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Using a genetic algorithm to improve oil spill prediction

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ABSTRACT

The performance of oil spill models is strongly influenced by multiple parameters. In this study, we explored the ability of a genetic algorithm (GA) to determine optimal parameters without the need for time-consuming manual attempts. An evaluation function integrating the percentage of coincidence between the predicted polluted area and the observed spill area was proposed for measuring the performance of a Lagrangian oil particle model. To maximise the objective function, the oil spill was run numerous times with continuously optimised parameters. After many generations, the GA effectively reduced discrepancies between model results and observations of a real oil spill. Subsequent validation indicated that the oil spill model predicted oil slick patterns with reasonable accuracy when equipped with optimal parameters. Furthermore, multiple objective optimisation for observations at different times contributed to better model performance.

1. Introduction

Oil spills are a major environmental concern and regarded as one of worst types of marine pollution, some of which may have disastrous consequences for open oceans and coastal seas. Considerable research has been conducted on the transport of spilled oil using field and laboratory investigations. Numerical oil spill models, which predict the transport and behaviour of oil spills, are an essential instrument for risk assessment and clean-up during an actual accident. However, it is still not possible to predict the actual trajectories of oil spills with any degree of certainty. Over the last three decades, numerous detailed oil spill models have been presented with the goal of improving oil spill forecasting (ASCE, 1996; Reed et al., 1999; Spaulding, 2017). These models have been developed from two-dimensional horizontal models to three-dimensional multiphase models, from considering only oil on the surface to oil distributed in multiple interacting phases, and from including a single environmental factor to atmosphere–wave–current coupled effects. Although these theories and data are valid, oil behaviour is complex, and many aspects of this behaviour are far from being clarified satisfactorily.

Currently, oil spill models incorporate a range of parameters, partly due to a lack of knowledge of the underlying mechanisms behind oil transport and reaction processes. Hodges et al. (2015) argued that empirical parameters are one of four major contributors to uncertainty in an oil spill model. Complicated environmental conditions and the complex mixture of hundreds of chemicals make every spill different, and determining a unique set of appropriate parameters for each event is impractical and difficult. For example, the 3% wind drift factor for oil movement considers average conditions, and the implication just represents average conditions and the actual factor ranges from 1 to 6%. Once submerged, oil particles driven only by water currents have a net lower drift speed than that assumed by the 3% rule. Moreover, oil converging in windrows accelerates, and the transport velocity becomes higher than the average 3%, and some variables, such as wind deflection angle, are disputed. Because an oil layer is too thin to experience the full Ekman spiral, the wind deflection angle has previously been set to zero (Coppini et al., 2011; Huntley et al., 2011). However, Samuels et al. (1982) argued that the veering angle is related to wind speed; when wind speeds are low, the average deflection angle can be as high as 20°.

Understanding the model structure and underlying principles is a key requirement for increasing model reliability. Parameter rationalities must first be widely accepted before model parameters can be optimised, and without extensive experimentation, a model using approximated parameters may not simulate satisfactory results. Although oil spill numerical results rely heavily on parameter rationality, near-optimal parameters have typically been estimated by manual calibration to match observations of real-world phenomena. However, because

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numerous parameters are related to oil movements, determining the most suitable ones is a time-consuming exercise that requires thorough experimental analysis.

Instead of obtaining universal parameters applicable to any condition, this study evaluated a method for seeking the most suitable parameters according to the location or event of interest. The genetic algorithm (GA) technique, inspired by the principles of biological evolution and natural genetics, has been widely adopted as an efficient tool for searching near-optimal solutions to nonlinear, nonconvex and multimodal problems (Gobeyn et al., 2017; Haupt and Haupt, 2004). Previous studies have demonstrated robust, modern approaches for employing GAs, which have been widely used in a variety of optimisation and search problems. However, few studies have employed GAs for optimising the parameter estimations of oil spill models.

When a GA is combined with an oil spill model under calibration, the model must be executed for a number of iterations; the computational bottleneck issue is no longer a limitation due to progress in computing equipment. Before GAs are implemented within oil spill modelling, an objective function evaluating the fitness of each model run should be provided in advance. Although there have been significant research advances in oil spill dynamics, the qualitative comparisons between simulation and observation is universal. At present, oil slicks on the sea surface can be accurately captured by observations from aerial images and satellites, which provide comprehensive evidence for the damage extent. Huntley et al. (2011) introduced two metrics for measuring simulation success: the percentage of the predicted spill area contained in the observed area and that of the observed polluted area contained in the simulated area. With the advent of fine-scale remote sensing techniques, an algorithm judging from scattered points to a whole plane seems more promising.

The purposes of this study are (1) to propose an objective function for the quantitative assessment of oil spill model performance and (2) to enhance model accuracy using of a GA. Following the introduction, Section 2 describes the basics of the oil spill model incorporating optimised design process. In Section 3, we apply the proposed model to the Dalian New Port accident that occurred on 16 July 2010. Section 4 presents the conclusions and applications of this study.

2. Methods

2.1. Environmental factors

Geographically, Dalian New Port is located on the boundary between the southern region of the Liaodong Peninsula and the North Yellow Sea (Fig. 1). It is a major seaport in North China, that has led to rapid economic growth in the region. However, this port has been affected by severe oil spills, including those from *Maya 8* in 1990, *Ya He* in 2001, *Arteaga* in 2005, and most recently, the Dalian New Port accident in 2010 (Guo and Wang, 2009; Guo et al., 2014; Xu et al., 2012). The Dalian New Port accident resulted in 35,000 t of crude oil being discharged into the coastal area on 16 July 2010, making this the largest marine oil spill in China's history. The spilled oil contaminated more than 300 km^2 of sea area and 80 km of coastline to varying degrees (Fig. 1(d)).

Oil spill behaviour is determined by the surrounding environment conditions as well as the physicochemical properties of the spilled oil; therefore, combining accurate environmental dynamic information is key for simulation accuracy. Hydrodynamic data (tides, currents and waves) to study oil spill behaviour were obtained from a wave–current coupled model. The current model in use is a semi-implicit Eulerian–Lagrangian finite-element (SELFE) model, which is a state-of-the-art, free-surface, primitive equation, hydrostatic model with Boussinesq and hydrostatic approximations (Zhang and Baptista, 2008). Considering that wave-driven current and wave breaking playing a significant role in spreading out oil slicks and propelling permeating oil droplets into the water column, wave data for this study were acquired from a third-generation wave model called the Simulating Waves Nearshore (SWAN) model (Booij et al., 1999), to solve transport equations of wave action density. Wave–current interactions occur over a wide range of both wave and current conditions; therefore, the SWAN model is iteratively two-way coupled to the SELFE model (Guo et al., 2016). Surface wind stress, bottom stress and radiation stress computed in SWAN model were provided to the SELFE model, and in turn, the SEFLE model offered current fields and water level elevation that were used in the SWAN model to calculate wave parameters for the next time step. The unstructured grid of the wave–current coupled model extended from Dalian New Port into the entire Bohai Sea and North Yellow Sea. The finest resolution occurred near Dalian New Port, with a grid spacing of approximately 20 m, and the resolution was relatively coarse, exceeding 1000 m, in areas far from the spill source (Fig. 1). The hydrodynamic model verification results were detailed in Guo et al. (2014). The maximum deviation of significant wave height from the measured values at the nearby monitoring location was within 0.2 m. The average root-mean-square error for water level simulation was less than 0.1 m, and the mean correlation coefficient of current speed between the observed and simulated values was over 0.9. Overall, the wave–current coupled model correctly reproduced the main hydrodynamic processes in the accident area waters and was capable of providing credible information for oil spill simulation.

Wind data, employed for wind driven currents, were acquired from re-analysis data based numerical results provided by the Weather Research & Forecasting Model (WRF) spanning 20°–52°N and 117.5°–152°E. Despite the fine temporal and spatial resolution of the WRF results (3-h time interval, and a horizontal resolution of 0.1° by 0.1°), the wind data used for calculating the oil particle trajectory were obtained from the records (1-h time interval) of a local meteorological station (Fig. 2), considering its vital role in determining spill trajectory accuracy. The region is characterised by a typical medium latitude monsoon climate, which consists of cold, dry winters and hot, wet summers.

2.2. Oil spill model

In this study, the fate and transport of spilled oil was governed by the advection under the actions of currents, wind, and surface waves; mechanical spreading of inertia, gravitational, surface tension and viscous forces; horizontal diffusion due to turbulence and shear effect; vertical entrainment and resurfacing; weathering processes such as evaporation, emulsification and dissolution; and the interaction of oil with the coastline (Fig. 3).

Considering the amount of oil released as a larger number of virtual particles that are tracked individually is an approach that has been widely adopted, and the model that employs this approach is known as the oil particle model. In this particle-based approach, oil spill movements are computed according to transport forced by advection (currents, winds, and surface waves) and turbulent diffusion. The advection velocity of an oil particle is computed as follows:

$$\vec{U}_a = C_{cr}\vec{U}_{cr} + C_{wind}D_{wind}\vec{U}_{wind} + C_{wave}\vec{U}_{wave} \tag{1}$$

where $\vec{U}_{cr}$ is the water current velocity interpolated from the hydrodynamic model; $\vec{U}_{wind}$ is the wind velocity 10 m above the water surface, C_{wind} is the wind drift factor, D_{wind} is a transformation matrix used to account for the wind deflection angle, $\vec{U}_{wave}$ represents the calculated wave Stokes drift, and C_{wave} is the wave drift factor.

The wind deflection angle is calculated as follows (Samuels et al., 1982):

$$\theta = D_a \exp(-10^{-8}{U_{wind}}^3/\nu g) \tag{2}$$

where ν is the kinematic viscosity of seawater. As opposed to its original form, the constant D_a is replaced by a variable.

$\vec{U}_{wave}$ represents the wave Stokes drift, calculated as follows: