented moving window decision-making algorithm, the moving window size S_{MW} is an important factor that could affect the optimization performance as it defines the time domain where the fouling proceeding is simulated for the algorithm to make cleaning decision at each moving-step. Hence, the effect of S_{MW} on the optimality of the obtained solution was intensively investigated in this study for the varied HEN cleaning schedule problems with different time horizons ranging from 12 to 84 months. Figure 3 shows the result for the case of $t_F = 18$ months (i.e., $N_P = 18$), where one can easily notice that there is an optimal S_{MW} to make the optimized objective function value (Obj_{opt}) be minimal (here, the optimal $S_{MW} = 4$).

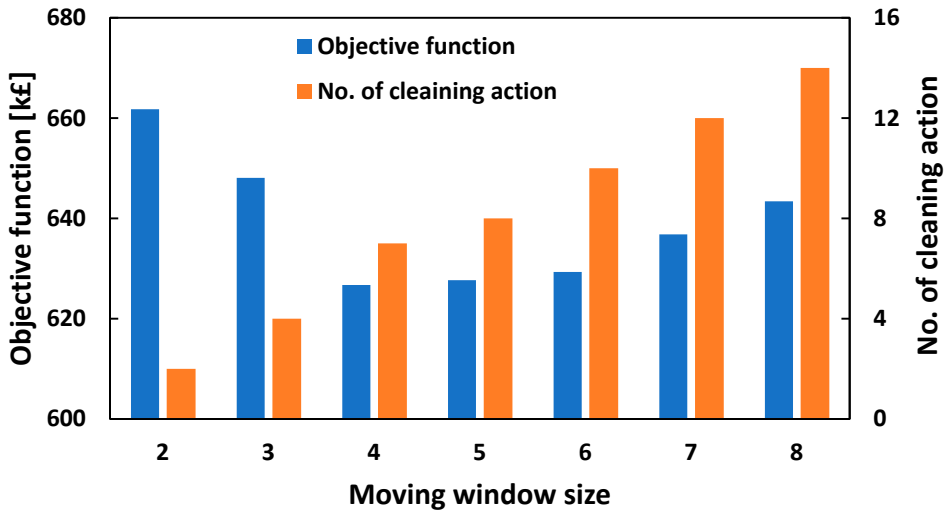


Figure 3. The effect of moving window size on the optimized objective function value and the number of cleanings for the case of $t_F = 18$ months.

The existence of the optimal S_{MW} can be explained by the trade-off nature inherent in the objective function to be minimized. When S_{MW} is too small, the fouling proceeding would be simulated to be trivial; hence the moving window algorithm could make less cleaning decisions far from the optimality because the cleaning cost term in the objective function would always be overestimated than the extra fuel cost term. When S_{MW} is too large, on the other hand, the algorithm would tend to make more frequent cleaning decisions since the extra fuel cost term would more significantly contribute to the objective function due to the severe fouling simulated.

Lavaja and Bagajewicz [15] tested a similar moving window technique combined with their MILP approach, but simply concluded that the moving window technique was not effective because making larger moving window size did not guarantee improved performance. However, they did not consider the effect of the moving window size in depth and missed the existence of the optimal S_{MW}. As can be seen in Figure 3, the use of larger S_{MW} just results in the increase of the total number of cleanings, which does not necessarily mean an improved solution. The existence of the optimal S_{MW} was always observed for the different time horizon problems tested in this study (see Table 2). When comparing the performance of the moving window method, therefore, its optimal S_{MW} should be determined first for the given time horizon.

Table 2. Optimization performance of the fixed-time horizon and moving window methods for the problems with different time horizons.

Time Horizon (Month)	Fixed-Time Horizon				Moving Window				
	Bang-Bang Solution Satisfied (True/False)	No. of Cleaning	Objective Function Value [k£]	Optimization Time (min)	Bang-Bang Solution Satisfied (True/False)	No. of Cleaning	Objective Function Value [k£]	Optimization Time (min)	Optimal Moving Window Size
12	True	2	385	0.46	True	2	385	0.17	4
18	True	10	620	2.35	True	7	627	0.51	4
24	True	16	852	6.39	True	18	863	0.49	5
30	True	22	1085	9.43	True	21	1099	0.51	5
36	False	25	1329	12.10	True	28	1332	0.67	5
42	False	35	1556	21.49	True	33	1568	0.75	5
48	False	44	1791	27.37	True	39	1807	0.91	5
54	False	47	2022	43.04	True	46	2035	1.02	5
60	False	55	2393	35.95	True	52	2271	1.13	5

In various industries, the HEN systems are usually operated continuously for several years between the whole system shutdowns [21,22]. Most precedent studies, however, have addressed the HEN cleaning schedule optimization problems only for a relatively short time period [18,24,25]. In this study, therefore, we have compared the performance of our moving window decision-making algorithm with its original version using a fixed time horizon [18] for a quite long time period up to 5 years (Table 2).

When the time horizon considered is less than 30 months, the fixed-time horizon method always shows a better performance than the moving window method regarding the optimality of the solution (i.e., less value of Obj_{opt}), generating bang-bang solutions stably. As the time horizon exceeds 36 months, however, the fixed-time horizon method begins to fail in converging to a bang-bang solution, so thus the optimality of the solutions becomes worse to the levels compatible with the moving window method. In the extreme cases of the time horizon of 60 months, the moving window method even shows a better optimality. It should be noted that the convergence to a bang-bang solution is critical to the optimality of the solution because both methods compared here basically adopts the multi-period OCP framework where the rounding up scheme is employed when the convergence fails [33]. The failure in convergence to a bang-bang solution observed in the fixed-time horizon method can be attributed to the increased complexity of the problem by the increase of the time horizon to be considered. Our moving window decision-making

algorithm, however, can be free from this complexity issue because its complexity only depends on the moving window size, not on the whole-time horizon.

Another important aspect to consider when solving an optimization problem is the computational time which is taken to obtain the solution. As can be seen in Table 2, the computational time of the presented moving window method always outperforms the fixed-time horizon method. As we used the same initial guess of $y_{np} = 1$ $(\forall n, p)$ in all simulation studies, it can be reasonably concluded that the moving window method is more efficient in obtaining an optimized solution regarding the computational time.

The details of the optimal solutions determined by two methods were analyzed more in depth for the case of $t_F = 18$ months, of which results are summarized in Figure 4. The total number of cleanings determined by the fixed-time horizon method is 10 while that obtained by our moving window algorithm is only 7. Moreover, the detailed cleaning schedules are clearly different from each other, showing only two common cleanings at the 7th and 12th month. Yet, the difference of the objective function values of two methods is just 7 k£ (see Table 2), which is very trivial indeed. All these results evidently support that the given HEN cleaning schedule optimization problem is very complicated even with the time-horizon of 18 months and there could be several local minimums very close to the global one. In Figure 4, it can be also noted that both methods give the same result that the heat exchanger unit 9 and 10 should be cleaned more often than the others, indicating they are important in the network. This is because they have a faster fouling rate constant than the others (see Table 1).

Exchanger	Time (months)																	Number of cleanings	
No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	+	○
1																			0	0
2																			0	0
3												○							0	1
4								○					+						1	1
5										○									0	1
6									○										0	1
7								○				+							1	1
8											○	+							1	1
9							⊕						+	○					2	2
10						+	○					⊕							2	2
Total cleaning action																			7	10
Moving window (+), Fixed time horizon (○), Common (⊕)																				

Figure 4. Detailed cleaning schedules for the case of $t_F = 18$ months.

Figure 5 shows the CIT (the crude inlet temperature to furnace) profiles obtained by applying the solutions of two compared methods for the extreme case ($t_F = 60$ months). From this figure, it can be seen that well-optimized cleanings could effectively restore the performance of the HEN system. Without cleaning, the CIT can be decreased from 401 °F down to 304 °F due to the fouling, which requires a tremendous extra fuel cost of 4574 k£. With optimized cleanings, the minimized Obj_{opt} values were 2271 k£ (moving window) and 2393 k£ (fixed time horizon), respectively (see Table 2), which implies that 122 k£ could be further saved if using our moving window algorithm. All these results clearly support that our moving window decision-making algorithm is not only fast but also robust especially when dealing with an extremely complex HEN cleaning optimization problem with a long-time horizon.

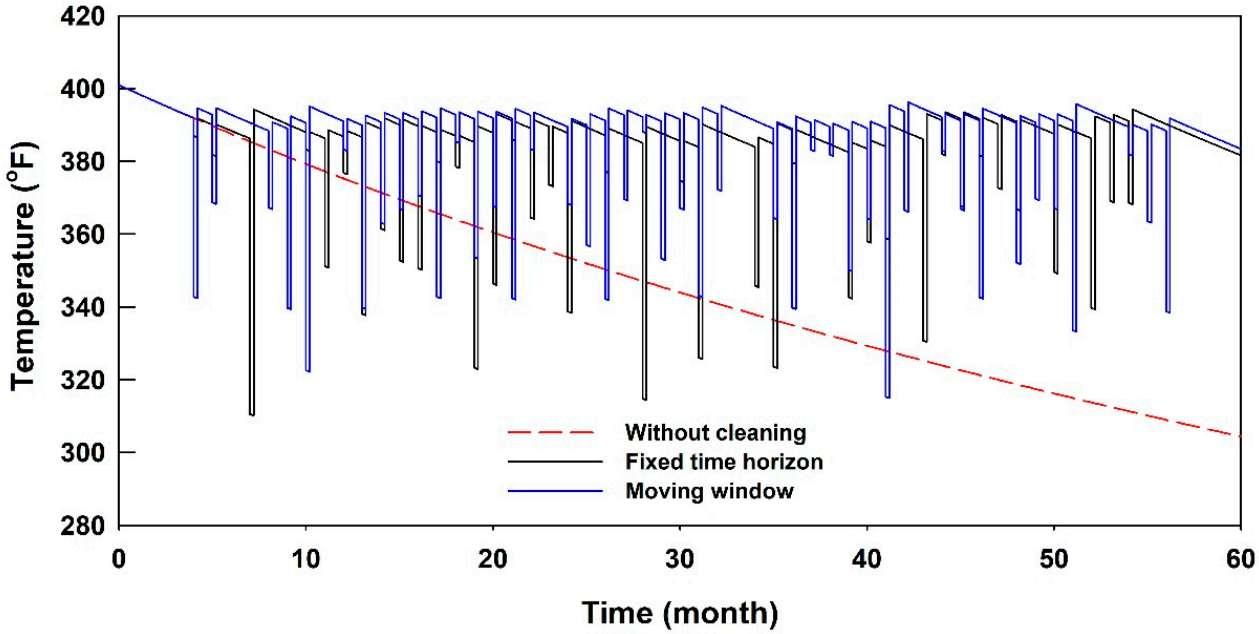


Figure 5. CIT (the crude inlet temperature to furnace) profiles for the case of $t_F = 60$ months.

5. Conclusions

In this study, a moving window decision-making algorithm based on the multi-period OCP framework was proposed for the HEN cleaning schedule optimization. This algorithm could efficiently handle an extremely complicated HEN cleaning schedule optimization problem with a long-time horizon owing to two distinct benefits: robustness can be guaranteed as it uses a conventional gradient-based algorithm within the given OCP framework; an optimal solution can be obtained in a greatly reduced computational time because the simulation is conducted only for the time domain corresponding to the moving window size. It was also proved that the optimality of the solution was compatible with the result of the conventional multi-period OCP method using the fixed time horizon if an optimal moving window size was properly used. Most HEN systems are usually operated in the fields for a very long time without shutdown. In this practical situation, we believe that our moving window algorithm could be an excellent alternative to other complex heuristic/stochastic methods in determining the optimal cleaning schedule.

Author Contributions: Conceptualization, M.-W.L.; methodology, S.B.D., G.-T.O. and M.-W.L.; software, S.B.D. and M.-W.L.; validation, S.B.D., G.-T.O. and M.-W.L.; formal analysis, S.B.D., G.-T.O. and M.-W.L.; investigation, S.B.D., G.-T.O. and M.-W.L.; resources, S.B.D., G.-T.O. and M.-W.L.; data curation, S.B.D. and M.-W.L.; writing—original draft preparation, S.B.D. and M.-W.L.; writing—review and editing, S.B.D., G.-T.O. and M.-W.L.; visualization, S.B.D., G.-T.O. and M.-W.L.; supervision, M.-W.L.; project administration, M.-W.L.; funding acquisition, M.-W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Bisa Research Grant of Keimyung University in 2018 [grant number 20180307].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

HEN	Heat exchanger network
MINLP	Mixed-integer nonlinear programming
GrA	Greedy algorithm
MILP	Mixed-integer linear programming
OCP	Optimal control problem
Q	Heat transfer rate [BTU/ h]
U	Overall heat transfer coefficient [BTU/ft^2 h °F]
A	Heat transfer area [ft^2]
ΔT_{lm}	Logarithmic mean temperature difference [°F]
T_h^{in}	Inlet temperatures of hot streams [°F]
T_h^{out}	Outlet temperatures of hot streams [°F]
T_C^{in}	Inlet temperatures of cold streams [°F]
T_C^{out}	Outlet temperatures of cold streams [°F]
F_h	Mass flow rate of hot streams [lb/h]
C_{ph}	Specific heat of hot streams [BTU/lb °F]
F_c	Mass flow rate of cold streams [lb/h]
C_{pc}	Specific heat of cold streams [BTU/lb °F]
U_c	Overall heat transfer coefficient at clean condition [BTU/ft^2 h °F]
R_f	Fouling resistance [ft^2 °F/BTU]
a	Fouling constant [ft^2 °F/BTU]
t_F	Entire time horizon [month]
Δt^{CL}	Cleaning sub-period [month]
Δt^{OP}	Operating sub-period [month]
y_{np}	Binary control (decision) variable
MIOCP	Mixed integer optimal control problem
DAEs	Differential-algebraic system of equations
$Q_F(t)$	Extra energy consumption depending on the difference between the actual and the target temperature of the crude oil entering the furnace [MM BTU]
C_E	Cost of fuel [£/MM BTU]
η_f	Furnace efficiency
C_C	Cleaning cost [£/cleaning action]
N_P	Number of the discretized time periods
N_E	Number of heat exchangers
S_{MW}	Moving window size
CIT	Crude inlet temperature to furnace [°F]
SQP	Sequential Quadratic Programming
Obj_{opt}	Objective function value [k£]

References

1. Diaby, A.L.; Luong, L.; Yousef, A.; Addai Mensah, J. A Review of Optimal Scheduling Cleaning of Refinery Crude Preheat Trains Subject to Fouling and Ageing. *Appl. Mech. Mater.* **2011**, *148–149*, 643–651. [CrossRef]
2. Ishiyama, E.; Heins, A.; Paterson, W.; Spinelli, L.; Wilson, D. Scheduling cleaning in a crude oil preheat train subject to fouling: Incorporating desalter control. *Appl. Therm. Eng.* **2010**, *30*, 1852–1862. [CrossRef]
3. Ishiyama, E.M.; Paterson, W.R.; Wilson, D.I. The effect of fouling on heat transfer, pressure drop, and throughput in refinery preheat trains: Optimization of cleaning schedules. *Heat Trans. Eng.* **2009**, *30*, 805–814. [CrossRef]
4. Diaby, A.L.; Miklavcic, S.J.; Addai-Mensah, J. Optimization of scheduled cleaning of fouled heat exchanger network under ageing using genetic algorithm. *Chem. Eng. Res. Des.* **2016**, *113*, 223–240. [CrossRef]
5. Santamaria, F.L.; Macchietto, S. Online Integration of Optimal Cleaning Scheduling and Control of Heat Exchanger Networks under Fouling. *Ind. Eng. Chem. Res.* **2019**, *59*, 2471–2490. [CrossRef]
6. Biyanto, T.R.; Khairansyah, M.D.; Bayuaji, R.; Firmanto, H.; Haksoro, T. Imperialist competitive algorithm (ICA) for heat exchanger network (HEN) cleaning schedule optimization. *Procedia Comput. Sci.* **2015**, *72*, 5–12. [CrossRef]
7. Diaby, A.L.; Miklavcic, S.J.; Bari, S.; Addai-Mensah, J. Evaluation of crude oil heat exchanger network fouling behavior under aging conditions for scheduled cleaning. *Heat Trans. Eng.* **2016**, *37*, 1211–1230. [CrossRef]
8. Trafczynski, M.; Markowski, M.; Kisielewski, P.; Urbaniec, K.; Wernik, J. A modeling framework to investigate the influence of fouling on the dynamic characteristics of PID-controlled heat exchangers and their networks. *Appl. Sci.* **2019**, *9*, 824. [CrossRef]

9. Müller-Steinhagen, H.; Malayeri, M.R.; Watkinson, A.P. Heat exchanger fouling: Environmental impacts. *Heat Transf. Eng.* **2009**, *30*, 773–776. [CrossRef]
10. Awad, M.M. Fouling of Heat Transfer Surfaces. In *Heat Transfer*; Belmiloudi, A., Ed.; In Tech: Rijeka, Croatia, 2011; pp. 505–542.
11. Biyanto, T.R.; Ramasamy, M.; Jameran, A.B.; Fibrianto, H.Y. Thermal and hydraulic impacts consideration in refinery crude preheat train cleaning scheduling using recent stochastic optimization methods. *Appl. Therm. Eng.* **2016**, *108*, 1436–1450. [CrossRef]
12. Zhu, X.; Zanfir, M.; Klemes, J. Heat transfer enhancement for heat exchanger network retrofit. *Heat Trans. Eng.* **2000**, *21*, 7–18.
13. Mule, B.A.; Hatkar, D.; Bembde, M. Analysis of Double Pipe heat exchanger with Helical Fins. *Int. Res. J. Eng. Technol.* **2017**, *4*, 961–966.
14. Awais, M.; Bhuiyan, A.A. Recent advancements in impedance of fouling resistance and particulate depositions in heat exchangers. *Int. J. Heat Mass Trans.* **2019**, *141*, 580–603. [CrossRef]
15. Lavaja, J.H.; Bagajewicz, M.J. On a New MILP Model for the Planning of Heat-Exchanger Network Cleaning. *Ind. Eng. Chem. Res.* **2004**, *43*, 3924–3938. [CrossRef]
16. Pogiatzis, T.A.; Vassiliadis, V.S.; Wilson, D.I. An MINLP formulation for scheduling the cleaning of heat exchanger networks subject to fouling and ageing. In Proceedings of the International Conference on Heat exchanger Fouling and Cleaning, Crete Island, Greece, 5–10 June 2011; pp. 349–356.
17. Goncalves, C.d.O.; Queiroz, E.M.; Pessoa, F.L.; Liporace, F.S.; Oliveira, S.G.; Costa, A.L. Heuristic optimization of the cleaning schedule of crude preheat trains. *Appl. Therm. Eng.* **2014**, *73*, 3–14. [CrossRef]
18. Al Ismaili, R.; Lee, M.W.; Wilson, D.I.; Vassiliadis, V.S. Heat exchanger network cleaning scheduling: From optimal control to mixed-Integer decision making. *Comput. Chem. Eng.* **2018**, *111*, 1–15. [CrossRef]
19. Al Ismaili, R.; Lee, M.W.; Wilson, D.I.; Vassiliadis, V.S. Optimisation of heat exchanger network cleaning schedules: Incorporating uncertainty in fouling and cleaning model parameters. *Comput. Chem. Eng.* **2019**, *121*, 409–421. [CrossRef]
20. Smaili, F.; Angadi, D.; Hatch, C.; Herbert, O.; Vassiliadis, V.; Wilson, D. Optimization of Scheduling of Cleaning in Heat Exchanger Networks Subject to Fouling. *Food Bioprod. Process* **1999**, *77*, 159–164. [CrossRef]
21. Smaili, F.; Vassiliadis, V.S.; Wilson, D.I. Mitigation of fouling in refinery heat exchanger networks by optimal management of cleaning. *Energy Fuels* **2001**, *15*, 1038–1056. [CrossRef]
22. Smaili, F.; Vassiliadis, V.S.; Wilson, D.I. Optimization of Cleaning Schedules in Heat Exchanger Networks Subject to Fouling. *Chem. Eng. Commun.* **2002**, *189*, 1517–1549. [CrossRef]
23. Smaili, F.; Vassiliadis, V.; Wilson, D. Long-term scheduling of cleaning of heat exchanger networks: Comparison of outer approximation-based solutions with a backtracking threshold accepting algorithm. *Chem. Eng. Res. Des.* **2002**, *80*, 561–578. [CrossRef]
24. Lavaja, J.H.; Bagajewicz, M.J. On a new MILP model for the planning of heat-exchanger network cleaning. Part II: Throughput loss considerations. *Ind. Eng. Chem. Res.* **2005**, *44*, 8046–8056. [CrossRef]
25. Lavaja, J.H.; Bagajewicz, M.J. On a new MILP model for the planning of heat-exchanger network cleaning. Part III: Multiperiod cleaning under uncertainty with financial risk management. *Ind. Eng. Chem. Res.* **2005**, *44*, 8136–8146. [CrossRef]
26. Patil, P.; Srinivasan, B.; Srinivasan, R. Cleaning schedule for heat exchanger networks subjected to maintenance constraints. In *Computer Aided Chemical Engineering*; Elsevier: Kyoto, Japan, 2022; Volume 49, pp. 511–516.
27. Georgiadis, M.; Papageorgiou, L.G. Optimal energy and cleaning management in heat exchanger networks under fouling. *Chem. Eng. Res. Des.* **2000**, *78*, 168–179. [CrossRef]
28. Fitriyani, N.; Nahdliyah, S.D.; Biyanto, T.R. Operational Optimization of Binary Distillation Column to Achieve Product Quality Using Imperialist Competitive Algorithm (ICA). In Proceedings of the 2016 6th International Annual Engineering Seminar (InAES), Yogyakarta, Indonesia, 1–3 August 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 112–115.
29. Rodriguez, C.; Smith, R. Optimization of operating conditions for mitigating fouling in heat exchanger networks. *Chem. Eng. Res. Des.* **2007**, *85*, 839–851. [CrossRef]
30. Pogiatzis, T.; Ishiyama, E.M.; Paterson, W.R.; Vassiliadis, V.S.; Wilson, D.I. Identifying optimal cleaning cycles for heat exchangers subject to fouling and ageing. *Appl. Energy* **2012**, *89*, 60–66. [CrossRef]
31. Kashani, M.N.; Aminian, J.; Shahhosseini, S.; Farrokhi, M. Dynamic crude oil fouling prediction in industrial preheaters using optimized ANN based moving window technique. *Chem. Eng. Res. Des.* **2012**, *90*, 938–949. [CrossRef]
32. Ishiyama, E.M.; Juhel, C.; Aquino, B.; Hagi, H.; Pugh, S.J.; Gomez Suarez, E.; Kennedy, J.; Zettler, H.U. Advanced Fouling Management through Use of HTRI SmartPM: Case Studies from Total Refinery CDU Preheat Trains. *Heat Trans. Eng.* **2021**, *168*, 1365–1377. [CrossRef]
33. Sager, S. Reformulations and algorithms for the optimization of switching decisions in nonlinear optimal control. *J. Process Control* **2009**, *19*, 1238–1247. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.