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Prediction of sediment transportation in deep bay (Hong Kong) using genetic algorithm

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ABSTRACT: The genetic algorithm (GA) is a powerful method which can be used to solve search and optimization problems. A genetic algorithm with tournament selection, uniform crossover and uniform mutation is used to optimize sediment transport parameters in this study. Two important parameters of sediment transport, the critical shear stress for deposition and resuspension, are optimized by GA. The results show that GA is efficient and robust for optimizing parameters of our sediment transport simulation of Deep Bay.

KEY WORDS: Sediment Transportation, Deep Bay, Genetic Algorithm.

1 INTRODUCTION

Sediment transport models [1-5] are commonly used to study the movement of sediment in coastal areas. However, it is difficult to obtain accurate results because the movement of sediment is very complicate in coastal areas. Some important parameters used in sediment transport models are empirical or not suitable. In order to get better results, optimization methods can be used to optimize these parameters. In this study, a genetic algorithm (GA) [6-8] is used to do the optimization.

GA is one of the most powerful optimization methods which inspired by biological processes of natural selection and the survival of the fittest. The major advantage of GA is that it makes relatively few assumptions and does not rely on any mathematical properties of the functions. Therefore, GA is suitable for solving non-linear and multi-objective optimization problems. In recent years, genetic algorithms have been successfully applied to solving a number of hydrology and water resource problems [9-15].

The purpose of this research is to investigate the use of GA in a hydrodynamic/sediment transport model. In section 2, our hydrodynamic/sediment transport model is described. In section 3, a brief introduction to genetic algorithm is presented. The parameters to be optimized by GA are discussed in section 4. In section 5, the application of GA to sediment transport model is studied. Finally, a conclusion is given in section 6.

2 MODEL DESCRIPTION

2.1 Hydrodynamic model

The numerical model used in this study is a three dimensional finite element model. Because the hydrodynamics in estuaries and coasts can be assumed to be isothermal and the vertical acceleration is small compared to the gravitational acceleration, the hydrostatic assumption is made for the governing equations of fluid flow. In this research, the sigma (σ) topographic following coordinate system is used in the vertical direction.

Fluid-flow equations for shallow water

Mass conservation equation

$$\frac{\partial \zeta}{\partial t} + \frac{\partial H u_j}{\partial x_j} = 0 \qquad (1)$$

Momentum equation (Navier-Stokes equations)

$$\frac{du_i}{dt} + f\beta_{ij} u_j + P_i^* + g\frac{\partial \zeta}{\partial x_i} = \frac{\partial}{\partial x_j}\left(\varepsilon_j \frac{u_i}{x_j}\right) \qquad (2)$$

Where

$$u_j = \{u, v, \omega\}, \qquad \omega = \frac{1}{H}\left[w + (1 - x_3)u_i \frac{\partial h}{\partial x_i} - x_3\left(\frac{\partial \zeta}{\partial t} + u_i \frac{\partial \zeta}{\partial x_i}\right)\right]$$

$\varepsilon_j = \left[\varepsilon_x, \varepsilon_y, \varepsilon_z H^{-2}\right]$;
$\varepsilon_{sali,j} = \left[\varepsilon_{sali,x}, \varepsilon_{sali,y}, \varepsilon_{sali,z} H^{-2}\right]$;
$x_j = \left[x, y, (z+h)H^{-1}\right]$;
$H = h + \zeta$; $\beta_{ij} = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$;

i=1, 2; j=1, 2, 3; P_i^* is the baroclinic term with Boussinesq assumption. t is the time; h is the water depth relative to the minimum water level; ζ is the water level from the minimum water level; f is the Coriolis parameter; x_1, x_2, x_3 are the spatial coordinates in the σ coordinates; u, v, ω are components of velocity of the x, y, z direction in σ coordinates, respectively; w is the vertical velocity in Cartesian coordinate; ρ_0 is the constant reference water density; ε_x, ε_y, ε_z are the eddy viscosity coefficients for water in the x, y, z direction, respectively; $\varepsilon_{sali,x}$, $\varepsilon_{sali,y}$, $\varepsilon_{sali,z}$ are the eddy diffusion coefficient for salinity in the x, y, z direction, respectively.

2.2 Sediment transport model

The following equation is used to describe the suspended sediment transport process in our model:

$$\frac{\mathrm{d}C_s}{\mathrm{d}t} - \frac{\partial w_s C_s}{H\partial x_3} = \frac{\partial}{\partial x_j}\left(\varepsilon_{sed,j}\frac{C_s}{x_j}\right) \tag{3}$$

where

$\varepsilon_{sed,j} = \left[\varepsilon_{sed,x}, \varepsilon_{sed,y}, \varepsilon_{sed,z} H^{-2}\right]$;

C_s is the cohesive sediment concentration, w_s is the sediment setting velocity; $\varepsilon_{sed,x}, \varepsilon_{sed,y}, \varepsilon_{sed,z}$ are the eddy diffusion coefficients for sediment;

3 GENETIC ALGORITHM

Genetic algorithms are search algorithms which imitate the evolution and natural selection process of biology. GA was developed by Holland in the 1960s [16-18]. The term "genetic algorithm" was first mentioned by Bagley [19] in work on game-playing programs. Holland's 1975 book Adaptation in Natural and Artificial Systems [6] presented the theoretical foundations and exploring applications of genetic algorithm. Work by De Jong [20] showed the effectiveness of GA for function optimization. Goldberg [7] contributed much to the popularity of GA with his successful applications. Since then, GA is widely used in various problems.

In general, genetic algorithm starts with a randomly generated population consisting of a number of individuals. Each individual represents a possible solution of a given optimization problem. Then the genetic process which includes the three major operators of GA, selection, crossover and mutation, is implemented. The selection is a process in which some individuals in current population are selected to form a new population according to their fitness. A fitness function is used to evaluate the ability of each individual to solve the optimization problem. When the selection is completed, the crossover operator is executed. The crossover is an important operator of GA which can generate dissimilar individuals. The last operator of GA is mutation which randomly alters the values of individuals. After that, the genetic process is repeated until the termination conditions are satisfied. A general flow chart of GA is shown in Fig. 1.

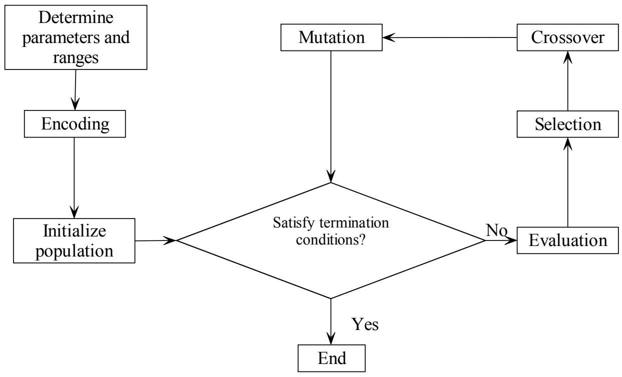

Fig. 1 Flow chart of Genetic Algorithm

4 PARAMETERS TO BE OPTIMIZED

In our application, two major parameters of our sediment transport model are selected to be optimized by GA, the critical shear stress for deposition and resuspension. They are important parameters of sediment transport model and our numerical experiments also show that sediment concentration is sensitive to these two parameters.

The vertical sediment exchange rate in the water column is defined as q_s in this study:

$$q_s = q_{dep} + q_{res} = -w_s C_s - \varepsilon_{sed,z}\frac{\partial C_s}{\partial z} \tag{4}$$

On the assumption that there is no net sediment exchange at the water surface, the first term on left side of Eq. (4) is the deposition rate on the sea bed which relates to the settling velocity, and the second term is the sediment resuspension rate caused by the bottom shear stress. The formula for deposition rate proposed by Krone [21] is adopted in this study:

$$q_{dep} = \begin{cases} -w_s C_s \left(1 - \dfrac{\tau_b}{\tau_{dep}}\right) & \tau_b < \tau_{dep} \\ 0 & \tau_b \geq \tau_{dep} \end{cases} \quad (5)$$

The formula for resuspension rate used in this research is suggested by Lick [22] based on the experimental data of cohesive sediment:

$$q_{res} = \begin{cases} 0 & \tau_b \leq \tau_{res} \\ a\left(\dfrac{\tau_b - \tau_{res}}{\tau_{res}}\right)^m & \tau_b > \tau_{res} \end{cases} \quad (6)$$

In these two exchange rate formulas, τ_b is the bed shear stress; τ_{dep} is the critical shear stress for deposition, with typical values between 0.04-0.15 N/m^2 [21]; τ_{res} is the critical shear stress for bed erosion/resuspension, with typical values between 0.07-0.17 N/m^2 [23]; *m* and *a* are constants, their values are 0.008 and 1.5 in this study.

5 APPICATION TO DEEP BAY

In this study, genetic algorithm is used to optimize the critical shear stress for deposition and resuspension of our sediment transport model. The optimized values are used to simulate the sediment transport in Deep Bay. Other values (See Table 1) of these two parameters obtained from two papers (Liu et al. and Wu et al. [24-25])are also used to do the simulation. These values are chosen because they are also used to simulate sediment transport in coastal areas. The suspended sediment concentration computed by these values are compared with the one calculated by the optimized values.

Table 1 Values of the parameters obtained from papers

Parameters	Liu's values (Liu et al 2002)	Wu's values (Wu et al 1998)
τ_{dep} (N/m^2)	0.05	0.07
τ_{res} (N/m^2)	0.1	0.15

5.1 Deep bay

Deep Bay is a large shallow bay which located in the eastern of Pearl River Estuary, between the longitudes of 113°53′06″E and 114°02′30″E 22°32′12″N, latitudes of 22°24′18″N and 22°32′12″N. The average water depth of Deep Bay is about 3 m and the tidal range is about 1.4 m.

The computation area includes most part of Pearl River Estuary (see Fig. 2). The mesh of our model is triangle and each triangle element has six nodes. There are a total of 4923 elements and 10736 nodes. The largest element size is 2.219 km^2 and the minimum is 0.005 km^2.

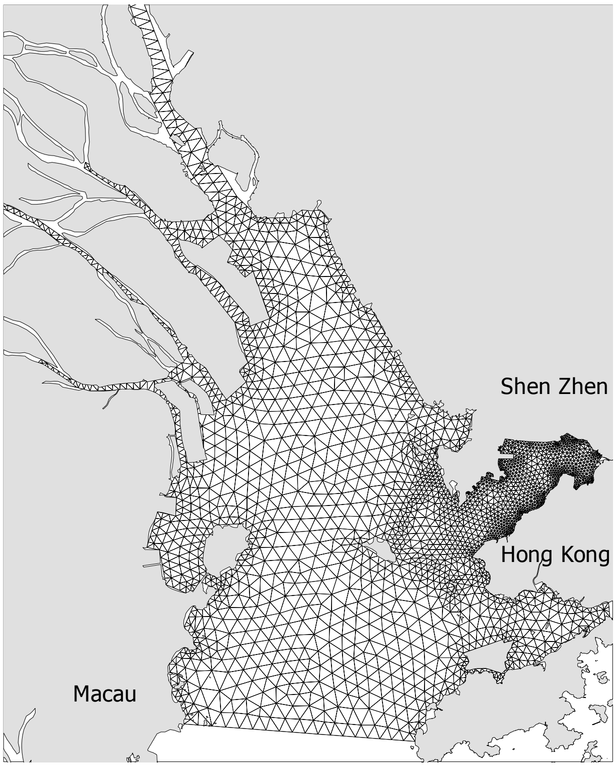

Fig. 2 Research domain and model mesh

5.2 GA operators and parameters in this application

Considering the time cost and handling ability of computer, the number of individuals is set to 30 in this research.

There are some selection strategies used for selecting individuals such as roulette wheel [20], tournament [26] and ranking selection [27]. The selection operator used in this study is a tournament selection [28]. This selection strategy is adopted because it can maintain diversity in the population [29]. The mechanism of this selection is that two individuals are randomly chosen from current population and the one with greater fitness value is selected. However, this selection strategy cannot ensure that the fittest individuals are selected. Thus, elitism selection [30] which can greatly improve the search speed is employed to guarantee the selection of best individuals for next generation.

Fitness function is used to evaluate the fitness of each individual. Relative error is usually used to estimate results of numerical models but relative error cannot reflect the actual error when the sediment concentration is small. In this study, absolute error is used to estimate the fitness of individuals. The fitness function is defined as:

$$F = \frac{1}{\sum_{j=1}^{n}\left(\sum_{k=1}^{m}\left(\left|\left(C_{obs} - C_{com}\right)\right|\frac{1}{m \cdot n}\right)\right)} \qquad (7)$$

Here F is the fitness of individual, n is the number of observation stations, m is the number of observed data, C_{obs} is the observed sediment concentration at station j, C_{com} is the computed sediment concentration at station j.

The uniform crossover [31-32] is adopted in this application since uniform crossover is probably the most effective crossover since it allows the offspring chromosomes to search all possibilities of re-combining those different genes in parents [33]. High crossover probabilities is claimed to have high search efficiency in GA. Goldberg [7] suggests a range of 0.6-1 for the crossover probability. In this study the crossover probability is set to 0.8.

There are several types of mutation such as single point, uniform, etc. A uniform mutation is adopted in this study. This kind of mutation permits the value of a gene to be mutated randomly within its feasible range of values, possibly resulting in significant modification of otherwise good solutions [29]. The mutation probability is set to 0.05.

GA will stop when the termination conditions are satisfied. Some rules are used to stop GA, for example: a maximum number of generations is reached and the solution has no improvement in several generations. In this study, the former one is adopted and the number of generations is set to 50.

5.3 Results and discussion

The computation results of GA are show in Table 2. The optimized values of the critical shear stress for deposition and resuspension are 0.075 and 0.118 N/m^2, respectively. The maximum fitness is 0.51. The CPU time is 25 hours, most of which is spent in running the sediment transport model. Values of each individual are substituted into sediment transport model to do the simulation and the results are estimated by the fitness function. So if the simulation time of each individual is one day, the total simulation time would be 1500 (30×50) days.

Sediment data of two observation stations are used to estimate the effect of the GA. The locations of the stations are shown in Fig3. Fig4 and Fig5 show the comparison of the results computed by the optimized values and the values from the two papers at station 1 and 2 respectively. It can be seen from these two figures that the results of the optimized values show the best match with the observed data. Our numerical experiments show that sediment concentration is very sensitive to the critical shear stress of resuspension (τ_{res}). Lower τ_{res} means the resuspension process will occur earlier and more sediment resuspend during a tidal cycle period. So the Liu's values have a higher sediment concentration. Contrarily, higher value of τ_{res} means less sediment resuspend during a tidal cycle. That is why the Wang's values have a lower sediment concentration. The mean absolute error is also computed, the result is shown in Table3. The optimized values have a least mean absolute error of 0.01.

Table 2 Computation results of GA

	Results of GA
CPU time(h)	25
Best fitness	101.7
τ_{dep} (N/m^2)	0.075
τ_{res} (N/m^2)	0.118

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Fig. 3 Locations of sediment observation stations

All those results show that GA can effectively improve the simulation result of sediment transport model in coastal areas. However, one drawback of applying GA to sediment transport model is that it requires huge amount of computer resource.

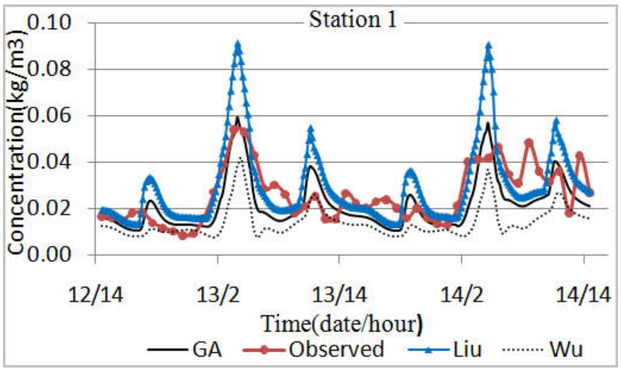

Fig. 4 Comparison of the results computed by optimized values and Liu and Wu's values at station 1

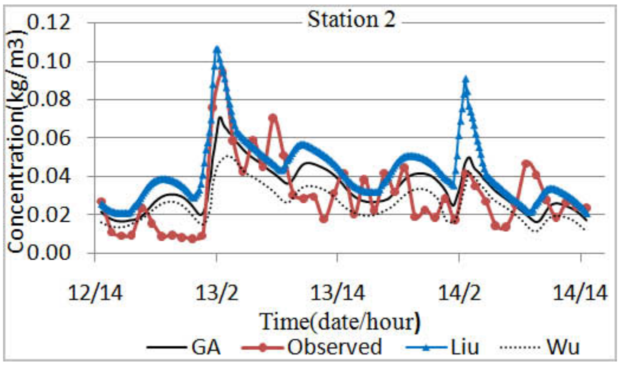

Fig. 4 Comparison of the results computed by optimized values and Liu and Wu's values at station 1

Table 3 Comparison of mean absolute error at the two stations

Parameters	Optimized values	Liu's values (Liu et al 2002)	Wu's values (Wu et al 1998)
Mean absolute error	0.010	0.013	0.012

6 CONCLUSIONS

In order to improve the accuracy of simulation results of sediment transport, a genetic algorithm with tournament and elitism selection, uniform crossover and uniform mutation operators is adopted to optimized parameters of sediment transport model. The critical shear stress for deposition (τ_{dep}) and resuspension (τ_{res}) are chosen as the parameters to be optimized by GA. Other documented values are also used. Result comparisons show that, with the application of GA, our model can attain more accurate results of sediment transport in Deep Bay.

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