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An Integrated Simulation-based Process Control and Operation Planning (IS-PCOP) System for Marine Oily Wastewater Management

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ABSTRACT. An ideal combination of process control and operation planning can reduce system cost and maximize economic and environmental benefits. This research proposed an integrated simulation-based process control and operation planning (IS-PCOP) system by using neural networks, genetic algorithm, multistage principle, and Monte Carlo simulation. It could well link process control and operation planning by simultaneously adopting different time-scales in computation. The hourly process control strategy forwarded the results to the operation planning module where long-term arrangements could be further evaluated. The use of ANN modeling also played a key role in predicting the nonlinear behavior of complex processes. In addition, Monte Carlo simulation yielded a better insight on uncertainties, which may arise from a number of different sources. A case study on marine wastewater management was carried out to demonstrate the efficacy of the proposed approach. Six different treatment standards (i.e., 5, 10, 15, 20, 25, and 30 μg L^{-1}) were examined over a 20-day period and the 20 μg L^{-1} standard appeared to be the most economic option with a mean net cost of \$18 per day. As compared to the traditional operation planning without process control, the integrated approach achieved more economically competitive results. By addressing the uncertainties and expressing the results in probability distributions, the decision makers would have more confidence in making decisions on both short- and long-term operations. It was concluded that the combination of process control and operation planning could help meet the economic objectives and ensure timely completion of the tasks.

Keywords: system planning, process control, marine wastewater treatment, uncertainties

1. Introduction

A large portion of marine oil pollution is caused by the operational discharge of oily wastewater, such as bilge water, offshore produced water, ballast water, and oil tank washing water (Jing et al., 2014a). Owing to the stringent environmental regulations, secondary polishing treatment systems, such as advanced oxidation processes (AOPs), have been advocated as a necessary supplement to the traditional gravity-based ones in terms of pollution reduction. Such advanced treatment systems, as compared to the traditional ones, are usually lack of in-depth understanding of process control requirements and long-term planning strategies. Operation planning, or so called system planning, usually refers to a longer period of time and is a prerequisite for process control (Rassam, 2011; Yang et al., 2015). Based on the required product characteristics and economic and environmental constraints, the most appropriate processes, resources, and standards can be properly selected. A good operation planning tool, particularly from the long-term perspective, is an important basis and guarantee for meeting basic needs, providing high-quality service, and making the best use of available resources. This is especially true for offshore operations where resources such as power supply, available space, and man power are usually limited. Contrastingly, process control is generally achieved by careful and accurate control and monitoring of the process parameters affecting the quality of the products (Cheng et al., 2002; Phattaranawik and Leiknes, 2011; Tan et al., 2015). It is defined as an engineering discipline that deals with mechanisms and algorithms for maintaining the output of a specific engineering process within a desired range. With the increasingly stringent standards and more sophisticated treatment systems, operators have become more and more reliant on mathematical tools instead of their personal experience to optimize the control strategy (Cai et al., 2009).

An ideal combination of both process control and operation planning can greatly reduce system cost and maximize economic and environmental benefits associated with marine oily wastewater treatment (Lee, 2012). It has been recognized in the literature that, regardless their difference, the combination of process control and operation planning can help meet the economic objectives and ensure timely completion of the tasks (Hans et al., 2007; Hüfner et al., 2009; Jing et al., 2012a, 2012b and 2013; Li et al., 2014; Nourani et al., 2015; Li et al., 2015; Ben-Awuah et al., 2015; Ahmadi et al., 2015). Hüfner et

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al. (2009) reported that a high-quality production planning needs to reflect the uncertainties associated with the market and technical parameters and to accommodate the feasible operation scheduling. Kamar et al. (2011) argued that if appropriate process control is not implemented during the system planning procedure, there might be potential benefit loss because traditional planning tends to be more conservative and less risk-taking. Verl et al. (2011) stated the importance of distinguishing between "detailed scheduling and process control" and "operation planning". Nonetheless, they also claimed that process control consists of the anticipatory consideration and the reaction to unexpected occurrences, while long-term planning is usually a prerequisite for detailed scheduling and process control. How to take process control and scheduling into account during operation planning have become a rapidly growing area of research and a subject of interest to academicians and practitioners alike (Huang et al., 1996; Yin et al., 1999).

However, the link between process control and operation planning is most often not available due to the complexity of integrated systems, the difficulty in capturing and modeling the behavior of the processes, and the uncertainties of parameters to be considered. The first challenging aspect is the multiscale nature of the integration, which arises as the fact that operation planning (e.g., capacity investment and design decisions) is typically made on a much coarser (and longer) time scale than process control decisions. It is common to have benefits, investments, or capacity growth reviewed on a seasonal or yearly basis, whereas process control requires decisions and actions on a much finer time scale (e.g., hours). Secondly, wastewater treatment usually consists of a number of complex physical, chemical, and biological processes that are described by nonlinear functions. Therefore, how to precisely simulate the process and predict the outputs has been an obstacle for learning the behavior of the treatment systems. Lastly, such coupling can be further complicated by uncertainties, which may arise from a number of different sources including process characteristics, technology features and limitations, as well as environmental standards (Chen et al., 2010; Lv et al., 2010).

How to accurately couple process control with operation planning has been a major gap in the development of an effective decision support system for marine oily wastewater management. To date, there has been no study reported in the literature on such integration. To fill the above knowledge gap, this paper, therefore, aims at demonstrating the possible integration of process control with traditional operation planning by using neural networks, genetic algorithm, multistage principle, and Monte Carlo simulation. A case study on offshore bilge water management is carried out to demonstrate the efficacy of the proposed integrated simulation-based process control and operation planning (IS-PCOP) approach.

2. The IS-PCOP Approach for Marine Wastewater Management

Consider the following operation planning problem:

$$Min\ f(x) = \sum_{i=1}^{n} f_n(x) \tag{1}$$

subject to:

$$g_j(x) = 0,\ j = 1, 2, ..., p \tag{2}$$

$$h_k(x) \leq 0,\ k = 1, 2, ..., q \tag{3}$$

$$lb \leq x \leq ub \tag{4}$$

where x are the decision variables, such as chemical dose and retention time; f is the objective function which equals to the sum of n sub-functions that are related to treatment cost or environmental risk; g and h are the equality and inequality constraints that can be associated with treatment capacity and man power/resource restraints, respectively; p and q are the numbers of equality and inequality constraints, respectively; and lb and ub are the lower and upper bounds of x, respectively. The bounds are usually set by consulting experts or literature documents. A common situation is that, some of the sub-functions may be associated with simulation processes, while the process control tool proposed in Jing et al. (2015) can be used to optimize these sub-functions. A prerequisite here is that the simulation process must have been well investigated, preferably supported by experimental observation data, such that an ANN simulation model can be developed (Figure 1). The detailed solution algorithm is summarized as follows:

Step 1: Define the operation planning objectives and constraints as introduced in Equations 1 ~ 4. Generate random numbers for the coefficients of objective functions and constraints within the corresponding upper and lower bounds. The bounds can be defined by consulting experts, field engineers or literatures.

Step 2: Generate random decision variables x within the predefined bounds lb and ub.

Step 3: Define the process control problems $f_n(x)$ with inputs and the number of stages. The inputs are defined by the wastewater treatment problem (e.g., UV does and salinity) while the number of stages are defined by the treatment period. Divide the simulation-based sub-functions $f_n(x)$ into multiple stages and obtain the corresponding minimized fn(x) using the ANN-DMINP approach (Jing et al., 2015). The ANN model(s) are developed according to experimental data prior to this problem solving process (Jing et al., 2014a, b).

Step 4: Evaluate the equality and inequality constraints to ensure the validity of the decision variables.

Step 5: Calculate the objective function $f(x)$ in terms of minimized $f_n(x)$ and record feasible solutions.

Step 6: Repeat Steps 2 ~ 5 for a number of iterations using Monte Carlo simulation. Note that the higher the number of iterations, the higher the chance to get a better solution distribution, and also the more computation time. The number of iterations should be set according to calculation accuracy and time/resource constraints. Find the minimum objective function value $f(x)$ and the value of decision variables corresponding to the random coefficients.

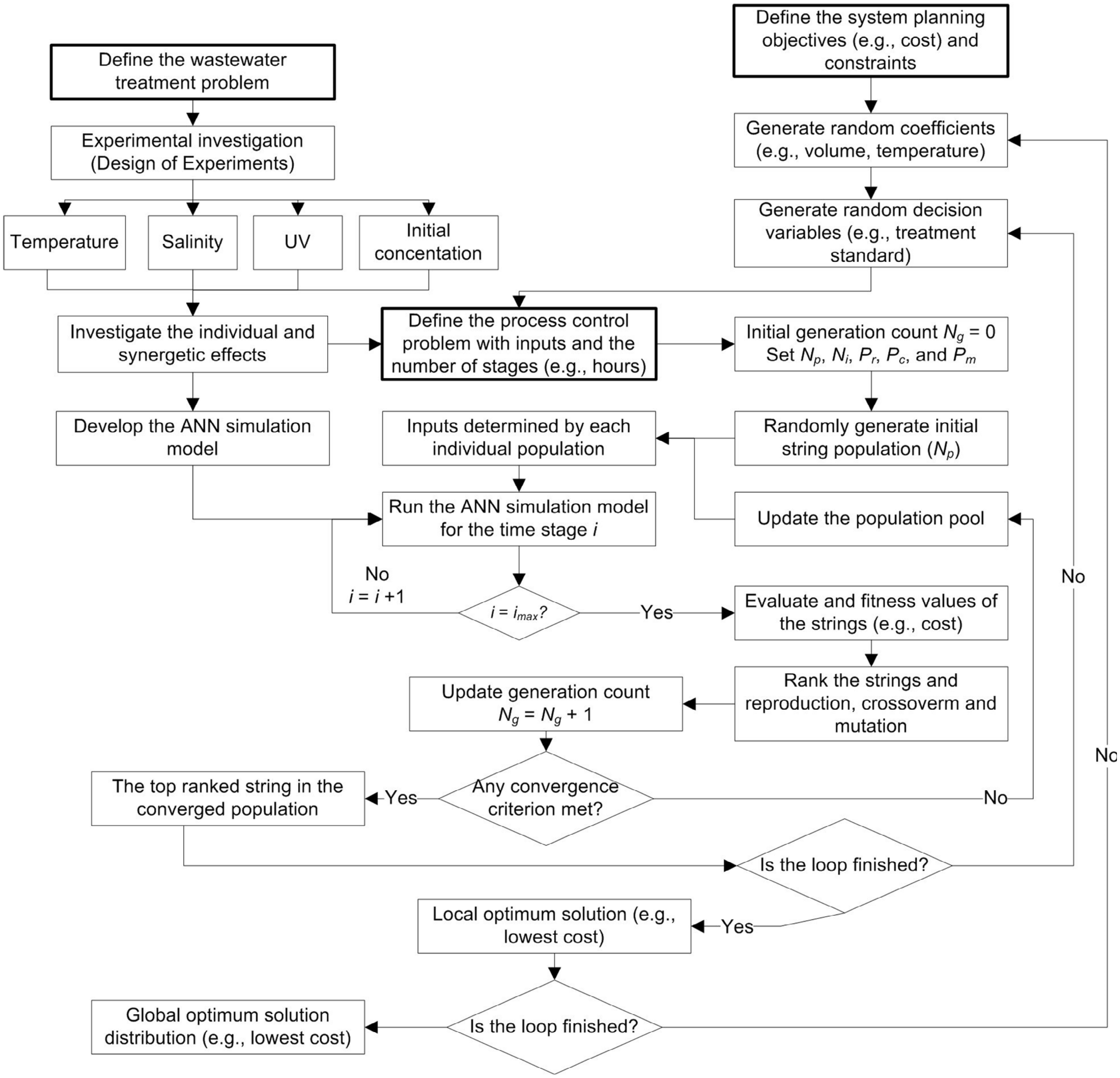
Define the wastewater treatment problem
Experimental investigation (Design of Experiments)
Temperature
Salinity
UV
Initial concentation
Investigate the individual and synergetic effects
Develop the ANN simulation model
Define the system planning objectives (e.g., cost) and constraints
Generate random coefficients (e.g., volume, temperature)
Generate random decision variables (e.g., treatment standard)
Define the process control problem with inputs and the number of stages (e.g., hours)
Initial generation count N_g = 0 Set N_p, N_i, P_r, P_c, and P_m
Inputs determined by each individual population
Randomly generate initial string population (N_p)
Run the ANN simulation model for the time stage *i*
Update the population pool
No
$i = i + 1$
$i = i_{max}$?
Yes
Evaluate and fitness values of the strings (e.g., cost)
Rank the strings and reproduction, crossoverm and mutation
Update generation count $N_g = N_g + 1$
The top ranked string in the converged population
Yes
Any convergence criterion met?
No
Is the loop finished?
No
Local optimum solution (e.g., lowest cost)
Yes
Global optimum solution distribution (e.g., lowest cost)
Is the loop finished?
No

Figure 1. Flowchart of the IS-PCOP Approach for marine wastewater management.

Step 7: Repeat Steps 1 ~ 6 using Monte Carlo simulation for a preset number of times. The objective function can be obtained as a probability distribution function in order to reflect the inherent uncertainty in the optimization process.

3. Case Study

3.1. Bilge Water Treatment System

This case study was simplified based on a real-world case in the North Atlantic where a Floating Production Storage Offloading (FPSO) vessel. To protect confidentiality, all identifications were removed. The onboard generated oily wastewater needed to be completely treated prior to discharge overboard or reuse. It should be noted that ballast water and produced water were not included in here. Produced water usually has its own separate treatment system due to the high volume. Ballast water is also not considered in this case as it is usually stored in segregated ballast tanks on new vessels and is free of any contact with oil. Therefore, in this case study, oily wastewater was mainly referred to bilge water that came from vessel sewage leak, cooling water leak, deck drainage, machinery drainage, and the leak of jet fuel, lubricant oil, diesel oil, hydraulic oil, and crude oil.

Bilge water on the FPSO was directed towards the slops tank where it mixed with collected rainwater and air conditioning condensate. Mixed bilge water then passed through an

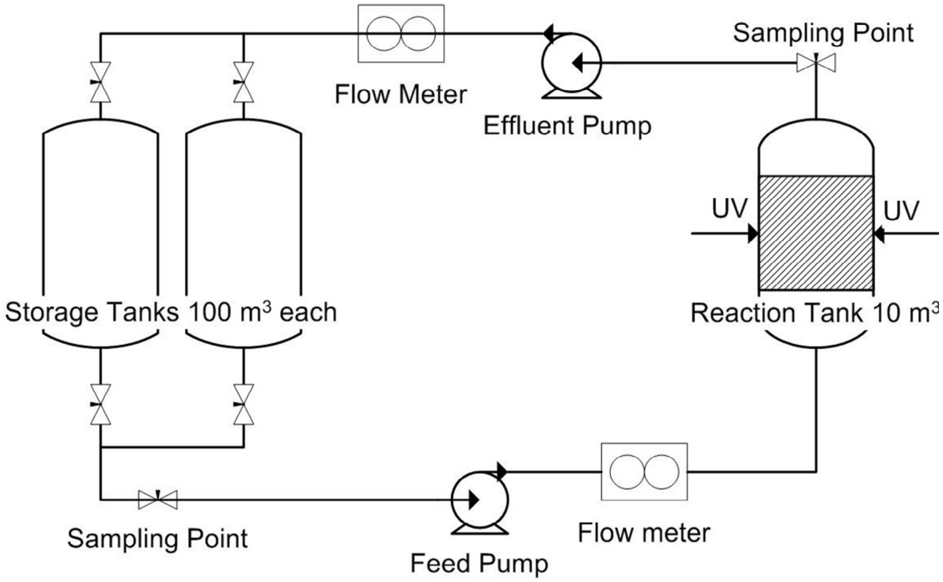

Figure 2. A schematic plot of the UV treatment system on the FPSO.

oil-water separation and an oil level testing to meet a discharge limit of 15 ppm (Behnood et al., 2014). Due to the growing concerns and more stringent regulations (e.g., zero discharge policy in the Arctic), further treatment was much desired to reduce the amount of dissolved organic pollutants (e.g., PAHs) left in the effluent from oil-water separators. In this case study, an UV secondary treatment system was deployed onboard to remove naphthalene, which is a typical PAH and of great environmental concern. Effluent from the oil-water separator was conveyed to storage tanks (100 m^3) and then pumped to the reaction tank for secondary treatment (i.e., UV irradiation) on a daily basis (Figure 2). There were two such storage tanks in order to make sure that one of them was available for storage while the other was under a treatment cycle. The storage tanks were connected to an UV reaction tank (10 m^3) where the average UV fluence rate could be controlled at 2.88, 4.27, 5.65, 6.96, and 8.27 mW cm^{-2}, respectively. This 5-level UV setting was the same as what has been used in Jing et al. (2014a, b), where different numbers of UV lamps (i.e., 2 ~ 6) were used to reflect different fluence rates. The treatment process could therefore be simulated using the ANN model developed by Jing et al., (2014a). Water contained in storage and reaction tanks was assumed to be completely mixed. The flow rate, by consulting local field engineers, was determined to be adjustable from 0.05 to 0.2 m^3 min^{-1} by using two centrifugal pumps between the storage and reaction tanks (Huang and Cao, 2011). Water flow contained in the pipes between two tanks was assumed to be negligible.

3.2. Bilge Water Characterization

According to the corresponding monitoring program technical reports, the daily average discharge of bilge water from the FPSO was approximately 39.64 m^3 day^{-1} with a standard deviation of 5.02 m^3 day^{-1}. The concentration of naphthalene in bilge water varied from 11 to 3,070 μg L^{-1}, with a mean value and standard deviation of 177.47 and 17.12 μg L^{-1}, respectively (U.S. EPA, 1999; Netherlands National Water Board, 2008). Assumptions were made here that the daily discharge volume and the concentration of naphthalene both followed normal distributions determined by their mean values and standard deviations. Salinity of bilge water was assumed to follow normal distribution with a mean value and standard deviation of 22 and 2 psu, respectively. Bilge water temperature, according to relevant reports and consultation with field engineers, also obeyed normal distribution with an average value and a standard deviation of 45 and 2 °C, respectively.

3.3. Problem Formulation

For each Monte Carlo run, random bilge water volume and naphthalene concentration were generated based on their corresponding normal distributions. Then the proposed process control approach was adopted to minimize the daily treatment cost by examining 24 hours treatment periods. Effluent from the UV treatment system, depending on its quality in terms of naphthalene concentration (i.e., should be less than 30 μg L^{-1} for safety concerns according to Kennedy (2006), could be reused onboard and generate varying benefits. The operation planning goal was to minimize the total treatment cost over a certain period of time, subtracting the reusing benefit, in order to economically meet the discharge standard for weeks, months or years, given the wastewater characteristics would remain unchanged. The problem of this case study, therefore, could be restated as to choose the best UV treatment goal (i.e., naphthalene concentrations in both storage and reaction tanks) that would be able to minimize the total net treatment cost over a 20-day period. Considering the available computation capacity and time constraint, the 20-day planning horizon was selected as a demonstrative example to show the effectiveness of the IS-PCOP Approach. Detailed problem formulation is summarized as follows:

Step 1: Set the UV treatment standard (β) to 30 μg L^{-1}.

Step 2: Generate random numbers for the daily volume of bilge water (z) and the concentration of naphthalene according to their pre-defined normal distributions, which are N(39.64, 5.02) and N(177.47, 17.12), respectively.

Step 3: Apply the ANN-DMINP approach (Jing et al., 2015) to minimize the daily net cost f, which equals the treatment cost subtracting benefits from reusing treated water. Note that the population size (N_p) and maximum generation count (N_g) were set at 10 and 20, respectively by taking computation time into account. All other GA optimization parameters were kept the same as referring to Jing et al. (2015):

$$Min\ f(x, y, z, \beta) = \sum_{i=1}^{n}(0.03 \times 60x_i + 0.5y_i) - z^{0.4} \times Ln(32 - \beta) \tag{5}$$

subject to:

$$h_1(x, y) \le \beta \tag{6}$$

$$h_2(x, y) \le \beta \tag{7}$$

$$lb \le x, y \le ub \tag{8}$$

where x and y are the flow rates (m^3 min^{-1}) and the intensity level of UV irradiation (i.e., 5 levels corresponding to 2.88, 4.27, 5.65, 6.96, and 8.27 mW cm^{-2}) during each hour, respectively; i is the number of hours; n in the total treatment period which could vary from 1 to 24 hours and must be integer (hour); z is the random daily volume of bilge water based on historical records (m^3); h_1 and h_2 stand for the final concentrations in the storage tank and the reaction tank, respectively; and β stands for the treatment standard. The cost coefficients in Equation 5 are arbitrarily predefined as \$0.5 per intensity level per hour and \$0.03 per liter, respectively. The flow rates of the pumps are equal and have to be greater than 0.05 and less than 0.2 L min^{-1}.

Step 4: Repeat Steps 2 ~ 3 for 20 iterations using Monte Carlo simulation to approximate a distribution of the daily net cost associated with the treatment standard of 30 μg L^{-1}. Note that the number of Monte Carlo iterations may be increased to obtain the output closed to the desired output. However, due to time and resource constraints, the number of iterations is set at 20. The total net cost over this 20-day period can also be obtained by summing up the daily net cost.

Step 5: Repeat Steps 1 ~ 4 for different treatment standards using Monte Carlo simulation. Ideally, the larger the number of iterations (e.g., 2000), the larger will be the computation time and the better will be the solution found. Due to concerns related to computation time, the standards are only examined at 5, 10, 15, 20 and 25 μg L^{-1} to demonstrate the efficacy of the proposed methodology. Then a comparison can be carried out to identify the most economically advantageous strategy that should be adopted for operation planning over this 20-day period.

4. Results and Discussion

Figure 3a demonstrates the optimization results with the treatment standard of 15 μg L^{-1}. By generating random wastewater conditions (e.g., volume, concentration, salinity) and following the procedure described in the Section 3.3, the probability density estimates of the minimized daily treatment cost and net cost were obtained using the kernel-smoothing method. It can be seen that the most probable value of the daily treatment cost was between \$22 and \$32, with a mean of \$30.92. As for the net cost, the most probable value ranged from \$10 to \$27 per day, with a mean of \$18.78 per day. As a comparison, the same probability density estimates of the 20 μg L^{-1} standard seemed to shift to the lower side of cost (Figure 3b). The most probably value of daily treatment cost and net cost were both less than \$30 with means of \$28.94 and \$18.00, respectively. This decreasing trend indicated that, from the probability perspective, the standard of 20 μg L^{-1} could be more economically competitive over the standard of 15 μg L^{-1}. Or in other words, choosing the more stringent standard (i.e., 15 μg L^{-1}) would result in an increase of treatment cost and reusing benefit. However, the increase of treatment cost was greater than that of benefit, leading to a higher net cost.

The same trend was observed with the standards of 5 and 10 μg L^{-1} from Figures 3c and 3d. As the tolerance of naphthalene concentration became stricter, sharp jumps in treatment cost were expected and could be attributed to the increased use of UV lamps and pumps. The mean treatment costs for the standards of 5 and 10 μg L^{-1} were \$55.96 and 44.97, respectively, which were drastically higher than those of 15 and 20 μg L^{-1}. On the other hand, stricter standards also offered more competitive reusing return. By reusing the treated effluent with naphthalene concentrations at 5 and 10 μg L^{-1}, the average economic returns were calculated as \$14.43 and 13.34, respectively. However, by subtracting benefits from the treatment costs, the average net costs were \$41.53 and 31.62, respectively, which were higher than those of the 15 and 20 μg L^{-1} standards. Contrastingly, the treatment costs associated with the standards of 25 and 30 μg L^{-1} were fairly close to that of the 20 μg L^{-1} standard but slightly at the lower side. Their average treatment costs were \$27.64 and 24.75, respectively; while the average net costs were \$18.70 and 21.72, respectively (Table 1).

Figure 4 depicts the optimal daily treatment cost, net cost, and benefit at different standards, where the central points are the average values over the iterations, and the bars represent the standard deviations of the estimates. It can be seen that treatment cost and reusing benefit both prominently went up when treatment standard became more stringent. Such increases are reasonably self-explanatory because reducing the concentration of naphthalene to a lower level would certainly require more energy and therefore provide better reuse potential. Nonetheless, the increase of treatment cost was significant as the standard was lowered from 5 to 15 μg L^{-1}; however, in between 20 and 30 μg L^{-1}, this trend was not statistically significant. As for the reusing benefit, the increasing behavior was only remarkable in between 25 and 30 μg L^{-1}. Such a difference resulted in the fact that the net cost tended to be higher at more

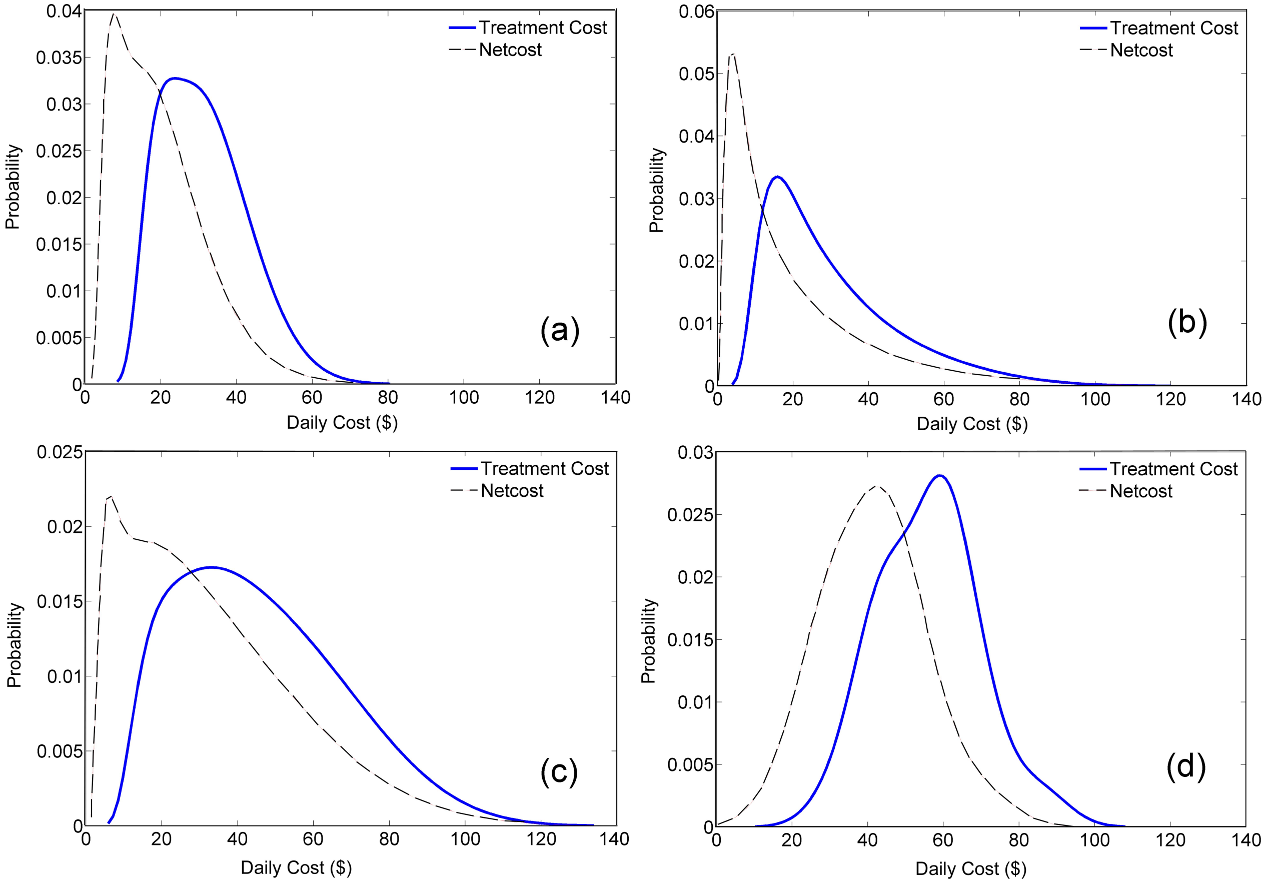

Figure 3. Probability density estimates of the daily treatment cost and net cost of the (a) 15 μg L^{-1} standard, (b) 20 μg L^{-1} standard, (c) 10 μg L^{-1} standard, and (d) 5 μg L^{-1} standard.

Table 1. Summary of the optimization results at different treatment standard

Standard (μg L^{-1})	Treatment cost ($/day)		Net cost ($/day)		CR*	Reusing benefit ($/day)	
	Mean	SD	Mean	SD		Mean	SD
30	24.75	12.20	21.72	12.10	0.999	3.02	0.17
25	27.64	13.64	18.70	12.95	0.999	8.94	0.87
20	28.94	14.71	18.00	14.42	0.999	10.94	0.63
15	30.92	9.09	18.78	8.74	0.997	12.14	0.78
10	44.97	18.30	31.62	17.88	0.999	13.34	0.72
5	55.96	12.69	41.53	12.29	0.999	14.43	0.73

*CR represents the correlation coefficient between daily treatment cost and net cost; and SD stands for standard deviation.

stringent standards (Figure 4), implying that the increase of treatment cost dominated that of benefit. A maximum and a minimum (i.e., $41.53 per day and $18.00 per day, respectively) were obtained at the standards of 5 and 20 μg L^{-1}, respectively, suggesting that 20 μg L^{-1} should be adopted by the decision makers as the most economically feasible option (Table 1). The distance between the error bars can be further reduced if more Monte Carlo iterations can be carried out. In addition, it should be noted that the calculation of reusing benefit would much dependent on the benefit function as shown in Equation 5. Here in this case study the reusing benefit decreased with increasing treatment standard; however, changing the benefit function may lead to totally different scenarios.

4.1. Comparison with Operation Planning without Process Control

To validate if the coupling between process control and operation planning was advantageous over the traditional planning with no process control module, a comparison study was conducted by using the single-stage one time planning over the 20-day period. Traditional planning tends to be more conservative and risk-avoiding such that the single-stage planning was based on the average problem settings including daily bilge water volume (39.64 m^3), the concentration of naphthalene (177.47 μg L^{-1}), salinity (22 psu), and temperature (45 °C). The UV intensity level and flow rate also remained unchanged with no process control efforts for each day within the 20-day period.

Six treatment standards (i.e., 5, 10, 15, 20, 25 and 30 μg L^{-1}) were evaluated and the results are demonstrated in Figure 5. It can be seen that the total treatment costs (20-day period) with process control, at each treatment standard, were lower than the results from the single-stage planning. This finding indicated that integrating process control with traditional operation planning would provide more economically competitive options in operating the treatment system. Another interesting point is that, the difference between operation planning with and without process control decreased with more stringent standard. This was in accordance with the trend shown in Figure 3b because when the treatment needed to be completed within a short period of time or the concentration had to be lower than a strict standard, the treatment system tended to be at its full capacity and had less potential for process control tools to make a difference.

The proposed IS-PCOP approach could well link process control and operation planning by simultaneously adopting different time-scales in computation. The hourly process control strategy forwarded the results to the operation planning module where long-term arrangements can be further evaluated. The use of ANN model also played a key role in predicting the behavior of complex processes. Many environmental processes, such as wastewater treatment processes, tend to have a nonlinear nature that makes the prediction complicated. Traditional process models that have been developed based on classic theorems may not effectively describe these complex sub-systems. This is because the models are usually created by applying different abstraction methods in which essential properties and key process indicators are preserved and insignificant details are left out. The use of ANN model, on the other hand, can well simulate the nonlinear processes using a black box nature which is more resilient to data uncertainty and lack of knowledge. In addition, the use of Monte Carlo simulation was able to address the uncertainties, which may arise from a number of different sources, such as demands for materials and finished products, feedstock supplies, environmental and economic conditions, and customers' willingness to pay. By addressing the uncertainties and expressing the results in probability distributions, the decision makers would have more confidence in making proper decisions regarding both the long- and short-term operation of the processes.

5. Conclusions

The coupling between process control and operation planning can help meet the economic objectives and ensure timely completion of the tasks. However, the link between them is most often not available due to the complexity of the integrated system, the difficulty in capturing and modeling the behavior of the processes, and the uncertainties of parameters to be considered. In response to these knowledge and technical gaps, this paper investigated the feasibility of integrating dynamic process control with traditional operation planning as an integrated simulation-based process control and operation planning (IS-PCOP) system. A case study related to oily wastewater management on a FPSO was conducted to examine the efficacy of this proposed integration. The process control approach

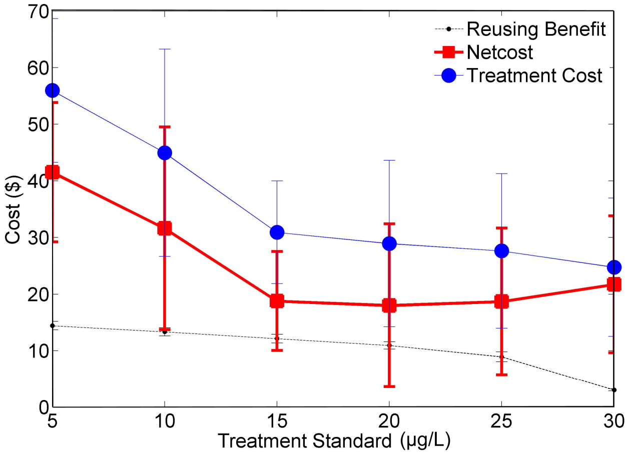

Figure 4. Error bar plot of daily treatment cost, reusing benefit, and net cost of each treatment standard.

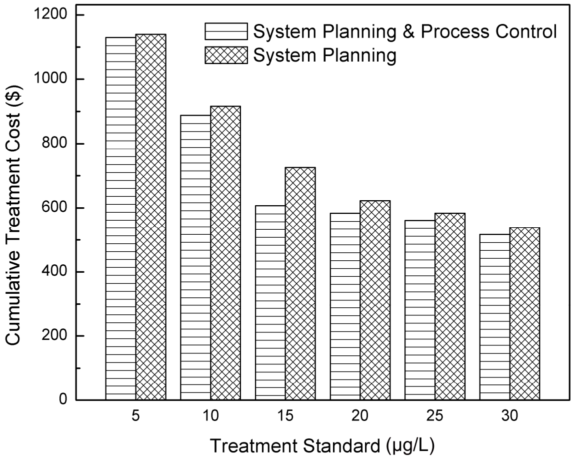

Figure 5. The cumulative treatment cost comparison over the 20-day period between operation planning with process control and without process control

was used to optimize the treatment cost of removing naphthalene from bilge water using UV irradiation. Treated effluent, depending on the remaining concentration of naphthalene, was reused and could produce benefit. Monte Carlo simulation was applied to generate the parameters (e.g., volume, concentration and temperature) of bilge water and examine the net cost to obtain the distribution of optimal solutions at a series of treatment strategies. The results showed that treatment cost and reusing benefit both prominently went up when treatment standard became more stringent. Such increases are reasonably self-explanatory because reducing the concentration of naphthalene to a lower level would certainly require more energy and therefore provide better reuse potential. The 20 μg L^{-1} standard seemed to be the most economically competitive option with a mean net cost of $18 per day and a mean reusing benefit of $10.94 per day. The distance between the error bars can be further reduced if more Monte Carlo iterations can be carried out. As compared to the traditional operation planning without process control, traditional planning tended to be more conservative and risk-avoiding, whereas the integrated approach achieved more economically competitive results from a statistical perspective. The proposed integration of dynamic process control and operation planning was successfully applied and demonstrated through the case study. Outputs from such integration can offer decision makers critical information and more confidence that is not likely to be provided by traditional techniques. It should be noted that the amount of time used for the case study was about 2.5 days, which can be further reduced by reducing the number of simulation time-step, adopting other advanced simulation-optimization methods, or using more powerful computational facilities. Nonetheless, the concept of experiment, simulation, and multi-scale optimization framework can be easily modified and applied to other environmental studies. Future research directions may focus on optimizing the computation procedure in order to accommodate larger numbers of Monte Carlo iterations, introduce fuzzy uncertainty into the proposed approach, and further validate by large-scale case studies.

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