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An Agent-based Simulation-optimization Coupling Approach for Device Allocation and Operation Control in Response to Offshore Oil Spills

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Abstract

The efficiency of offshore oil spill response not only relies on an efficaciously global decision/planning in devices combination and allocation, but also depends on the timely control for response devices (e.g., skimmers and booms). However, few study has reported on such decision framework with timely integration of global planning and operation control to support the offshore oil spill recovery. This study developed an agent-based simulation-optimization coupling approach to provide sound decisions for devices combination and allocation for offshore oil spill recovery in a fast, dynamic and cost-efficient manner under uncertain conditions. At the same time, the approach aimed at providing operation control for specific devices, reflecting the site conditions, and correspondingly real-time adjusting the global planning, which was especially helpful to harsh environments prevailing in the Newfoundland offshore areas. In the case study, the developed approach was applied to determine the allocation of 3 response vessels from 7 different locations of the spilled oil slicks. The routes of the response vessels for response operation were optimized and reflected by the principle agent-based programming. The modeling results indicated a minimal time of 21 hours for vessels allocation and recovery operation when only considered oil recovery, leading to an oil recovery rate of 90%. The proposed approach can timely and effectively support optimal allocation of devices and control of operation as well as real-time adjustment of global decision for oil recovery under dynamic conditions and improve recovery efficiency.

Keywords: oil spill response, optimization, uncertainty, dynamic, agent-based programming

Introduction

Offshore oil spill is a common type of coastal and marine pollution. It is defined as an accident release or discharge of petroleum hydrocarbons due to human operations natural disasters. Tankers, offshore platforms and drilling rigs, as well as subsea piping lines are among the most common sources of oil spills. Various types of hydrocarbon contaminants can be involved in an oil spill accident, including crude oil, refined oil products, heavier fuels, and waste oil, etc. (Jing et al., 2012; Li et al., 2012). In history, oil spills have brought significant damages to the marine environment and local ecosystems. Two of the most predominant cases during the recent few decades are the Exxon Valdez Oil Spill in 1989 and the BP Deepwater Horizon Oil Spill in 2010. Given that specific situation vastly distinguished from each other, different strategies and technologies were deployed during the clean-up processes. Both of the spills led to tremendous economic losses and durable social/environmental impacts, for which, the inefficient decision support systems during the emergency response were consistently blamed (Picou, 2009; Atlas and Hazen, 2011; Griggs, 2011; Gill et al., 2012).

Accompanied by the booming of offshore oil production and transportation, particularly during the recent few decades, prompt response to oil spills has been realized as a critical issue. Growing research effort has been taken into developing an effective and efficient tool for oil spill emergency decision support systems. For example, Baruque et al. (2010) applied a Case-Based Reasoning (CBR) methodology in forecasting the presence and trajectory of oil slicks in open ocean areas by analyzing the previously solved problems, thus to shorten the time needed for decision makings. In another study, Krohling and Campanharo (2011) combined fuzzy theory with the concept Technology for Order Preference by Similarity to Ideal Solution (TOPSIS) in offshore oil spill decision makings, in which multi-scenarios can be simulated using different combat strategies to establish contingency plans based on the prioritized criteria. Meanwhile, Kokkonen et al. (2010) applied a mapping tool integrating both geological and ecological data for boom allocation under dynamic local sensitivities to potential oil spills, and have it tested under representative cases.

In addition to simulating oil spill scenarios, optimizations need also be involved to provide decision support under various conditions when oil spills actually happen. Zhong and You (2011) developed a multi objective linear model for cleanup operational schedules and coastal protection plans during an oil spill event. Sheu et al. (2005) used a fuzzy clustering technique for optimizing resource allocation during disasters other than oil spills. Verma et al. (2013) formulated a two-stage stochastic programming to optimize the allocation of oil spill facilities for the southern coast of Newfoundland. Besides, many studies also considered to integrate optimization with simulation, particularly under dynamic situations. For example, You and Leyffer (2011) took into account the time-dependent factors regarding oil properties, hydrodynamics, and weather conditions while optimizing the response plans. Li et al. (2014) introduced uncertainties into the decision making processes during oil spills, by developing a Monte Carlo based dynamic mixed integer nonlinear programming for devices allocation optimization.

Despite that dynamic conditions have been considered within previous studies, harsh environment makes emergency response to oil spills even more challenging by changing the fate and properties of oil dramatically within short period of time, which will inevitably impede the recovery and cleanup processes unless timely updates of operational schedules are made (Brandvik et al., 2006; Bjerkemo, 2011). Few studies up to date have been carried out specifically to address this issue. Therefore, a real-time decision support systems taking into account of restrictions of devices and logistical efficiency is urgently desired.

To fill this gap, agent-based modeling (ABM) is hereby proposed to render a certain degree of autonomous characteristic to the system, thus to achieve a better simulation of the process and make the optimization of the operational schedule more practical. The study aims at developing an agent-based model, which couples both simulation and optimization under a dynamic condition, to provide a real-time decision support regarding devices allocation and operation control for a hypothetical oil spill case. The outcomes of the study is expected to be capable of facilitating a more effective and efficient tool for emergency oil spill response under highly dynamical conditions.

Agent-based simulation-optimization (ASO)

Simulation-based dynamic mixed integer nonlinear programming (DMINP)

Consider a linear program as follows:

$$Min \quad f = C_j X_j \tag{1a}$$

s.t.

$$\sum_{j=1}^{n} A_{ij} X_j \leq B_i , \quad i = 1, \cdots, m \tag{1b}$$

$$X_j \geq 0 \tag{1c}$$

where $C \in \{R\}^{1\times n}$ is the matrix of coefficients of the objective function; and $A_{ij} \in \{R\}^{m\times n}$ as well as $B_i \in \{R\}^{m\times 1}$ are matrices of variable constraint coefficients.

When C_j are not just constants but also functions linking with some other parameters with a relation of $g_j(y)$, the **Equation 1** will be a simple linear model and can be solved by linear programming if $g_j(y)$ is independent from the decision variables (X_j). However, when $g_j(y)$ are dependent on the decision variables, the model becomes non-linear. Especially when $g_j(y)$ are dynamically relating with the decision variables (usually with time series), the model becomes dynamic and non-linear, and cannot be easily solved. It will be more convenient to break the time series into certain stages based on a controllable time interval, leading to a simulation-based dynamic mixed integer nonlinear programming (DMINP) as follows:

$$Min \quad f = \sum_{s=1}^{N} \left[\int_0^{t_s} \psi\left(f_{s-1}\left(g_j(y_{t-1}) X_j\right), g_j(y_t) X_j, t \right) dt \right] \tag{2a}$$

s.t.

$$\sum_{j=1}^{n} A_{ij} X_j \leq B_i , \quad i = 1, \cdots, m \tag{2b}$$

$$X_j \geq 0 \tag{2c}$$

where t_s is the time interval in the stage s. In some cases, $g_j(y)$ in the same stage can be assumed to be unchanged and the **Equation 2** can be correspondingly converted to:

$$Min \quad f = \sum_{s=1}^{N} \psi\left(f_{s-1}\left(g_j(y_{t-1}) X_j t_{s-1}\right), g_j(y_t) X_j t_s \right) \tag{3a}$$

s.t.

$$\sum_{j=1}^{n} A_{ij} X_j \leq B_i , \quad i = 1, \cdots, m \tag{3b}$$

$$X_j \geq 0 \tag{3c}$$

Oil recovery simulation

In offshore oil spill recovery, the net oil recovery rate (*ORR_n*, defined as the amount of recovered oil per hour) of skimmer is usually determined by slick thickness (*ST*). The function between ORR_n and *ST* are as follows:

$$ORR_n = a \times ST^2 + b \times ST \tag{4}$$

where *a* and *b* are empirical coefficients obtained from experimental tests. Correspondingly, the objective function of the offshore oil spill recovery problem by skimmer can be expressed as follows:

$$Max\ \ V = \int_0^t SK_i \times ORR_{ni} dt \tag{5}$$

where *V* is the volume of recovered oil, *t* is the operational time, SK_i are the numbers of skimmer type *i*, and ORR_{ni} are the recovery rates of the corresponding skimmer.

As ORR_{ni} are dynamically related with the objective value (*V*), the problem becomes dynamic and non-linear, and cannot be easily solved. It will be more convenient to break the time series into multiple stages based on a controllable time interval defined as the minimal time required for shifting one operational condition to another. The duration of a stage is usually determined by the time for device deployment and allocation, resource arrangement, etc. This leads to a multiple-stage simulation based nonlinear programming as follows:

$$Max\ \ V = \sum_{s=1}^{N} SK_i \times ORR_{nis} \tag{6}$$

where *N* is the length of an operational period, *s* is the number of operational stages, ORR_{nis} are net oil recovery rates for SK_i at stage *s*, which is calculated by the slick thickness or the collected oil from the stage *s-1*:

$$ORR_{nis} = f_{ORR_{ni}}(ST_{s-1}) = f_{ORR_{ni}}\left(\frac{V_0 - \sum_{h=1}^{s-1} V_h}{A} \right) \tag{11}$$

where V_0 is the initial volume of spilled oil, *A* is the area, and *h* is the stage index.

Agent-based model for device interaction and agent-based simulation-optimization coupling

In offshore oil spill response, strong interactions exist in the response devices (e.g., vessels, recovery devices, storage barge), responders, decision makers, etc. These interactions dynamically occur during the whole process of an offshore oil spill response. It may lead to unreliability or compromise of the response actions if these interactions are not considered in the global optimization. In order to facilitate the reflection of these interactions, an agent-based model is introduced.

According to Wooldridge and Jennings (1995), an agent can be defined as "a software or hardware entity that is situated in some environment, and is capable of performing autonomous actions in that environment in order to meet its design objectives". As shown in **Figure 1**, an agent usually contains some basic properties as follows: (1) able to survive and response to the environment; (2) able to dynamically receive the information from the local environment; (3) driven by certain goals or purposes; and (4) has certain intrinsic behaviours reacting with the environments and other agents (Liu, 2001). Thus, an agent can be characterized by its autonomy, social ability, reactive and protective behaviour. The autonomy can allow an agent independently completing any complex tasks. The social ability can drive an agent to interact and negotiate with the other agents to achieve its task, and the system goal can be achieved based on the interaction and negotiation from all agents. The reactive behaviour of an agent can help dynamically perceive and respond to the changing environment, while the proactive behaviour can make an agent dynamically change its behaviour according to the change of environment to achieve its goal. Some other properties of agents include mobility, temporal continuity, collaborative behavior, etc. (Liu et al., 2003).

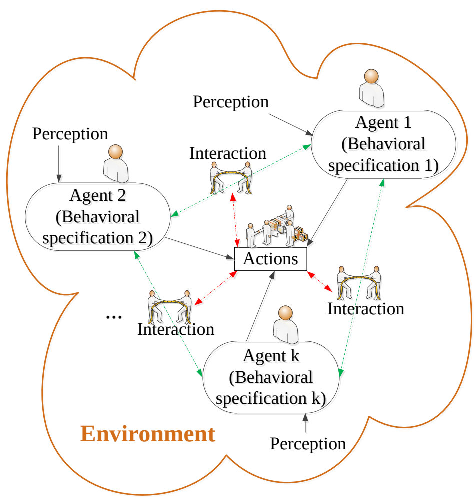

Figure 1. Basic structure of an agent-based model.

This agent model can be embedded in the DMINP approach as simulative constraints to reflect the dynamic interactions of devices (e.g., ship mount devices) during offshore oil spill response, leading to an agent-based simulation-optimization coupling (ASO) approach. This approach can utilize the global objectives as the goals for agents and dynamically adjust the plan settings according to the agent-based modeling.

Case study

Background

Consider an offshore spill of Statfjord oil with a total amount of 1,000 m^3. Due to advection and spreading, the spilled oil was separated to 7 slicks within a 70 km * 30 km area. The volumes and location of these oil slicks are shown in Table 1. The initial thickness of each slick is 50 mm.

Table 1. Locations and volumes of oil slicks.

Slick	Location		Oil volume (m^3)
	X (km)	Y (km)	
1	24.03	10.03	132.44
2	5.80	18.46	219.37
3	19.97	20.99	146.69
4	14.07	3.43	137.82
5	27.49	5.42	81.07
6	16.61	29.39	79.86
7	3.27	13.84	202.76

Three ships (Ship A, Ship B, and Ship C) with three types of ship mounted skimmers were applied in this area to collect the spilled oil. Each ship was located in a different harbor and required a specific period of time for allocation.

Oil spill skimming

In order to determine their efficiencies, *ORRs* and *OREs* of these skimmers were collected from the previous tests conducted by Environmental Canada and OHMSETT (Schulze, 1998). According to the collected information, a series of ORR_{n1}, ORR_{n2} and ORR_{n3} were generated based on calculating *ORRs* * *OREs* using different oil thickness with a viscosity of 1,000 cSt (Schulze, 1998). Fittings were then applied based on quadratic functions to generate the regression models of ORR_n with the change of spilled oil thickness, representing the recovery efficiencies of the three types of skimmers. Such change of slick thickness is usually caused by the processes of spreading, shifting, weathering (e.g., evaporation, dispersion, dissolution, emulsification, etc.), as well as oil recovery. The details about the ORR_n of the skimmers as well as the regression models of the efficiencies are shown in **Table 2**.

Table 2. Time of devices allocation as well as model parameters of ORR_n (Li et al., 2012, 2014).

Types of skimmers	Model parameter for ORR_n	
	a	b
SK_1 (Ship A)	0.01437	0.01602
SK_2 (Ship B)	-0.00791	0.84975
SK_3 (Ship C)	-0.01591	1.54975

Due to the challenge of transportation, no more skimmers and vessels can be supplied at this stage. The objective of the response in the current stage is to determine the allocations (routes) of ships to achieve 90% of oil recovery with a minimum time window. According the above information and the algorithms of DMINP and ASO, a global optimization model can be generated as follows:

$$Min\ T \tag{12a}$$

s.t.

$$\sum_{t=1}^{T} TV_t \geq 0.9 \times 1000 \qquad (12b)$$

$$TV_t = f_t(Agent_i, ST_{tk}) \qquad \forall t = 1, \cdots, T; i = 1,2,3; k = 1, \cdots, 7 \qquad (12c)$$

where T is the time window of operation (hour); t is the indicator of stage; TV is the recovered oil in each stage (m^3); and f_t ($Agent_i$, ST_{tk}) is the function of the agent-based modeling at stage t; ST_{tk} is the slick thickness of each slick k at stage t (mm); and *Agent* is the referring to each skimmer mounted ship. The development of the agent function is as follows:

Results and discussion

The modeling results indicated that, without consideration of weathering processes, the time window for achieving 90% of oil recovery was 21 hours based on the optimal routes of response vessels determined by the ASO modeling.

The routes of three response vessels are indicated by **Figure 2**. The routes and schedules of vessels indicated that due the closest distances to two large slicks (Slicks 2 and 7) and stable relatively stable efficiency of oil recovery, Ship B with SK_2 was mainly working on these two slicks. No interactions between Ship B and other two ships until the late stage (after the 15th hour). Furthermore, strong interactions were observed between Ships A and C. However, due to the long distance from Ship C to the slicks, it took 2.9 hours for Ship to reach the first slick for operation. No oil recovery was proceeded by this vessel at the first three hours and no interaction occur between Ships A and C. From 3rd to 19th hours, strong interactions happened between these two ships. Because the recovery efficiency of skimmer on Ship C (SK_3) was high on and had less significant decrease than the one on Ship B (SK_1), the allocation of the Ship A was always changed according to the allocation of Ship B. Since the distances were far from these two ships to Slicks 2 and 7, the interactions of Ships A and C happens on Slicks 1 and 3-6. Due to the significant decrease of recovery efficiency the Ship A stopped operation after 19th hour. Interactions of all three ships happen after the 17th hour.

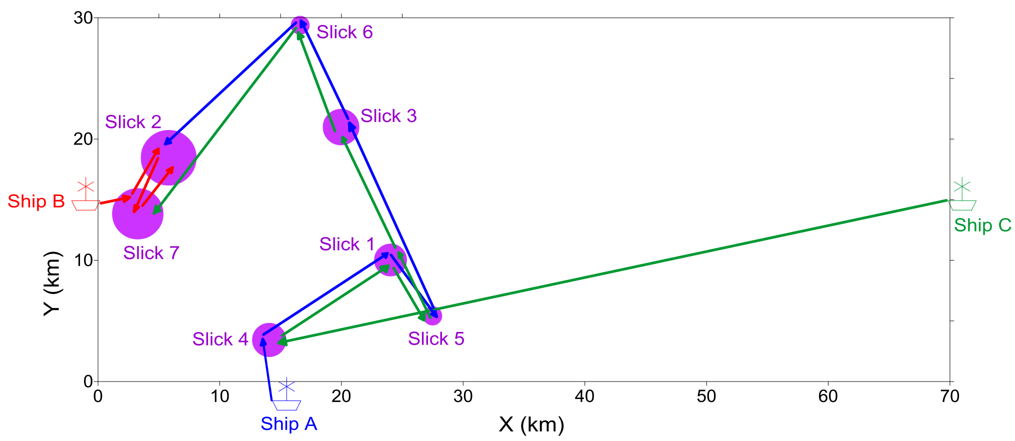

Figure 2. Optimal routes of response vessels based on ASO modeling.

Figure 3 indicated the amount of oil recovered by each ship at each stage, while **Figure 4** indicated the cumulated amount of recovered oil. Although the recovery amounts were fluctuant during the whole operational period, the global trends of recovery were decreased along with time. Because of strong interactions between Ships A and C, the fluctuation of oil recovered by this two ships were more significant than which by Ship B. Furthermore, controlled by the global objective, the overall oil recovery by all ships keep increasing until the ultimate goal was achieved.

In order to demonstrate the advantages of the ASO approach, a comparison was made between the ASO and shortest distance optimizations in offshore oil spill recovery. In the shortest distance modeling, the allocations of ships were only driven by the short distance between each ship and each oil slick. The ships left the slicks until 90% of oil recovery was achieve on each slick. The comparison result is illustrated on **Figure 5**. At the early stage (1st to 5th), the oil recovery efficiencies based on the two approaches were almost the same. Since the 5th stage, the recovery efficiency based on the shortest distance approach became lower than the one based on the ASO. Furthermore, this inferiority became significant along with time. To achieve 90% of oil recovery, the settings from the shortest distance required 23 hours while the settings from ASO only required 21 hours.

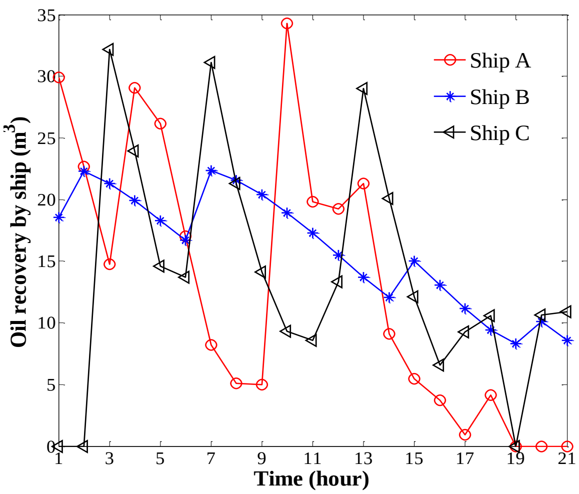

Figure 3. Oil recovery by each ship at each stage.

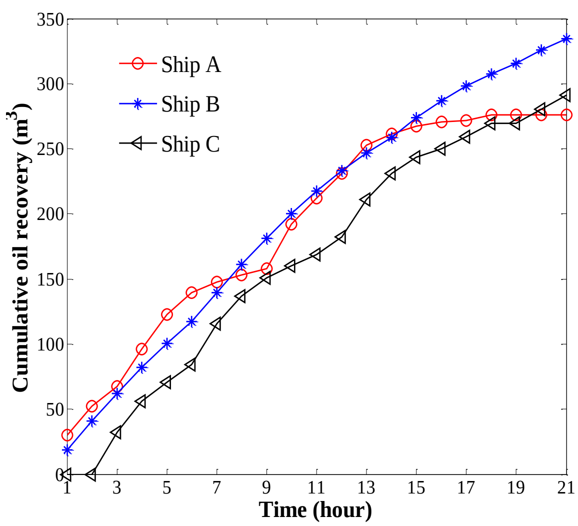

Figure 4. Cumulated oil recovery by each ship.

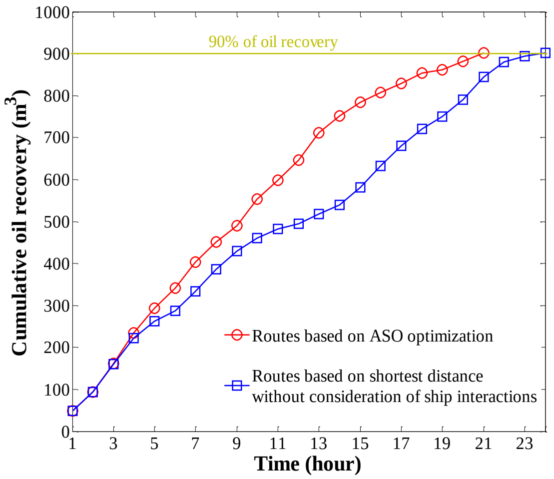

Figure 5. Comparison of oil recovery by ship routes determined by ASO and shortest distance.

Conclusions

An agent-based simulation-optimization (ASO) coupling approach has been developed to support oil recovery and devices allocation during offshore oil spill responses, providing sound decisions for oil recovery in a fast and dynamic manner. The ASO approach was developed based on the integration of a global optimization approach, Simulation-based dynamic mixed integer nonlinear programming (DMINP), and an Agent-based model (ABM) for reflecting devices interactions. The MC-DMINP approach converted the simulation model into constraints which dynamically linked to the decision variables, and broke the time series into certain stages according to controllable time intervals in practical manner, leading to a multiple stages dynamic programming. The ABM can reflect the interactions of components in offshore oil spill recovery system and integrate with the global optimization. Therefore, The ASO approach can provide sound decisions for oil recovery under highly interactive conditions and improve recovery efficiencies

In the case study, the developed approach was applied to determine the allocation of 3 response vessels from 7 different locations spilled oil slicks. The modeling results indicated that the optimal routes of vessels could lead to a minimum operational time window of 21 hours to achieve 90% of oil recovery, which was improved from the traditional method based on shortest distance (23 hour). This demonstrates the advance of the ASO. The proposed approach can timely and effectively support optimal allocation of devices and control of operation under dynamic conditions and improve recovery efficiency.

Although a case study of supporting the oil recovery by skimming is provided in this paper, the ASO approach can globally and dynamically support the whole process of oil recovery oil, including the devices allocation, deployment, and operation of containment, skimming, surfactant utilization, in-situ burning, etc.

In future study, hydrodynamic simulation and weathering processes will be considered to further test the feasibility and capability of the developed ASO. Future research efforts may also include the consideration of possibilistic uncertainties for incorporating expert knowledge into the decision making process of offshore oil spill responses. Testing of the developed method through real-world applications is undergoing with the collaboration with local oil spill responders.

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