

OPTIMAL PLACEMENT OF MONITORING SENSORS IN LAKES

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REFERENCE: *Proceedings of the 2007 Georgia Water Resources Conference*, held March 27–29, 2007, at the University of Georgia.

Abstract. Long-term surveillance of aquatic environments is a costly endeavor, thus a sound strategy is necessary to select the locations of monitoring stations to improve the quality of a monitoring system. This can be accomplished by optimizing the locations of a sensor network with respect to the hydraulic and fate and transport characteristics of the surface water system. It is expected that such an approach may improve the effectiveness of the monitoring system and also reduce the cost.

To determine the optimal sensor placement pattern, the hydrodynamics of the target environment must be understood first. Based on this information, the contaminant transport behavior can be simulated. Since the hydrodynamics and the contaminant pathways in the surface water environment are complex, it is not possible to optimize a surface water network using simple optimizing methods. To solve this problem in a simplified form, a 2-dimensional hydrodynamic simulation model is developed using a finite element method. The best sensor locations are selected to minimize detection time of the contaminant presence. Genetic algorithm is used for the solution of the optimization formulation in selection of the best sensor network due to the nonlinear nature of the model. Further, these computation processes require a significant amount of computational time, thus parallel computing is adopted to reduce computation time.

INTRODUCTION

People have always been attracted and enjoyed recreational environments near surface water bodies. But these recreational locations are getting more and more unsafe as various human activities degrade these environments (Blackburn et al., 2004; Natural Resources Defense Council, 2006). Hence, requirement of a water quality monitoring system or early water quality warning system is increasing in order to provide a safer environment. To set up and run a surveillance system that meets this requirement is costly and not trivial. The performance of the system varies depending on several factors including sensor or sampling locations. Location of sensors is one of the most important factors in a monitoring network and it need to be optimized to maximize system performance and reduce cost of the system.

To find an optimal solution for this problem, an optimization model is developed and solved using genetic algorithms. The hydrodynamics of the system and the contaminant transport patterns is solved using finite element method. This approach is applied to a simple circular lake to demonstrate the proposed process.

NUMERICAL MODELS

Understanding hydrodynamics and transport of contaminants in an aquatic environment is the first step in optimizing sensor locations since sensor distribution depends on the hydrodynamics and transport characteristics of a surface water body. In order to ensure the connectivity among hydrodynamics, transport simulations and optimization following numerical codes are developed.

Navier-Stokes and continuity equations are the governing equations of the hydrodynamic's phase. They can be depth-integrated with hydrostatic pressure distribution assumption in the vertical direction in order to reduce the problem into a 2-D vertically averaged system:

$$\frac{\partial h}{\partial t} + \frac{\partial(hU)}{\partial x} + \frac{\partial(hV)}{\partial y} = 0 \quad (1)$$

$$\begin{aligned} & \frac{\partial(hU)}{\partial t} + \frac{\partial(hU^2)}{\partial x} + \frac{\partial(hVU)}{\partial y} \\ & - E_H \left(\frac{\partial^2(hU)}{\partial x^2} + \frac{\partial^2(hU)}{\partial y^2} \right) + gh \frac{\partial \eta}{\partial x} - \tau_{sx} + \tau_{bx} = 0 \end{aligned} \quad (2)$$

$$\begin{aligned} & \frac{\partial(hV)}{\partial t} + \frac{\partial(hUV)}{\partial x} + \frac{\partial(hV^2)}{\partial y} \\ & - E_H \left(\frac{\partial^2(hV)}{\partial x^2} + \frac{\partial^2(hV)}{\partial y^2} \right) + gh \frac{\partial \eta}{\partial y} - \tau_{sy} + \tau_{by} = 0 \end{aligned} \quad (3)$$

where h is water depth, U and V are vertically-averaged velocities in x - any y - Cartesian coordinate directions respectively, E_H is a horizontal momentum diffusion coefficient, g is the gravitational acceleration, η is water level measured from a mean water level, τ_{sx} and τ_{sy} are wind friction in x - and y -direction and τ_{bx} and τ_{by} are the bot-

tom friction in x - and y -direction. The Coriolis force effect is ignored in the above equations.

A governing equation for contaminant transport can be developed in the same manner which results in the following equation:

$$\begin{aligned} \frac{\partial(hC)}{\partial t} + \frac{\partial(hCU)}{\partial x} + \frac{\partial(hCV)}{\partial y} = \\ \frac{\partial}{\partial x} \left(D_{xx} \frac{\partial(hC)}{\partial x} \right) + \frac{\partial}{\partial x} \left(D_{xy} \frac{\partial(hC)}{\partial y} \right) \\ + \frac{\partial}{\partial y} \left(D_{yx} \frac{\partial(hC)}{\partial x} \right) + \frac{\partial}{\partial y} \left(D_{yy} \frac{\partial(hC)}{\partial y} \right) \end{aligned} \quad (4)$$

where C is the concentration of a contaminant, D_{xx} , D_{xy} , D_{yx} , and D_{yy} are dispersion coefficients. No reaction is included because a tracer model is suitable to determine the effectiveness of a monitoring network by understanding simple transport of a conservative contaminant.

The governing equations (1) through (4) are solved numerically using the finite element method (Zienkiewicz and Taylor, 1991), which has been widely used for this type of mathematical. To save computational time, numerical method is implemented using a parallel computing technique. An open-source library, libMesh (Kirk et al., 2006) is used for this purpose. The code is written in C++ on a 64-bit 4-core Linux machine.

OBJECTIVE FUNCTION

A good surveillance system must detect the aftermath of a contaminant spill as soon as possible with maximum reliability. Earlier detection gives more time for system managers to react, for example, issuing a beach closure. Thus an objective of the optimization is minimizing detection time that can be defined in an average sense and an objective function can be expressed as follows:

$$\min \left(\frac{1}{S_n} \sum_{s=1}^{S_n} t_d^s(X, t_r^s, \mathbf{x}_r^s) \right) \quad (5)$$

where $t_d^s(X, t_r^s, \mathbf{x}_r^s)$ is time elapsed from a contaminant release to detection for a scenario s with a sensor distribution $X = \{\mathbf{x}_1, \dots, \mathbf{x}_i, \dots, \mathbf{x}_n\}$, \mathbf{x}_i is a location of sensor, t_r^s is contaminant release time, \mathbf{x}_r^s is contaminant release location of scenario s and S_n is the total number of scenarios. Decision variables of the objective function are sensor locations, X , and the number of sensors. In this study, the number of sensors is kept fixed for simplicity.

A scenario s implies a contaminant spill that happens at time t_r^s and location \mathbf{x}_r^s under a certain hydrodynamics

situation. A set of scenarios can be generated to evaluate the average of detection time with some assumptions. All scenarios can be run before the optimization since hydrodynamics and transport of contaminants are not affected by the optimization of sensor distribution. The simulation results of scenarios can be stored for further use in the optimization algorithm.

Each detection time t_d^s is calculated by calculating the time when concentration at any of sensor locations in a sensor distribution X becomes over a detection threshold. If concentration at none of sensor locations reaches the threshold within a detection time limit, the detection time is set at twice of the detection time limit as a penalty.

DEVELOPMENT OF GENETIC ALGORITHM

To find the optimal solution of the objective function given in the previous section, genetic algorithm is used. Genetic algorithm is well known due to its simplicity and robustness in the solution of complex problems (Goldberg, 1989), and these characteristics fit well to the problem described here.

In this application, the chromosome of an individual member consists of a string of integer numbers that represent the nodal indices in a finite element mesh where sensors are located. This approach makes the optimization computation simpler. The length of an individual chromosome depends on the number of sensors and all integer numbers in a chromosome should be unique.

Since the optimization routine involves numerous evaluations, an island model for genetic algorithm (Gordon and Whitley, 1993) is implemented in order to improve solution efficiency and obtain better results as well. An Island model has several separate populations and genetic operations occur only among individuals in a same population called an island. After several generations are evolved separately, some portions from each population are exchanged. This algorithm keeps diversity in populations so that it may yield more chances to obtain better optimal solutions while utilizing parallel computing capability. In addition, elitism is used to keep the best individuals over generations.

Optimization code to run the genetic algorithm described above is written in C++ using an open-source library, ParadiseO (Cahon et al., 2004).

APPLICATION AND RESULTS

The methods described in the previous sections are applied to a simple circular lake in order to test its capability. The shape of the lake is 10km-diameter circular without any inlet or outlet. The bathymetry of the lake is para-

abolic with maximum depth 5 m at the center and minimum depth 1m along the circumference of the lake. Only one hydrodynamics condition is considered in this application, which is wind forcing from east to west. The hydrodynamics of the lake reaches a steady state condition in less than half a day of simulation time starting from a flat water level and no-flow initial condition. The numerical result of the hydrodynamics is shown in Figure 1 and shows a gyro pattern, which is a typical phenomenon in a wind-driven flow in a lake (Hamilton et al., 1982).

Only the landside of the lake is considered as possible locations of contaminant sources. In the contaminant transport model, spill scenarios are developed as mass input in elements along the boundary of the lake. The time of release of all spills is identical because of the steady hydrodynamic condition. Total 64 scenarios are set up. All scenarios are run for half a day, which is a detection time limit, with the hydrodynamic condition described above and the results are stored. Each result contains concentration profiles that cover half a day transition of concentration in the lake.

One of the results of contaminant transport simulation is shown in Figure 2 as an example. Contaminant is injected at simulation time 43,200 seconds. It is transported and dispersed along the lakeside and to the center of the lake following the wind-driven flow pattern as shown in the hydrodynamics pattern in Figure 1.

The optimization of sensors distribution runs with the all the results of contaminant transport simulation in order to evaluate fitness of individuals as described in the previous sections.

Figure 3 shows the optimal distribution of sensors with 3 and 4 sensors. The sensors are placed along the shoreline with fairly even spacing, which can be expected from the transport pattern as shown in Figure 2. The even spacing of sensor distribution is due to uniform flow velocity along the shoreline. For both cases, the optimal distributions are obtained within 50 generations. The population size is 50 and the number of islands is 4 for the optimization runs.

CONCLUSION

An optimization scheme to decide sensor distribution using a genetic algorithm on a parallel computing machine is proposed and tested with simple lake geometry. The optimal distribution from the results of the test application shows the capability of this approach. When this method is applied to real problems, more meaningful results would be obtained. Currently, this approach is being implemented to find the optimal distribution of sensors on Lake Pontchartrain, New Orleans.

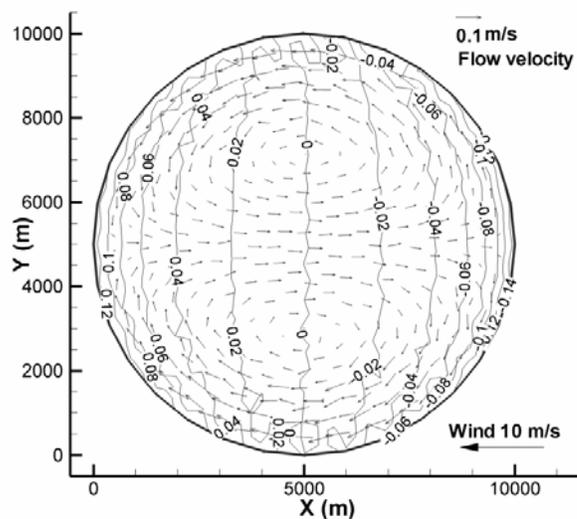


Figure 1. Hydrodynamics of a circular lake due to wind effects

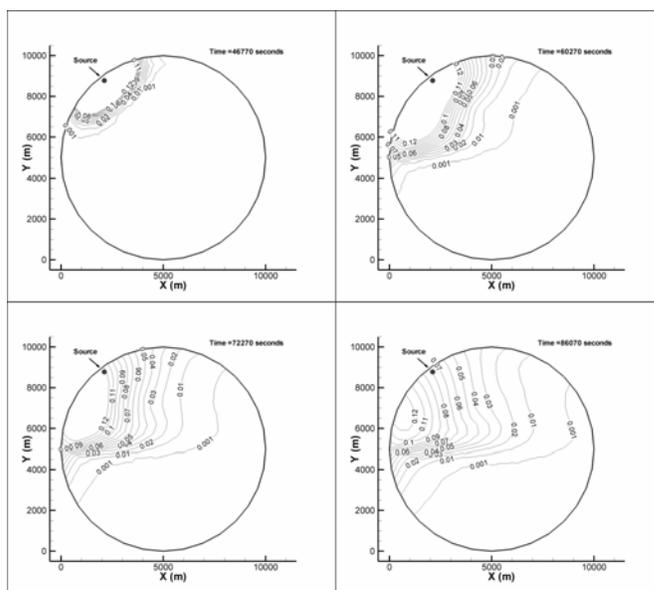


Figure 2. An example of transport of contaminant

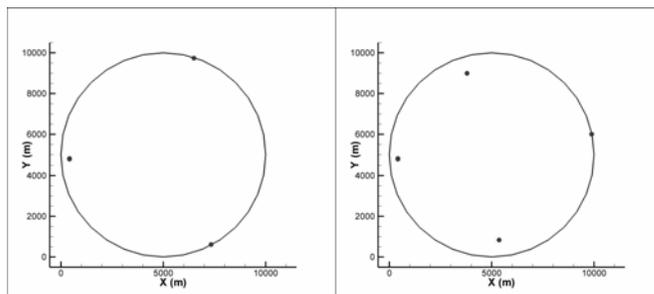


Figure 3. Optimal distribution of sensors (left: 3 sensors, right: 4 sensors)

There is room to improve this approach. The objective function may include other factors such as reliability of the system, minimization of number of sensors, and protection of a certain coastal area for determining more meaningful distribution of sensors with less computational cost.

The computational time is still a big issue in this approach even with parallel computing because it involves many evaluations that require huge amount of data transaction. Therefore, the number of scenarios needs to be minimized without degrading the evaluation of the average detection time, especially for a complex non-steady state case. Implementing the algorithm on a larger computing grid, for which the approach is ready, is another way to overcome the computational burden. In addition, further optimizing in the procedures and codes will help to reduce computation time and make the approach more readily usable.

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