A Lagrangian model for tracking surface spills and SaR operations in the ocean

J.M. Sayol,*, A. Orfila, G. Simarro, D. Conti, L. Renault, A. Molcard

*IMEDEA (CSIC-UIB), 07190 Esporles, Balearic Islands, Spain
bICM-CSIC, 08003 Barcelona, Spain
cICTS SOCIB, 07121 Palma, Spain
dUniversité du Sud Toulon-Var (MIO), 83957 La Garde cedex, France

1. Introduction

Marine pollution at sea as a consequence of accidental and/or illegal spills is among the largest threats to the marine environment. Spills involving oil or hazardous materials cause every year large economical and ecological damages that, depending on the severity of the spill, its nature and the affected environment, could require decades to be recovered (Elliot and Jones, 2000). In the last decades, the large number of incidents involving oil tankers, offshore platforms or oil pipelines resulted in an increasing concern among stakeholders and scientists on the need of developing accurate and reliable tools to forecast the evolution of those spills in the ocean (Reed et al., 1999; Sebastião and Soares, 2006; Kirby and Law, 2010; Wang and Shen, 2010; Neuparth et al., 2012; Olascoaga and Haller, 2012). To prevent the impact of oil spills in the environment, response plans recommend continuously monitoring the ocean and the use of forecasting systems based on Operational Oceanography to get routinely information from observations and models (Kamachi et al., 2002; Siddorn et al., 2007; Gonzalez et al., 2008). Besides, the approaches developed to forecast the trajectory of spills have been very useful for Search and Rescue (SaR) operations at sea being now routinely used by the Operational SaR Agencies.

Operational systems, that can be composed by numerical models and/or observational platforms, provide the Eulerian velocities of the ocean which constitute the basic information of any operational model for oil spill and SaR operations. The evolution of the spill is then assessed using a Lagrangian model, hereinafter Lagrangian Particle Tracking Algorithm (LPTA) coupled with the Operational system (Beegle-Krause, 1999; Breivik and Allen, 2008; Davidson et al., 2009). A recent review on oil spill models can be consulted in Berry et al. (2012) and on SaR models in Breivik and Allen (2008).

Errors in the predicted trajectories of drifting objects are common and minimizing them constitutes a very active area in Operational Oceanography where initiatives to improve both oceanic/atmospheric Operational systems and LPTAs are being undertaken (Olascoaga and Haller, 2012). The main sources of errors in oil spill and SaR operations are the result of the intrinsic complexity of ocean dynamics and can be summarized as:

(i) The Navier–Stokes equations governing the physics of the ocean are non-linear and therefore due to the chaotic nature of the ocean small variations of the initial conditions will...
provide large deviation of the forecast fields that will increase with time.

(ii) Operational models for ocean and atmospheric forecasting do not resolve the small scale but they parametrize the turbulent motions. In other words, no information at the sub-grid scale is provided.

(iii) At the first stages of a real crisis the exact position of the accident is usually unknown resulting in wrong initial conditions for the forecasting model.

(iv) The drift of an object on the ocean surface depends on the area exposed to wind and its angle of attack. These influences are usually included in the wind drag coefficient which is empirically determined sometimes after a trial-error process.

To mitigate to some extent these challenges, LPTA models usually follow a stochastic approach (Abascal et al., 2010; Mingué et al., 2011); the uncertainty in the unknown parameters is quantified either in terms of a probability distribution or by any of the usual optimization procedures minimizing an error against available real ocean data (e.g. using drifters or HF-radars).

In this work we present an Operational numerical model for oil spill modelling or SAR operations where the LPTA falls within the stochastic methodology. However, since our model is designed for operational purposes, it differs in many aspects from previous ones. Here, the LPTA computes the trajectory of an ensemble of particles departing from the Eulerian velocity field provided by an Operational (oceanic plus atmospheric component) using past and future model forecasts plus a random walk contribution term linked to the eddy diffusivity (Proehl et al., 2005). A Monte Carlo method is applied to each particle at every computational time step. The diffusivity is assumed to be constant in time and spatially variable depending on the object to track, being either in terms of a probability distribution or by any of the usual optimization procedures minimizing an error against available real ocean data (e.g. using drifters or HF-radars).

The wave induced currents are derived from the weakly nonlinear wave propagation Stokes theory,

$$\mathbf{u}_p^{\text{waves}}(x_p) = \frac{H^2 \omega^2}{8c} \mathbf{k},$$

where $H$ is the wave height, $\omega = 2\pi/T$ the wave angular frequency, $c = \omega/k$ the wave celerity, $\mathbf{k}$ is the vector wave number and $k$ its module ($k = \omega^2/g$).

Leaving aside the treatment of the diffusive component of the velocity, which will be addressed below, under this deterministic approach, the two-dimensional position of the particle at the ocean surface can be computed by integrating the velocity given by Eq. (1):

$$x_p(t + \Delta t) = x_p(t) + \int_t^{t+\Delta t} \mathbf{u}_p^{\text{adv}}(x_p, t) \, dt + \int_t^{t+\Delta t} \mathbf{u}_p^{\text{diff}}(x_p, t) \, dt,$$

being $x_p(t) = (\text{lat}, \text{lon})$ the position at time $t$. The last term in the right hand side of Eq. (4) represents the diffusive component of the velocity field and is the result of turbulent processes of unresolved scales. As will be discussed in the following sections, the presented model introduces in the diffusion uncertainties derived from inaccuracies of the Operational numerical models or due to incorrect initial location.

Following Ross and Sharplees (2004); Marinone (2006); Marinone et al. (2011) the diffusive term can be computed as,

$$\int_t^{t+\Delta t} \mathbf{u}_p^{\text{diff}}(x, t) \, dt = R_j \sqrt{6D \Delta t}, \quad j = 1, 2$$

with $R_j(x,t)$ a random number between in $(-1,1)$ and $D(x)$ the diffusivity to be empirically determined.

2. Ocean modeling subsystem

As stated, the core for an LPTA is composed by an Operational system which provides a regular basis wind, waves and currents on a specific area. Many Operational Systems (both under an observational or numerical perspectives) are available around the globe such as the Mediterranean Operational Oceanography Network (MOON) or the Global Ocean Data Assimilation experiment GODAE (Pinardi et al., 2003; Downbrwsky et al., 2009). In this work we use the Western Mediterranean Operational model (WMOP) that is a regional configuration for the Western Mediterranean Sea of the ROMS model. WMOP is operated by the Balearic Islands Coastal Observing System (http://www.sociob.es) and provides operationally ocean currents every 3 h in a 3 days horizon (Tintoré, 2012). The area under study covers the Balearic Sea extending from 5.8° W to 9.2° E and from 34.9° N to 44.7° N (see Fig. 2). The grid has 631 x 539 ($N_x, N_y$) nodes with a resolution of ~1.8 km, allowing a good sampling of the first baroclinic Rossby radius of deformation (about 10–15 km) throughout the whole area (Send et al., 1999).

The ocean model is ROMS, a three-dimensional free-surface, sigma coordinate (30 vertical levels), split-explicit equation model with Boussinesq and hydrostatic approximations. The reader is referred to the work of Shchepetkin and McWilliams (2005) for a complete description of the numerical code. Bottom topography is derived from a 1 min resolution database, ETOPO1 (Smith and Sandwell, 1997). The model is daily restarted using temperature, salinity, horizontal velocities, and Sea Surface Height from the daily previous forecast. At the two lateral open boundaries (South and East) an active, implicit, upstream biased, radiation condition
connects the model solution to the surrounding ocean (Marchesiello et al., 2001). Daily fields from the Mediterranean Forecasting System are used to infer the thermodynamics at the open boundaries (Dobricic et al., 2007; Oddo et al., 2009). The atmospheric forcing is obtained from the Spanish Agency of Meteorology based on the HIRLAM model with a spatial resolution of \( \sim 5 \) km at a temporal resolution of 3 h (Unden et al., 2002). Waves were acquired from the WAM operational model for the Western Mediterranean Sea (Ponce de León et al., 2012).

2.2. Advevtive velocity tensor

The Operational model provides surface currents, wind and wave fields for the following 72 h at a 3 h interval. Velocity fields (ocean surface currents and wind speed) are arranged in a cube (tensor) with dimensions \((N_x, N_y, N_t)\), where \(N_t = 25\) corresponds to the forecasting times of \(t\) (hours) = 0, 3, 6, ..., 72, provided by the WMOP.

An hypothetical spill occurring at a certain time \(T\) and in a location \((\text{lon}, \text{lat})\) is transported by the velocity \(\_\_x\) represented by a single point inside the cube with eight neighbor vertexes where the velocities \(u_i,\{i = 1:8\}\) are given by the Operational model. These vertexes correspond to the closest model grid points of past and future time steps, as shown in Fig. 1. The velocity field at \((\text{lon}, \text{lat})\) is then readily interpolated by weighting the velocities at the surrounding (in space and time) vertices as,

\[
\textbf{u}_p^{adv}(\text{lon, lat, } T) = \sum_{i=1}^{8} w_i \textbf{u}_i^{adv},
\]

where \(w_i = V_i / V_T\) are weighting coefficients obtained by computing the volume formed by the position of the fluid particle with their eight vertexes \(V_i\) divided by the total volume \(V_T\) (see Fig. 1). This is a very convenient procedure since allows very fast computations of the velocity for operational purposes taking also the advantage of the use at each computational time step past and future values of the velocity fields. After a certain time \(\delta t\) the position of the spill is obtained by integrating Eq. (4) with the velocity Eq. (6) and new weighting coefficients computed with the updated particle position as previously described. We remark that the velocities \(u_i\) will change either when the spill crosses the original grid of the Operational system or when a new field is required as evolving in time. Otherwise, only coefficients \(w_i\) are modified at each computational time step.

2.3. Diffusivity

To solve the random walk term in Eq. (5) one has to determine the value of the diffusivity \(D\) at the ocean surface at the time scales of interest. This term is usually taken spatially and temporally constant and different values are found for a specific regime (referred as eddy diffusivity in the literature) for a specific area (Okubo, 1971). Hernandez-Carrasco et al. (2012) analyzed the role of diffusion in the Western Mediterranean by measuring the error in the computation of Finite Size Lyapunov Exponents by changing the resolution of the model data. These authors found that diffusion introduces small scale irregularities on the trajectories, and also substantial dispersion at large scales. Mantovanelli et al. (2012) through the deployment of several surface drifters in a coastal
region studied the spatial and temporal variability of diffusivity showing the different dispersion regimes in accordance with other authors (Lacasce and Bower, 2000; Lacasce and Ohlmann, 2003): an exponential regime at small separations, a ballistic regime at a mesoscale range and a diffusive regime at asymptotic distances.

Therefore, errors in the prediction of trajectories given by the LPTA will mainly be the result of wrong or poorly solved ocean fields provided by the Operational model it is reasonable to compute diffusion directly from these data. Here, we have assumed the diffusivity in our model as the results of inaccuracies in the ocean model and constant in time but grid dependent estimating its value directly from model data as follows. A neutrally buoyant particle was placed daily at each grid point for the period between January 2009 and December 2011 and advected during 24 h using the velocity fields derived from the daily re-initialization and from the daily forecast. For each grid point this distance was temporally averaged and the numerical diffusivity obtained as,

\[ D(\text{lon, lat}) = \frac{\varepsilon^2(\text{lon, lat})}{\Delta t} \]  

being \( \Delta t = 86,400 \) s. This pseudo-diffusivity is the result of numerical uncertainties and introduces in the LPTA the stochastic nature of the current field. For the operational model, we have temporally averaged the three year diffusivity data (Fig. 2) producing a map of diffusivity for the Western Mediterranean area. Larger values of diffusivity are located in the more dynamic regions (Alboran Sea, Algerian current, Liguro-Provenzal current as well as around shelf seas) with values over 15 m\(^2\)/s. The influence of the northern winds in the Gulf of Lions and the northern Catalan coast also increase the value of the diffusivity. On average, in the Western Mediterranean \( D \approx 10 \) m\(^2\)/s which has also been suggested for the eddy diffusivity in other oceanic areas, with values oscillating between 1–100 m\(^2\)/s (ASCE, 1996; Marinone, 2006).

### 2.4. LPTA numerical scheme

A basic condition for any Operational System is that the response time is required to be small and efficient numerical schemes have to be implemented without sacrificing the accuracy of the forecasts.

To assess the best numerical scheme to be implemented in the LPTA in terms of accuracy, we performed a numerical experiment using analytical currents derived from a streamline function \( \Psi(x) \) randomly generated from a specific isotropic spectrum with random phases (Garau et al., 2005). We impose that the peaks of the spectrum are separated at a specific spatial scale in order to obtain homogeneous eddies. A velocity field is generated on a mesh of 200 \( \times \) 200 and is derived from the streamline function as,

\[ u = \frac{\partial \Psi}{\partial y}, \quad v = \frac{\partial \Psi}{\partial x}, \]

which immediately satisfies incompressibility of the flow (i.e. \( \nabla \cdot u = 0 \)). The grid size is 1 km in both \( x \) and \( y \) directions. The fields evolve in time by using the potential barotropic vorticity equation (Gill, 1992). These fields have been chosen so as they have similar characteristic values than those in the study area. Velocity fields are generated every 6 min for a total of 75 h and stored following the methodology described in Section 2.2.

A set of particles is launched at random positions and their trajectories integrated in time with a Cooper-Verner algorithm of eighth order (hereinafter CV8). These trajectories will constitute the reference path. We note that this integration method is computationally expensive and its application is not recommended for an operational LPTA. Three more well known numerical schemes were also implemented: an explicit Euler Scheme (ES), a 4th order Runge–Kutta (RK4) and a 5th – 4th order Runge–Kutta–Fehlberg with an adaptive time step (RKF54).

The error, defined as the separation in meters after 75 h of simulation, between the final position of particles for the three numerical schemes relative to the position given by the CV8 method is presented in Fig. 3 for ten randomly selected initial positions. The internal computational time step, \( \Delta t \), has been set as \( \Delta t = 6 \) minutes for all numerical schemes (a small value). As expected, the largest deviations are presented when the ES is used with an average error of \( 10^3 \) m. In oceanic flows, with rapid variations or strong gradients, this method could provide large deviations in the final position of the advected particles. The other two methods, RKF54 and RK4 give similar results with differences respect the CV8 below 1 m. We adopted the RK4 since it requires less computational effort (Liu et al., 2011; Liu and Weisberg, 2011).

In order to get an insight for the optimal integration time step for the RK4-LPTA we computed the distance between the final positions of 20 particles after 75 h for different time steps, \( \Delta t(\text{min}) = 6,12,18,24,\ldots,180 \) and the position given by the CV8 method using the minimum time step (\( \Delta t = 6 \) min). The averaged difference in meters (error) is displayed in Fig. 4 resulting in small (<25 m) differences for computational time steps of 6–36 min increasing exponentially for larger integration time steps. Based on those results, the integration time step for the Lagrangian integration was set to 30 min (below 15 m of error) in accordance with the time step used in Abascal et al. (2010) where the time step was imposed to ensure particles to remain within the same grid point at each computational time step.

### 3. Probability contours

The chaotic nature of ocean will result in inaccuracies of the predicted fields from both the velocity data provided by the

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**Fig. 3.** Error in meters for 10 random positions between the trajectories computed with the ES (circles), RK4 (squares) and RKF54 (triangles) and those obtained by the CV8 method.

**Fig. 4.** Error after 75 h between the CV8 and the RK4 method for different temporal time steps.
Operational model as well as inaccuracies in the LPTA. Besides, at the initial stages of spill accidents the exact spill location is not always well determined resulting in large errors in predictions. To delimit these constraints, the present approach computes the contours of probability of the final positions of a group of neutrally buoyant particles instead of providing the individual track of them. A set of particles is distributed around a spill location in a circular area of small radius defined by the user. The path for each particle is solved by integrating Eq. (4) and the probability density function of them computed by a Gaussian kernel estimator (Martinez and Martinez, 2002) as,

\[ f_{ker}(x, y) = \frac{1}{2\pi N h x h y} \sum_{j=1}^{N} \prod_{l=1}^{2} \exp \left( -\frac{1}{2} \left( \frac{x - x_{jl}}{h_{x j}} \right)^2 \right), \]

where \( N \) is the number of particles launched, \( x_{i} \) is the final position \( (j = 1 \text{ longitude and } j = 2 \text{ latitude}) \) of the particles, \( X_{ij} \) is the \( j-th \) component of the \( i-th \) observation and \( h_{j} \) is the bin width given by the normal reference rule, e.g.,

\[ h_{j} = \left( \frac{1}{N} \right)^{1/6} \sigma_{j}, \]

being \( \sigma_{j} \) the standard deviation of final positions. With this methodology the model provides to the user contours of accumulated probability at the desired confidence intervals (e.g., 90%, 75%, 50%) which coincide with the isolines of the kernel. Several tests have been made to estimate the optimal number of particles finding that the shape and size of the density contours are usually constant using more than 200 particles within a typical radius of 5 km. To illustrate this, Fig. 5 displays the contours of accumulated probability of 50%, 70% and 90% for 200 particles launched at random positions of the above generated analytical flow. The distribution of probability is shown for the 24 h forecast (left), 48 h forecast (center) and 72 h forecast (right). Notice that despite neglecting the diffusion velocity, a bimodal distribution of the probability is obtained as a result of the chaotic aspect of the flow (see Fig. 5, right).

4. Results and discussion

The model presented here has been designed to be easily relocatable as well as machine independent. Moreover, requests for SaR operations can be made by stakeholders or civil protection personnel with little oceanographic knowledge, so the interface between model and users has to be as simple as possible providing the least unknown parameters undetermined.

Presently, atmospheric, oceanic and wave models (HIRLAM, WMOP and WAM respectively) are written in Fortran as well as the LPTA module, providing data in NetCDF format. After LPTA computations the resulting probability contours are displayed by GeoJSON scripts through a web based Java interface (see Fig. 6 for the model block diagram). The end-user is allowed to select some basic parameters such as the initial position (latitude and longitude), the total advection time (up to 72 h), the number of particles to be initially deployed or the confidence intervals to be displayed. Snapshots of the Java interface for a hypothetical spill occurring at 39.93° N and 0.72° E on October 7th 2013 are shown for different times in Fig. 7 (right panels). In these snapshots the specific contours correspond to the 50%, 75% and 90% of accumulated probability. The corresponding model forecast is shown in the left panels of Fig. 7.

In September 2011, three Surface Velocity Program (SVP) ClearWater drifters were deployed in the Balearic Sea (North-Western Mediterranean) to measure surface currents. Each drifter is composed by a surface buoy and a subsurface drogue. The drifter transmitted its position hourly through Argos-2. Positioning time series from drifters were linearly interpolated every 15 min.

When a spill is simulated, a set of 200 particles is initially placed inside a circle of 5 km radius, centered at the spill location. The LPTA computes the trajectory of each particle as described in the previous Sections. To compute the diffusion term random numbers with uniform distribution and zero mean are generated at each
Fig. 7. Snapshots of the WMOP model output (left panel) for October 7th, 8th and 9th (top, center and bottom respectively). The outputs given by the visual interface of an hypothetical spill occurring at October 7th (00 UTC) are displayed in the left panels. Snapshots are taken at 21 (top), 40 (center) and 61 (bottom) hours after the spill. The green flag indicates the initial location of the virtual deployment. Contours display the accumulated probability after 24 h for levels of confidence of 50% (gray), 75% (dark gray) and 90% (black). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
computational time step \((\Delta t)\) \((\text{Eq. (5)})\) \((\text{Hunter et al., 1993})\) and adopting the corresponding value of \(D(x)\) for the specific location at the time step \(\Delta t\).

To explore the ability of the model in tracking accurately the path of surface spill under different real conditions, two different areas were selected for the deployment. On September 11th, 2011 two SVP were launched in the vicinity of Cabrera Islands \((\text{south-western side of Mallorca Island, see Fig. 9})\) at locations \((3^\circ 00^\prime E, 39^\circ 00^\prime N)\) and \((2^\circ 51^\prime E, 39^\circ 10^\prime N)\). This area can be under the influence of the deflected flow from the Algerian current and is driven by the diurnal sea breeze \((\text{Ponce de León and Orfila, 2013})\).

During September 2011 different SVP-surface drifting buoys were deployed around the Balearic Sea. The modulus of surface current, wind drift \((\tau = 0.03)\) and Stokes drift at \((2^\circ 06^\prime E, 39^\circ 36^\prime N)\) for the period studied are shown in Fig. 8. Moreover, Stokes drift was calculated from Eq. (3). As seen, while surface currents and the applied wind velocity are of the same order of magnitude, the value of the Stokes drift is an order of magnitude smaller for this experiment. On September 26th, a third drifter was deployed at \((3^\circ 33^\prime E, 39^\circ 14^\prime N)\) on the eastern shelf of Mallorca \((\text{Fig. 10})\). The first drifter simulated a spill occurring at \((3^\circ 00^\prime E, 39^\circ 00^\prime N)\) on September 11th \((\text{displayed by a cross in Fig. 9})\). In the same figure are shown model results corresponding to the accumulated probability density contours of the 50% \((\text{black line})\), 70% \((\text{gray line})\) and 90% \((\text{gray dashed})\) probability, as shown, can be multi-modal which can optimize the final position of a SVP-drifter for each snapshot is depicted by a cross and the final position by a dot. For completeness, the path traveled is also displayed by the gray line \((\text{dashed for the past and solid by the last 24 h forecast})\). Not surprisingly, using the daily re-initialization results in a reduction of the area covered by the accumulated probability, which importance was referred by Liu et al. \((2011)\).

5. Conclusions

An operational model to simulate oil spill trajectories and Search and Rescue operations has been presented. Two innovations differ from extended traditional LPTA operational models. First, we propose the use of numerical simulations to infer the diffusivity of the area which include errors inherent in the oceanic and atmospheric model. Second, the model rather than providing the final position of particles, provides the contours of accumulated probability of particles transported by the flow. As previous models, the forecast fields of winds, waves and currents provided from Operational forecasting models are used to estimate the final position of a relatively small number \((\sim 200)\) of neutrally buoyant particles but providing a density of probability instead of the cloud of final positions. The diffusive component of the velocity is computed as the result of inaccuracies or unknowns of the Operational component and is spatially dependent. Finally, the curves of accumulated probability are displayed. The distribution of the curves of probability, as shown, can be multi-modal which can optimize the available searching resources when dealing with SAR operations. The deployment of several particles inside a circle centered in the initial \((\text{given})\) position introduces in the forecast the uncertainties from not perfectly determined coordinates, while the diffusion term introduces errors from the Ocean numerical model \((\text{pseudo-diffusivity})\) as well as providing the stochastic component of the

![Fig. 8. Time series of surface currents (gray), wind speed -weighted by 0.03- (black dashed) and Stokes drift (black solid) at (2° 6.39° 36°) for September 2011. The dark boxes indicate the periods of the SVP experiments.](image)

![Fig. 9. Contours of 50% (black), 70% (gray) and 90% (gray dashed) accumulated probability of spill incidence for a spill occurring on September 11th initially located at (3°39°). Each plot corresponds for a 24 h forecast. The trajectory of the SVP drifter is displayed as the gray solid line where the position corresponding to September 12th, 13th and 14th as black dot (left, center and right panels respectively).](image)
surface current fields (length of diffusion). Although the information is the same that those obtained from previous LPTA models, the interpretation of the information moves from the deterministic approach to the probabilistic one being more suitable for oceanic flows.

To solve the Lagrangian algorithm we used a Runge–Kutta 4th order algorithm which provides similar results than a variable time step method (e.g., RKF54) when compared with an 8th order Cooper-Verner method. Regarding the computational time step, we found that 1800 s is a good commitment between accuracy and computational efficiency. For the advective component of the currents the described LPTA use at each time step future values of the wind and the current interpolating the eight known velocities. Besides, arranging the advective velocities in the “cube-tensor” results in fast computations of the trajectories being a very suitable approach for operational purposes. The model is hosted in a web server and has been designed to be run online giving the trajectory of a spill for the next 2 days in a few seconds.

Research is devoted to include improvements in the model both for oil spill modeling as well as for the use for SAR operations. Regarding oil spill, a database for different oils is being compiled to include the evaporation as well as the mechanical spreading. So far, the numerical diffusivity implemented is fickian (e.g., white noise) but as recently stated a non-fickian distribution for the random term is recommended and will be implemented. With reference to SAR operations, analysis of the wind drag coefficient $\gamma$ has to be done with in situ measurements with dummies.

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Escondido, CA.


