

An Integrated System Planning and Process Control System for Marine Wastewater Management

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Abstract

An ideal combination of both system planning and process control can greatly reduce system cost and maximize economic and environmental benefits associated with marine oily wastewater treatment. If appropriate process control is not implemented during the system planning procedure, there might be potential benefits lost because traditional planning tends to be more conservative and less risk-taking. However, such integration is oftentimes complicated by many factors such as multi-scale nature of decisions, the lack of knowledge of process dynamics and control, and various types of uncertainties. How to more accurately couple process control with system planning has been a major roadblock in the wide application of the marine oily wastewater treatment systems. To date, there has been no such attempt made to investigate the feasibility and efficacy of coupling system planning and process control on marine oily wastewater treatment. This research therefore aims at demonstrating the possible integration of process control with traditional system planning by using neural networks, genetic algorithm, multistage principle, and Monte Carlo simulation. A case study that is related to offshore water use and wastewater treatment is carried out to demonstrate the efficacy of the proposed approach.

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

Introduction

Operation planning, or so called system planning, usually refers to a longer period of time and is a prerequisite for process control. Based on the required product characteristics and economic and environmental constraints, the most appropriate processes, resources, and standards can be properly selected. Contrastingly, process control is generally achieved by careful and accurate control and monitoring of the process parameters affecting the quality of the products. 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. 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. Recently, it has been recognized that, regardless their difference, the combination of process control and operation planning can ensure the meeting of the economic objectives and timely completion of

the tasks associated with the plans (Hans et al., 2007; Hüfner et al., 2009). Hüfner et 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. Anuar Mohamad Kamar (2010) argued that if appropriate process control is not implemented during the system planning procedure, there might be potential benefits lost because traditional planning tends to be more conservative and less risk-taking.

However, the link between process control and operation planning is most often not available due to the complexity of the integrated system, the difficulty in capturing and modeling the behavior of the process, and the uncertainty of parameters to be considered. How to more accurately couple process control with operation planning has been a major roadblock 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 of offshore wastewater management is carried out to demonstrate the efficacy of the proposed integrated simulation-based process control and operation planning (IS-PCOP) approach.

The IS-PCOP Approach for Marine Wastewater Management

Consider the following operation planning problem:

$$\text{Min } f(x) = f_1(x) + f_2(x) + \dots + f_n(x) \quad (1)$$

subject to:

$$g_j(x) = 0 \quad j = 1, 2, \dots, p \quad (2)$$

$$h_k(x) \leq 0 \quad k = 1, 2, \dots, q \quad (3)$$

$$lb \leq x \leq ub \quad (4)$$

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 restraint, 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 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.

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 $f_n(x)$ using the ANN-DMINP approach (Jing et al., 2014c).

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.

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.

Case Study

Bilge Water Treatment System

This case study is simplified based on a real-world case in the North Atlantic where a Floating Production Storage Offloading (FPSO) vessel. The onboard generated oily wastewater needs to be completely treated prior to discharge overboard or reuse. Oily wastewater is mainly referred to bilge water that comes 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.

Due to growing concerns and more stringent regulations (e.g., zero discharge policy in the Arctic), further treatment becomes desired to destruct dissolved organic pollutants (e.g., PAHs) left in the effluent from oil-water separator. In this case study, UV secondary treatment system is deployed onboard to remove naphthalene, which is a typical PAH and of great environmental concern. Effluent from the oil-water separator is conveyed to storage tanks (100 m³) and then pumped to the reaction tank (10 m³) for secondary treatment (i.e., UV irradiation) on a daily basis (Figure 2).

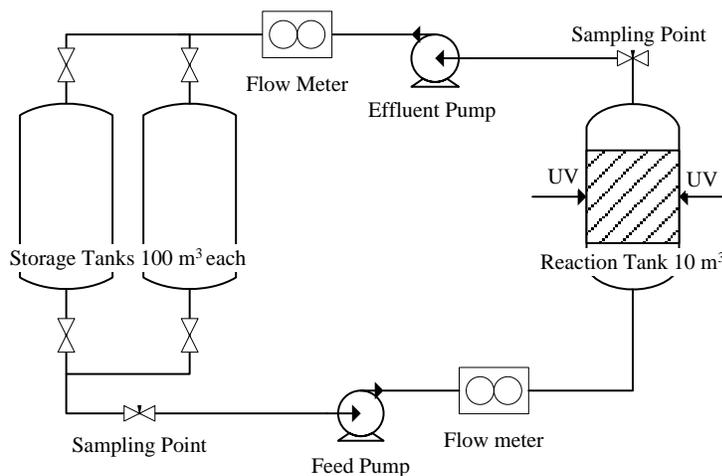


Figure 2. A schematic plot of the UV treatment system on the FPSO

There are two such storage tanks in order to make sure that one of them is available for storage while the other is under treatment cycle. The storage tanks are connected to an UV reaction tank (10 m^3) where a 5-level UV setting (2.88, 4.27, 5.65, 6.96, and 8.27 mW cm^{-2}) is used and described in Jing et al. (2014a and 2014b). The treatment process is simulated using the ANN model developed by Jing et al., (2014a). Water contained in storage and reaction tanks is assumed to be completely mixed. The flow rate, based on consulting local field engineers, can be adjusted from 0.05 to $0.2 \text{ m}^3 \text{ min}^{-1}$. Water flow contained in the pipes between two tanks is assumed to be negligible.

Bilge Water Characterization

According to the corresponding monitoring program technical reports, the daily average discharge of bilge water from the FPSO is approximately $39.64 \text{ m}^3 \text{ day}^{-1}$ with a standard deviation of $5.02 \text{ m}^3 \text{ day}^{-1}$. The concentration of naphthalene in bilge water varies from 11 to $3070 \text{ } \mu\text{g L}^{-1}$, with a mean value and standard deviation of 177.47 and $17.12 \text{ } \mu\text{g L}^{-1}$, respectively (U.S. EPA, 1999; Netherlands National Water Board, 2008). Assumptions are made here that the daily discharge volume and the concentration of naphthalene both follow normal distribution determined by their mean values and standard deviations. Salinity of bilge water is 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 obeys normal distribution with an average value of $45 \text{ }^\circ\text{C}$ and a standard deviation of $2 \text{ }^\circ\text{C}$.

Problem Formulation

Step 1: Set the UV treatment standard (β) to $30 \text{ } \mu\text{g L}^{-1}$.

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., 2014c) 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. (2014c).

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

subject to:

$$h_1(x, y) \leq \beta \quad (6)$$

$$h_2(x, y) \leq \beta \quad (7)$$

$$lb \leq x, y \leq ub \quad (8)$$

where x and y are the flow rates ($\text{m}^3 \text{ min}^{-1}$) 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 $30 \mu\text{g L}^{-1}$. Note that the number of Monte Carlo iterations may be increased to obtain the output closed to desired output. However, due to time and resource constraints, the number of iterations was sets as 20 in this case study to demonstrate the feasibility of the proposed methodology. 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 other 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 $\mu\text{g L}^{-1}$ 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.

Results and Discussion

Figure 3 demonstrates the optimization results with the treatment standard of $15 \mu\text{g L}^{-1}$. By generating random wastewater conditions (e.g., volume, concentration, salinity) and follow the procedure described in the methodology section, the probability density estimates of the minimized daily treatment cost and net cost are plotted using the kernel-smoothing method. It can be seen that the most probable value of daily treatment cost lied between \$22 and \$32, with a mean of \$30.92. As for the net cost that takes reusing benefits into account, the most probable value ranged from \$10 to \$27 per day, with a mean of \$18.78 per day. Figure 4 depicts the optimal daily treatment cost, net cost, and benefit at different standards, with the central points showing the average over the iterations, and the bars representing the standard deviation of the estimates. It can be seen that treatment cost and reusing benefit both prominently went up with more stringent treatment standard. 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. As for reusing benefit, the increasing behaviour was only remarkable in between 25 and $30 \mu\text{g L}^{-1}$. Such a difference resulted in the fact that the net cost tended to be higher at more stringent standards (Figure 4), implying that the increase of treatment cost dominated over the increase 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 $20 \mu\text{g L}^{-1}$, respectively, suggesting that the $20 \mu\text{g L}^{-1}$ standard should be adopted by the decision makers as the most economically feasible option (Table 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 m³), 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. The combination of process control and operation planning can ensure the meeting of the economic objectives and timely completion of the tasks associated with the plans. The proposed IS-PCOP approach can well link process control and operation planning by simultaneously adopting different time-scales in computation.

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 |

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

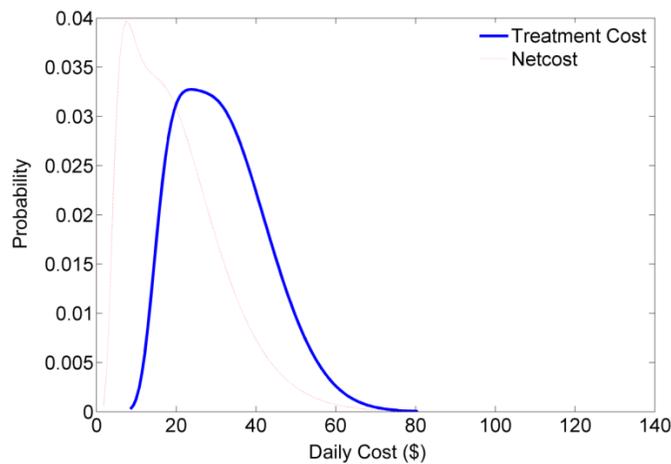


Figure 3. Probability density estimates of the daily treatment cost and net cost of the 15 µg L⁻¹ standard

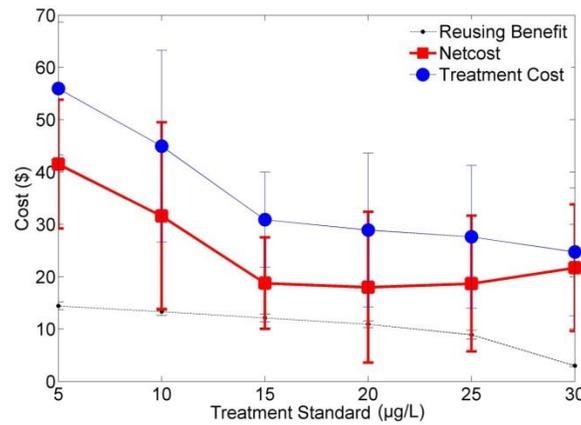


Figure 4. Error bar plot of daily treatment cost, reusing benefit, and net cost of each treatment standard

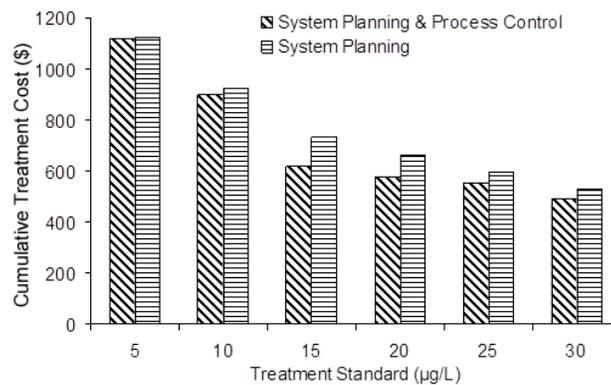


Figure 5. The cumulative treatment cost comparison over the 20-day period between operation planning with process control and without process control

Conclusions

This paper investigates 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 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 choosing the 20 µg L⁻¹ treatment standard was the most economically competitive option. As

compared to the traditional operation planning without process control, the integrated approach achieved more economically competitive results. The proposed integration of dynamic process control and operation planning was successfully applied and demonstrated through this 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. Future research directions may focus on optimizing the computation procedure in order to accommodate larger number of Monte Carlo iterations, introduce fuzzy uncertainty into the proposed approach, and further validate by large-scale case studies.

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