Chapter 11
The Optimization of Maritime Search and Rescue Simulation System Based on CPS

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11.1 Introduction

In recent years, a series of major maritime accidents have caused serious casualties and economic losses. It is urgent to deal with maritime emergencies properly. After the accident happened in the sea, the most urgent task is to quickly and accurately locate the rescue target or determine the rescue area where the target is in distress.

The drift of the distress target is a dynamic time-varying process. To locate the position of the target in distress accurately, the ideal method is to establish communication with it. However, due to the limitation of the actual situation and technical skill, the current maritime search and rescue methods still adopt conventional methods such as the blanket search or the search depending on the previous search experience, which spends a lot of manpower and material resources for blindly searching the whole ocean of wreck. Therefore, prime time for search and rescue might be wasted since it is difficult to determine the search area efficiently and effectively using the existing maritime search and rescue decision-making system.

Due to the emergence of the maritime search and rescue requirement and the urgency of the processing, commands and decisions must be made thoroughly as soon as possible. However, related real-time data need to be sufficient, such that scientific commands and decisions can be determined. Therefore, developing an effective way of gathering, sharing, and comprehensively processing data from various sources has become the key to improving the performance of the maritime

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search and rescue nowadays so that decision-making can be intuitively and visually assisted. It is also the main difference between the modernized emergent commanding based on informatization and intelligentization and the traditional emergent commanding based on regional, departmental, and empirical closure methods.

With the fast development of computational sciences, a new proposed prediction model (MSRSS) [1], which has shown its advantages of rapidity and efficiency, is widely put into use in departments of maritime search and rescue. The model is able to calculate the drifting trajectory and predict the further trace of the target in distress according to the existing measurements by using a data-inversion way. The main characteristics of the model lie in three aspects: (1) Intuitiveness. The information of the distress, the search and rescue force, and the scene can be precisely positioned spatially; (2) Rapidity and intelligence. Depending on the modern computer technology, communication technology, and information processing technology, once the relevant parameters and the meteorological and hydrological conditions are defined, information including graphs and the data of target in distress can be automatically generated fast to assist decision-making; (3) Capability of simulating and replaying. All the decision-making procedures of search and rescue events can be recorded, processed, replayed, and analyzed repeatedly using numerical simulation, in order to conclude the optimal model of handling distress with similarities.

The core algorithm SSRF (Solver of Search and Rescue Formula) of the prediction model is the solution of the embedded formulas based on the boundary conditions which in practice are stored in the database. Simulation results can be predicted based on the core algorithm; however, the embedded formulas contain a large number of empirical parameters which need to be adjusted and validated properly to guarantee the accuracy and optimize of the model. The model optimization process has attributes of the cyber physical system (CPS) [2–5]. As shown in Fig. 11.1, various types of physical quantities are collected and transformed into analog quantities through corresponding sensors firstly. In this stage, all data collected by sensors are saved in the system. After that, the saved data are extracted as the basis of meteorological and hydrological conditions for numerical simulations. Based on it, the scope of search and rescue are able to be predicted by computational facilities. In the end, the accuracy of the model can be verified and optimized by comparing the difference between numerical results and experimental measurements. Iteratively looping the above procedure, the accuracy of the model can be improved and meet the requirement of the prediction eventually. The optimized model based on the cyber physical system is of vital importance to the decision-making of maritime search and rescue and the positioning of the target in distress [6].

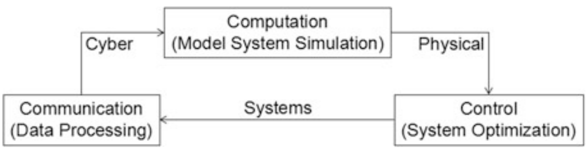

Fig. 11.1 Sketch of the model optimization based on the cyber physical system

The marine environment prediction model plays an important role in the decision-making system of marine search and rescue, which includes the prediction drift trajectory of the search target, the survival time of the surviving person, and the detection ability of the search unit. However, the prediction accuracy and resolution of the marine environment prediction model are generally imperfect at present. Using CPS technology can further improve the prediction accuracy and horizontal resolution of the existing ocean forecasting models. The results of the model prediction can provide an important reference for the search and rescue decision. After the optimization of the MSRSS based on the CPS, the prediction accuracy of the model is improved, which is contributing to the marine safety guarantee.

This article explains the optimization procedure of the maritime search and rescue model in detail, organized as follows. The second section introduces the model of maritime search and rescue. The third section gives the procedure of the model optimization. The fourth section provides an example to illustrate the optimization process of the model. The fifth section lists conclusions.

11.2 Maritime Search and Rescue Model in MSRSS

In MSRSS, the hydrodynamic environments of the maritime search and rescue model are simulated depending on the weather research and forecasting model (WRF) and the finite volume coastal ocean model (FVCOM) [7], while the targets in distress are modeled using the Lagrangian particle tracking method. The LEEWAY model is used to determine the wind-induced divergence angle

The vertical coordinate of the WRF model is defined as the terrain-following static pressure coordinate. Main modules of the WRF model are listed as follows:

(1) WRF Preprocessing System (WPS) module, which is used to provide the background field of the simulation, initializes the area of the numerical simulation and sets the difference of the topographic data and the meteorological data (data from other patterns such as the Global Pattern) into the simulation area.
(2) WRF Data Assimilation (WRFDA) module improves the initial and boundary conditions needed in the simulation by applying scheme in assimilating objective data from observation stations, satellites, and radars.
(3) Main Simulation Program module generates the initial background field and the time-varying boundary conditions needed in the simulations to calculate formulas through numerical integration.
(4) Post-Processing module analyzes the output data of the model and illustrates the result graphs.

It is well known that precise predicted results rely highly on the quality of the initial field. In this model, single-step 3DVAR is used to assimilate data into the initial field of the time-varying prediction, however, on condition that the convergence rate of grids is high and the observation data are big enough, multi-

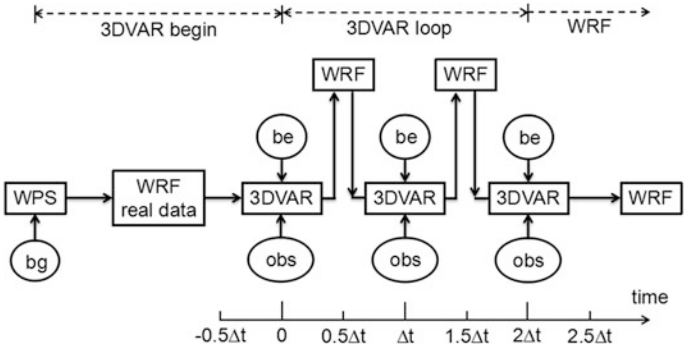

Fig. 11.2 Loop 3DVAR process

step 3DVAR (looping 3DVAR process) can be applied to form an initial field with higher quality, shown in Fig. 11.2.

In the figure, the first initial field is generated by the WRF preprocessing system (WPS) and real data, while WRF data drives the forward-time integration of WRF. “bg,” “obs,” and “be” represent the background field, observation field, and covariance between the observation field and the background field. “0,” “Dt,” and “2Dt” represent the assimilation moment, for example, assuming the assimilation window at a time Dt to be 0.5 Dt–1.5 Dt, all the observation data from this period are assimilated at the time Dt. FVCOM is used as the hydrodynamic prediction method which adopts integration of the volume flux to solve the governing equations of the fluid domain. Mass conservation is satisfied in every single grid of the whole domain, which is one of the important laws in ocean-related numerical simulations. Wet-dry boundary judgment method is applied in FVCOM to deal with boundary moving of the tidal flats.

The greatest feature and advantage of FVCOM in dealing with offshore and coastal events lie in the combination of finite element method and finite difference method. The finite element method adopts triangular grids and linearly independent basis functions, which is predominant in the boundary fitting and local refining, while the finite difference method discretizes the original fluid governing equations directly, which is predominant in the certainty of hydrodynamic theory, intuitiveness of difference, and efficiency of calculation. FVCOM has merits of both methods, which applies the integral forms of governing equations and better formats of computation to guarantee the better conservation of mass, momentum, and energy.

Governing equations of FVCOM contain the mass conservation equation, momentum conservation equation, temperature equation, salinity equation, and density equation. In the MSRSS, only the hydrodynamic modules are considered, which include the mass conservation equation and momentum conservation equation. The mass conservation equation which is also called the continuity equation is written as

$$\nabla \mathbf{u} = 0 \tag{11.1}$$

The momentum conservation equation is written as

$$\frac{\partial \mathbf{u}}{\partial t} + (\mathbf{u} \cdot \nabla)\mathbf{u} = \mathbf{f} - \frac{1}{\rho}\nabla \rho + \nu \nabla^2 \mathbf{u} \tag{11.2}$$

where ∇, u, ρ, f, ρ are the Hamiltonian operator, fluid velocity vector, the density of sea-water, mass force, and fluid pressure, respectively.

Comprehensively considering the force of sea surface wind on the drifting target, LEEWAY model proposes the concept of wind-induced divergence angle. The wind-induced drift is decomposed into two components, which are parallel to the wind direction and perpendicular to the wind direction. In the search and rescue system, nine parameters fully describe the characteristics of the drifting path, including the slope in the wind direction, offset in the wind direction, statistical fluctuation in the wind direction, slope in the right direction of the wind, offset in the right direction of the wind, statistical fluctuations in the right direction of the wind, slope in the left direction of the wind, offset in the left direction of the wind, and statistical fluctuations in the left direction of the wind. Additionally, the motion of the target corresponding to the marine meteorological environment can be more accurately portrayed by considering the force of surface currents on it. The velocity decomposition diagram of LEEWAY drift vector is shown in Fig. 11.3.

In Fig. 11.3, L_{drift} is the LEEWAY drift vector, while the two decomposed components of L_{drift} are L_d and L_c. The relationship between the LEEWAY drift vector and wind velocity is shown in Eq. (11.3):

$$L_{c,d} = a_{c,d} W_1 0 + b_{c,d} \tag{11.3}$$

where $a_{c,d}$ is the wind drift coefficient or LEEWAY factor determined from the experimental data.

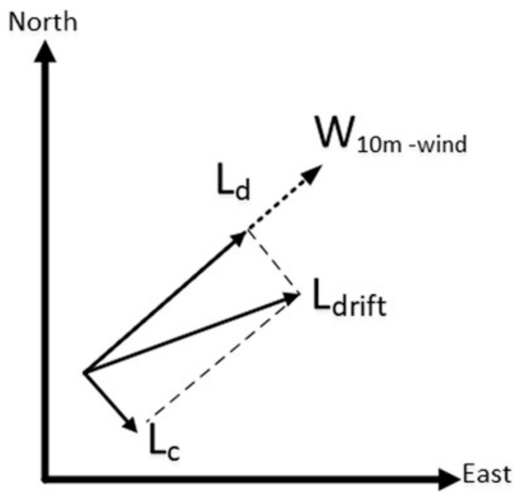

Fig. 11.3 Velocity decomposition diagram of wind

Lagrangian particle tracking method is adopted to predict the behavior and drift of the target in distress based on the hydrodynamic environmental parameters provided by the WRF and FVCOM. The prediction of the drifting traces on the ocean surface employs the Monte-Carlo random statistic theory, which considers the uncertainty of time and position of persons and goods in distress to define the initial search and rescue area, and generates several randomly distributed floaters within the initial area. For any single drifting floater, drifting positions and search and rescue areas with random statistical characteristics are obtained through the prediction of drifting traces by considering the uncertainty of drifting directions affected by wind (deviations from the wind direction) and the error of forecasted wind speed.

11.3 The MSRSS Model Optimization Process

The optimization process of maritime search and rescue simulation system based on CPS is shown in Fig. 11.4.

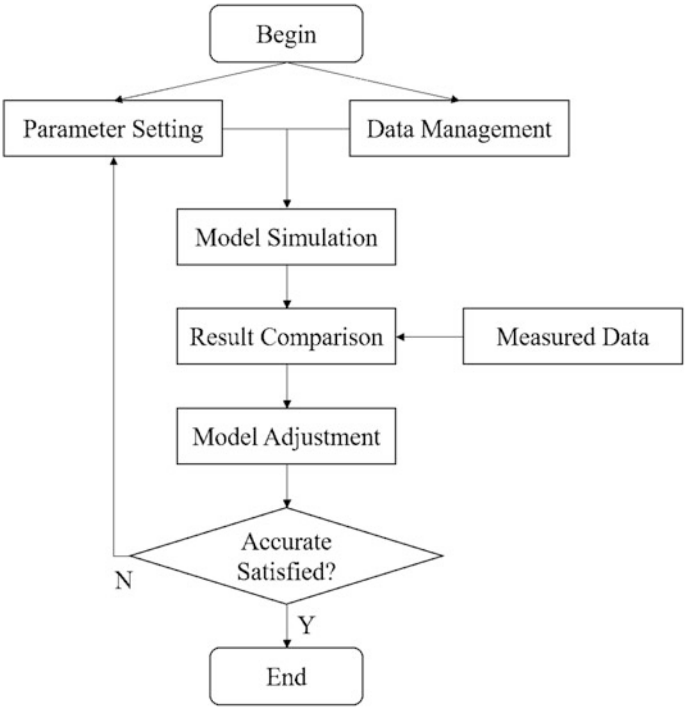

Fig. 11.4 The optimization process of maritime search and rescue simulation system

At the connection end of the system, the marine, meteorological, and hydrological data, forecast data from the global spectral model, NEAR_GOOS-SST, conventional ground and sounding observation data, and other data requested by the model operation are input, decoded, quality-controlled, and formatted. The multi-source observation data are performed by using variational assimilation technology. The system drives the WRF and FVCOM models using the above data to complete the calculation of equations, through which the simulation results are obtained and saved. In the meanwhile, the wind field, flow field, and the time-varying search and rescue range of the drifting trajectory based on Monte-Carlo's particle tracking method is physically measured during the simulation time. The accuracy of the prediction system is verified by comparing results between simulations and measurements. According to the simulation results, parameters in the system are adjusted and controlled to optimize the system. Assimilation of the optimized system and measured data, the data-collecting process, and simulation of the prediction model, etc., are repeated to complete a new cycle of system optimization until the accuracy of the simulation meets the calculation requirements [8]. Detailed steps of the optimization of maritime search and rescue system are as follows:

11.3.1 Data Management

1. Data classification:
   (a) Marine, meteorological, and hydrological data: temperature, salinity, flow field about velocity and direction, tide, wind field, temperature, pressure, etc.;
   (b) Marine basic geographic data: digital raster map, marine digital orthophoto map, digital elevation data, and terrain data;
   (c) Marine disaster reduction data: the impact assessment data of sea level change, benchmark tidal level verification and leveling data, marine tide forecast product data, and forecast inspection product data;
2. Data collection methods:
   (a) Near-shore currents, waves, sea ice, and meteorological data are collected by observation of shore-based radar;
   (b) Tide levels are collected by tide gauges of tide observation stations at port and dock;
   (c) The marine and meteorological elements in ocean–atmosphere interaction are collected by ocean weather station;
   (d) Ocean observations are undertaken by the scientific expedition ships, floats, satellites, volunteer ships, etc. The observations are focused on marine science, climate change, and ocean–atmosphere interaction.

3. Data repository:

   (a) Search and rescue resource database;
   (b) Basic and special geographic information database;
   (c) Dynamic ship and aircraft resource database connected with China Ship Reporting Center (CHISREP), Vessel Traffic Services Center (VTS), and Air Traffic Control Center (ATC);
   (d) Positional information database of marine perils;
   (e) Database of various types of search and rescue plans;
   (f) Weather and sea state information database;
   (g) Dynamic mathematic models to predict possible areas for drift and pollution diffusion;
   (h) Satellite remote sensing and aerial remote sensing information (Monitor oil spill at sea).

4. Data display:

   Based on three-dimensional sphere and integrated numerical analysis, the visualization of multi-dimensional profile of marine elements, such as ocean temperature, salinity, density, current, the display of three-dimensional scenes on the seabed, water, and island coast, the simulation of storm surge, sea level rise, and coast change and other phenomena can be realized.
5. Data processing and transmission:

   In order to ensure the reading of the data required by the next loop of model simulation, the collected data needs to be processed and stored in a readable format for the MSRSS model.

11.3.2 Model Simulation and Prediction

In the prediction model, the calculation methods include Lagrangian particle tracking method, the convex hull algorithm in Monte-Carlo theory, and topological geometry. The process of the model simulation is shown in Fig. 11.5.

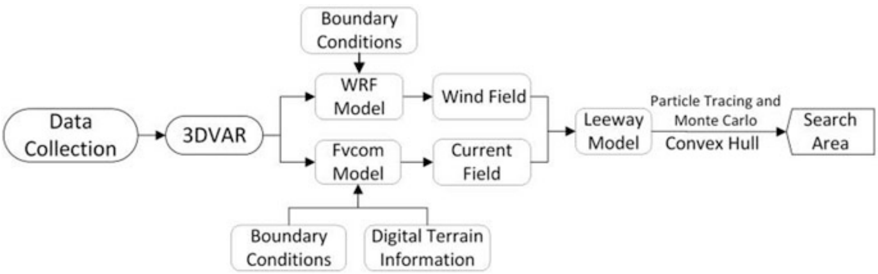

Fig. 11.5 The process diagram of model simulation

1. WRF model.

   WRF model is a fully compressible and non-hydrostatic model, the control equations of which are written as flux forms. Predicted data from the global spectral model are read, extracted, objectively analyzed, and interpolated to create the initial field and boundary conditions required by the WRF model.

   The WRF model mainly consists of the WRF preprocessing system (WPS), WRF data assimilation (WRFDA), main simulation program, and post-processing modules, which relies on three-dimensional variational data assimilation (3DVar) to assimilate meteorological observation data for obtaining a more accurate initial condition. According to the search and rescue requirement, WRF model provides outputs such as forecast wind field as the initial forced conditions for the FVCOM model.
2. FVCOM model.

   FVCOM model reads the WRF prediction results directly using the Fortran program and the wind field output from WRF as a forcing condition. Depending on the simulation of the FVCOM model, different resolution data for the target in distress are provided. General steps of data extraction from WRF to FVCOM are listed as follows:

   (a) Extracting sea surface wind data from the WRF forecast results.
   (b) Translating sea surface wind data from Lambert projection to regular latitude and longitude coordinates.
   (c) Processing the sea surface wind data in the latitude and longitude grids with NetCDF format.

   The interconnection between modules controlled by Linux/UNIX shell programs is fully automatic. Combined with initial boundary conditions such as tides and terrain, FVCOM model provides the necessary flow field information for the trajectory prediction of the target in distress.
3. Lagrangian particle tracking and search and rescue range predicting

Based on the environmental dynamic fields from WRF and FVCOM associated with LEEWAY model, particle model is used to predict the drifting process of the target in distress. The prediction model of drifting trajectory in the sea surface uses the Monte-Carlo random statistic theory to define the initial search range, with uncertainties such as the initial time and location of persons or goods falling into the water taking into account. The convex hull algorithm is used to determine the search range over time according to the trend of the initial distribution of particles.

It should be mentioned that the search and rescue system provides 13 h's prediction results of drifting trajectory and search range.

11.3.3 Comparison Between Measured Data and Simulation Data

The simulation results of the model are compared with the measured data, while the reasons for the difference between the two results are analyzed. Depending on the analysis, model parameters or empirical formulas are adjusted to optimize the model. The comparison between the predicted results and the measured data is as follows:

(1) Tidal harmonic constant.

The prediction harmonic constants are compared with the observation harmonic constants, with the amplitude error and mean late angle error between observational data and simulated data analyzed. These errors may be mainly caused by two aspects. On the one hand, the horizontal grid spacing of the model ranges from tens meters to thousands of meters, thus the resolution of the grids is not high in the vicinity of the coastline. The locations of grid-points in the model are different from the locations of tide gauge stations, leading to errors. On the other hand, the change of the shore boundary and the error of topography and water depth are responsible for the errors. In addition, it is possible that the errors might be related to the harmonic constant precision and other conditions as well.

(2) Tidal current.

The tidal current values from model simulations and measurements are compared, including tidal flow velocity and tidal flow direction. Meanwhile, causes of the error are analyzed, which lay the foundation for model adjustment.

(3) Water elevation.

The water elevations at verification points are obtained and compared with the measured data. The relative error, the root mean square (RMS), and the correlation coefficient between the simulated values and the measured values are analyzed. It is specified that usually under condition of the RMS error to be basically within 0.1 cm; the ratio of the observed deviation and the mean value to be less than 10%; and the correlation coefficient to be more than 0.9, could the simulation results of the water level be deemed as accurate, otherwise, the model should be adjusted.

(4) Track and scope of search and rescue model.

Numerical simulation of the prediction model is carried out on the trajectory and scope of the target in distress, while the accuracy of the simulation is analyzed by comparing the prediction results with the test results. If the distance between the simulation location and the experimental location is within 3 km, the prediction accuracy of the model can meet the requirements.

11.3.4 Model Adjustment

There are significant random features in the motion of objects drifting on the sea. A large number of empirical parameters are introduced into the model calculation. Moreover, several probability formulas are also introduced to the model operation to deal with the uncertain factors. Therefore, in order to improve the precision of the simulation, it is necessary to find the governing equations in the model based on the comparison of the results. The parameters and variables associated with the governing equations are analyzed, while various empirical parameters are optimized. By adjusting different parameters that impact the trajectory of objects, the probability density function which is part of the Monte-Carlo theory of the position of the object can be improved.

According to the comparison of tidal harmonic constant, tidal current, water level, search and rescue model track and range, the influence parameters are mainly included in the several aspects:

In the force equation of a drifting object, the time step parameter of the model depends on the time and space of the force (wind and flow) acting on the object. The control parameters of the influence of surface laminar flow on the drifting path: the real sea surface laminar flow is composed of various frequencies, and the combined control parameters of different frequency flows have an important influence on the prediction of the simulated particle trajectories.

The wind drift coefficient $a_{c,d}$ denotes the wind force on the drifting path. The empirical relationship between wind drift and wind velocity appeared here is obtained through the fitting formulas of many years observation data, which needs to be adjusted and checked continuously.

The drifting path is under the combined action of wind and current. The second-order Runge–Kutta iterative algorithm is used in the combination of wind and flow, and the proportion of wind and sea current in this algorithm is controlled by different parameters.

The perturbation term of wind drift coefficient, wind velocity, and flow velocity in Lagrangian particle tracking trajectory calculation equation also need to be optimized constantly. Besides, particle swarm optimization (PSO) is used in the particle drifting optimization [9], which is a computational method that optimizes a problem by iteratively improving candidate solutions with regarding a given measure of solution quality. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search space according to the simple mathematical formula over the position and velocity of particles. Each movement of a particle is influenced by its local best-known position and is also guided toward the best-known positions in the search space, which are updated as better positions found by other particles. Note that in each loop of optimization, the model needs to be verified again until it gets the best solution [10].

11.4 The Example of Model Optimization

This section analyzes the whole optimization process of the MSRSS, taking the loss of Malaysia Airlines flight MH370 as an example [11]. On 8 March 2014, the flight MH370 disappeared when it flew from Malaysia to Beijing. On 29 July 2015, a piece of marine debris was found on Reunion Island in the South Indian Ocean.

Firstly, the observation data about the environmental condition are collected and managed. Based on the LEEWAY sea drift theory and the Monte-Carlo theory, the prediction model in the South India Ocean is established to predict the drifting trajectory of the target. Different drifting objects have different wind pressure characteristics, and the drift parameters of 63 common drifters are given in the LEEWAY drift model. However, the drift parameter of the aircraft flap is not given. In the empirical experiment, three different drift parameters of the flap are taken, which are 1.2%, 1.5%, and 1.8%, respectively. After the calculation, the simulation results and the observation data are compared. Depending on the solution analysis, the optimal drift parameter is selected to be used in the MSRSS.

In the optimization of the MSRSS, the mesh of the suspected crash area should be established with the resolution of 5°. The physical data of coastal lines, bathymetry, and boundary conditions are collected from NOAA and physical sensors. Various types of physical quantities are transformed into the analog quantities, which can be read by models of FVCOM and WRF. All the collected data are saved in the system. The coefficients of both models are set as the constants without the drift coefficients in the LEEWAY model. In the first simulation, the drift coefficient is set at 1.2%. 1024 drift targets were distributed in the crash zone. After that, the research model is working, and the drift trajectory of the distressed target is predicted. Comparing the zone of the simulation targets with that of real debris, the accuracy of the prediction model is verified. If the simulation scope of research and rescue is agreed well with the real area of the debris, the optimization of the simulation model is finished. Otherwise, the drift coefficient is set to the 1.5% and the model is adjusted. Depending on the saved collected data, the adjusted model is working again and predicts the rescue area. The second loop of the model optimization is implemented until the prediction accuracy of the model meets the requirements of the forecast.

Due to the fact that initial time of target release has a certain effect on the drift of the target, the drift targets are released at three different initial times, which are March 6, 2014, March 10, 2014, and March 14, 2014. The end time of the prediction is July 30, 2015. The time step of calculation is 1 h. The optimization simulation results of three experiments are shown in Fig. 11.6.

The final drift position of 9000 targets in each simulation is shown in Table 11.1. In the three simulations, the number of targets passing through the ocean near the Reunion Island is 540, 490, and 480, and the corresponding probability is 6 per hundred, 5.4 per hundred, and 5.3 per hundred, respectively. It shows that the calculation results are very close at different initial times. The number of targets with different wind drift parameters is statistically analyzed, revealing that when the wind

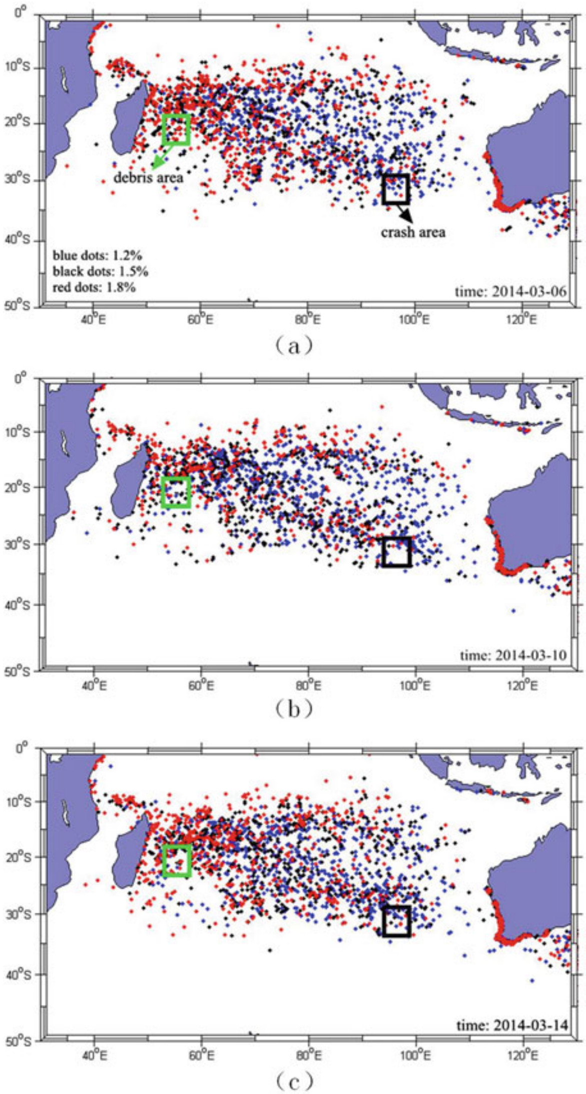

Fig. 11.6 The process diagrams of model simulation at three different times; (**a**) March 6, 2014; (**b**) March 10, 2014; (**c**) March 14, 2014

drift parameter is 1.8%, the accuracy of the prediction is the highest. Therefore, the drift parameter of 1.8% is selected and used in this MSRSS.

In short, the optimal wind drift coefficient is extracted with the CPS technique. Based on the wind drift coefficient, the maritime search and rescue system is optimized. The drift trajectory of the MH370 debris is predicted by the optimized system.

Table 11.1 The number (possibility) of the objects that finally reach Reunion Island area

Experiment condition	Exp. 1(2014-03-06)	Exp. 2(2014-03-10)	Exp. 3(2014-03-14)	Probability
Leeway factor 1.2%	110	50	80	2.6%
Leeway factor 1.5%	140	130	140	4.5%
Leeway factor 1.8%	290	310	260	9.5%
Total	540	490	480	
Probability	6%	5.4%	5.3%	

11.5 Conclusion

Based on CPS, this paper analyzes the optimization processing of the marine search and rescue model. In this optimization, sensing and communication systems are used to obtain the database required in the model. Helped by the power of the efficient computing server, the maritime search and rescue model quickly solves the inlay formula and predicts both the drift trajectory of the target and the range of search and rescue, and a large number of the calculation prediction results are stored. The accuracy of the search and rescue model is verified by comparing the measured data with the predicted data. By analyzing the verification results, empirical parameters and formulas are adjusted to optimize the model until the prediction accuracy of the optimized model meets the requirements. An example of the optimization processing is also described in the paper. The proposed optimization model based on CPS will be helpful to the implementation of the decision-making of maritime search and rescue in China.

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