INTEGRATED WASTE MANAGEMENT USING A SYSTEMS THEORY APPROACH

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Abstract

This work proposes to use a systems theory based approach for integrated management of pollutants. The idea is presented by considering the case of watershed level mercury management by studying management options at industrial sector and ecosystem level. At the industrial sector level, an optimization based decision making framework for mercury trading is presented, while at the ecosystem level, stochastic optimal control is proposed to improve liming quality leading to better pH control and subsequently lower mercury bioaccumulation.

Keywords

Mercury pollution, Systems theory, Pollutant trading, Lake liming, Uncertainty.

Introduction

In the wake of increasing pollution and over-exploitation of natural resources causing overall ecosystem degradation, systems theory based approach provide a suitable framework for informed decision making to ensure sustainable management. A decision making framework using such an approach can be used to study the implications and trade-off of policy decisions and therefore ensure the balance of stakeholder objectives. This work presents the idea for such a framework for watershed level mercury pollution management. The next section highlights the critical issues in mercury pollution and introduces two different management options, pollutant trading and lake liming. The work on these aspects is then discussed in the subsequent sections. The final section summarizes the work and proposes the future possibilities.

Mercury Pollution and Management Options

Mercury has been recognized as a global threat to humans and our ecosystem. For humans, the primary targets for toxicity of mercury and mercury compounds are nervous system, kidney, and developing fetus leading to various adverse health effects (USEPA, 1997). Mercury is also known to adversely affect mortality and reproduction rates in aquatic and terrestrial biota. The task of mercury pollution management is arduous due to the complex environmental cycling of mercury compounds. Although a majority of mercury is emitted in air, a significant portion is deposited in water bodies such as lake and river where it bioaccumulates along the aquatic food chain. The consumption of mercury contaminated aquatic animals ultimately causes human exposure to mercury.

Owing to the complex issues in mercury cycling, successful management of mercury pollution should consider management strategies at various stages of the cycle. This work proposes management options at two stages of mercury cycling: industrial sector level and ecosystem level. At the industrial sector level, where majority of pollution originates, the work proposes to use pollutant trading to balance the economic and ecological objectives. A decision making framework based on optimization for the polluting industries is proposed which is extended to incorporate uncertainty and nonlinearity for technology models. At the ecosystem level, lake liming has

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been proposed in literature to mitigate mercury bioaccumulation. This work proposes to use stochastic optimal control to ensure efficient control of lake pH, leading to diminished adverse effects of mercury pollution. The following sections discuss the approaches, the contribution by this work and the results.

Mercury Trading: Optimization Approach

Pollutant trading is an approach to environmental protection that uses market based mechanisms to efficiently allocate emission or pollutant reductions among sources with different marginal control costs. Trading programs allow facilities facing higher pollution control costs to meet their regulatory obligations by purchasing environmentally equivalent (or superior) pollution reductions from another source at a lower cost. For watershed based trading, a target discharge level, typically represented by Total Maximum Daily Load (TMDL), is decided. TMDL establishes the loading capacity of a defined watershed area, identifies reductions or other remedial activities needed to achieve water quality standards, identifies sources, and recommends waste load allocation for point (and non-point) sources. Given the discharge load allocations and reduction targets, each point source (such as a plant) has three options to achieve the target: implementation of an end of pipe treatment method; trading of the pollutant to another point source in the watershed; or combination of the two (USEPA, 1996).

It can thus be seen that point source (PS) level decisions affect the overall success of trading. Moreover, given the added flexibility of trading, decisions of the PS such as choosing between trading and waste treatment installation as well as waste treatment plant design can be difficult. Proposed here is an optimization framework to optimize these decisions.

Optimization framework

The formulation considers that TMDL regulation has already been developed by the state in consultation with USEPA, translating into a specific load allocation for each point source. Consider a set of point sources (PS_i; $i=1,...,N$), disposing mercury containing waste water to a common water body or watershed. The various point source specific parameters are:

D_i = Discharge quantity of polluted water from PS_i [volume/year]

red_i = Desired pollutant quantity reduction in discharge of PS_i [mass/year]

P_i = Treatment cost incurred by PS_i to reduce pollution when trading is not possible.

Every PS has the option of trading or implementing a particular waste reduction technology. Let $j=1,...,M$ be the set of reduction technologies available to the point sources for implementation. The technology specific parameters are:

$f_j(\varphi_j,D_i)$ = Cost function for total plant cost for technology j [\$]

q_j = Pollution reduction possible from the technology j implementation [mass/volume]

where, φ_j is the set of design parameters of technology j. Trading is possible between all point sources. Let r be the trading ratio and F be the transaction cost (in \$/mass) to be paid by the point source trading its pollutants. The objective of the model is to achieve desired TMDL at minimum overall cost. Let b_{ij} be the binary variable representing point source-technology correlation. The variable is 1 when PS i installs technology j, and 0 otherwise. Let t_{ik} (mass/year) be the amount of pollutant traded by PS i with PS k, i.e. PS i pays PS k to take care of its own pollution. All the parameters are on annual basis. The optimization model can then be formulated as:

$$Minimize \quad \sum_{i=1}^{N}\sum_{j=1}^{M} f_j(\varphi_j, D_i).b_{ij} \tag{1}$$

$$t_{ii} = 0 \quad \forall i = 1,..., N \tag{2}$$

$$red_i \le \sum_{j=1}^{M} q_j D_i b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \quad \forall i = 1,..., N \tag{3}$$

$$P_i \ge \sum_{j=1}^{M} f_j(\varphi_j, D_i).b_{ij} + F\left(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki}\right) \quad \forall i = 1,..., N \tag{4}$$

The objective function gives the sum of the technology implementation cost for all PS. The first set of constraints eliminates trading within the same PS. The second set of constraints ensures that all the regulations are satisfied. The reduction of the pollutant discharge at the end of technology implementation and/or trading must be at least equal to the targeted reduction, for all PS. The last constraint ensures that the expenses incurred by each PS with trading are not more that those without trading. The problem given by Eq.(1)-(4) is a mixed integer linear/nonlinear programming problem depending on the nature of cost function f_j for technology j. The decision variables in the problem are binary variables b_{ij} and continuous variables t_{ik}.

The optimization model presented above assumes that all data are deterministically known. However, there are various possible sources of uncertainty in this framework. Particularly, data related to many mercury treatment technologies can be uncertain, either be due to uncertain performance characteristics of the technology (e.g. conversion efficiency, catalyst life etc.), or due to relatively scarce data about a new treatment technology. This motivates the formulation of a stochastic programming extension of the optimization model. The objective function for the modified formulation is given as:

$$Minimize \qquad E\left[\sum_{i=1}^{N}\sum_{j=1}^{M} f_j(\varphi_j, D_i, u_j).b_{ij}\right] \tag{5}$$

where, E represents the expectation operator. The nonlinear cost functions f_j depend on uncertain parameter set u_j in addition to design parameters φ_j and discharge volume D_i. In addition to b_{ij} and t_{ik}, φ_j also represent a set of decision variables. The nature of the constraints is same as that for the deterministic model. This problem is converted into a two-stage stochastic programming problem with recourse which makes it computationally easier for solving.

Savannah River Watershed Case Study

The work applies the optimization models discussed in the preceding sections on a mercury pollution management case study in Savannah River basin in the state of Georgia, US. TMDL of 32.8 kg/year and corresponding waste load allocation have been computed by the authorities (USEPA, 2001). Following three treatment technology options are considered: coagulation and filtration, activated carbon adsorption and ion exchange process. The details for the three technologies are based on date found in USDOI (2001). The trading ratio r is 1.1. Since mercury trading in water has not been practiced yet, transaction fee is not easy to decide. However, based on the hypothetical example of water quality trading (USEPA, 1996), the transaction cost is fixed at \$ 1.5 Million per Kg. To explore a wide range of possibilities, the work assumes that a PS can implement any of the three technologies and the cost depends only on the waste volume.

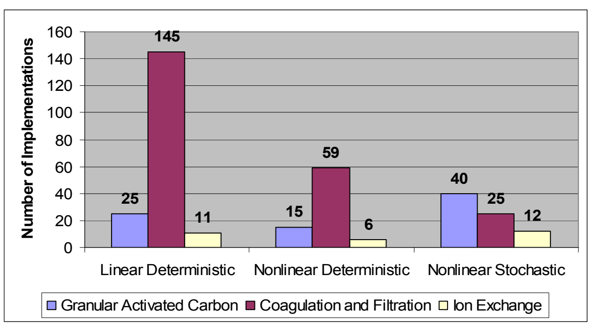

Figure 1. Impact of nonlinearity and uncertainty on technology selection

Results

The results show that trading expectedly leads to reduced compliance cost but results in higher discharge of mercury (although below the permitted level). This can increase the exposure and long term health care costs. The goal of the study is also to understand the implications of trading on technology selection and impact of nonlinearity and uncertainty on the decisions. The models are solved for a range of TMDL values from 26-36 kg/year. Figure 1 shows how technology selection is affected by these considerations. With linear technology models, various small industries (with low waste volume) implement technologies along with large industries (with high waste volume). However, when nonlinear technology models are used, large industries implement most of the technologies and smaller industries satisfy the regulations by trading with these large industries. The distribution of technology selection is observed to be similar for both models. This however changes when uncertainty is introduced. An uncertainty of ±20% is assumed in selected parameters of each technology. It can be seen that this changes the preferred technology, which has implications on the total amount of mercury traded in the watershed. Only a few representative results are presented here in the interest space. However, the important messages from this study are: the perceived advantages of trading might be diminished considering the higher actual discharge (although satisfying the regulations); and considering accurate technology models is essential for a true optimum solution to the problem.

Lake Liming: Stochastic Optimal Control

Mercury cycles in all media as a part of natural as well as anthropogenic effects, and bioaccumulation along the aquatic food chain is an important aspect of this cycling. Mercury, in the form of methylmercury, bioaccumulates up the aquatic food chains so that organisms in higher trophic levels have higher mercury concentrations. Since methyl mercury is the primary bioaccumulative form of mercury, controlling the conversion of mercury in water bodies to methylmercury is a possible option to control bioaccumulation. It has been shown that acidic water conditions enhance the formation of methylmercury in the water body and hence aid bioaccumulation (Winfrey and Rudd, 1990). External addition of lime to the water body, therefore, has been proposed as a management strategy. The idea is that lime addition will control the lake pH and will consequently control methylation and hence mercury bioaccumulation. This approach has been successfully used in the Scandinavian countries for the last two decades. The liming operation is though not very popular in North America primarily due to the following reasons: lack of accuracy in liming, and difficulty of accounting for various inherent uncertainties in the operation. This work proposes to use optimal control theory to derive time dependent liming profiles for a contaminated lake which will ensure efficient pH control. To account for uncertainties, the work incorporates established uncertainty modeling techniques from finance literature. The control problem consequently is extended to a stochastic optimal control problem. The stochastic lake liming model is explained next, followed by the results for the liming problem.

Stochastic Lake Liming Model

The basic deterministic lake liming model is presented in Ottoson and Hakanson (1997). It is a compartmental model with three different compartments, namely, water, active sediment and passive sediment. Accordingly, the three model variables are: lime in water (y_1), lime in active sediment (y_2) and lime in passive sediment (y_3). The lake pH value (variable y_4) is computed as function of the lime in water variable (y_1). Four continuous flows of lime connect the three compartments: sedimentation to active sediments, internal loading from active sediments to water, outflow from the lake water and transport from active to passive sediments. In addition, two flows give the inflow of lime from the liming, one to the lake water and one directly to the active sediments. The model requires the values of some basic lake chemical and physical properties such as: lake area, lake mean depth, lake maximum depth, lake color, lake total phosphorous concentration, drainage area, mean annual precipitation. This model has been modified in this current work to include stochasticity. Here, natural lake pH variation is considered as an uncertain parameter and modeled using a mean reverting Ito process. The parameters of the Ito process are decided so that the modeled pH fluctuations are a reasonable match with observed fluctuations in real lakes. The natural pH therefore constitutes the additional model variable (y_5). The stochastic lake liming model equations are not given here for the sake of brevity. The model though consists of a set of four ordinary differential equations and one algebraic equation (calculating pH from lime in water variable y_1). In brief, it correlates lime additions to water (through liming operation) with the water pH in the presence of background natural pH variations (modeled as Ito process).

Lake Liming Results

The lake liming problem is solved for various case study lakes. The target pH in all cases is 7 and the objective is to minimize the variation of the actual lake pH (absolute value) around the target value over the complete time horizon. Since liming operation is generally expensive, a multi-objective control problem with an additional cost objective is also formulated and solved. The cost function is modeled assuming direct lime dumping in lakes using boat or barge and is formulated as a power law with decreasing marginal cost for increasing lime addition. The results for one particular lake are shown in Figure 2. It can be seen that the single objective problem (with cost function weight equal to zero) gives very satisfactory control of the pH. As expected, addition of a cost objective degrades the pH control quality. However, numerical values of the various objectives indicate that the relationship is non-linear. Thus, increase in the cost objective weight from 0.003 to 0.005 leads to marginal cost savings but significant degradation in quality of pH control. Such trade-offs can be studied with the proposed model. A comparison of continuous (weekly) with intermittent (monthly or quarterly) liming suggests similar non-linear relationship between quality of control and cost.

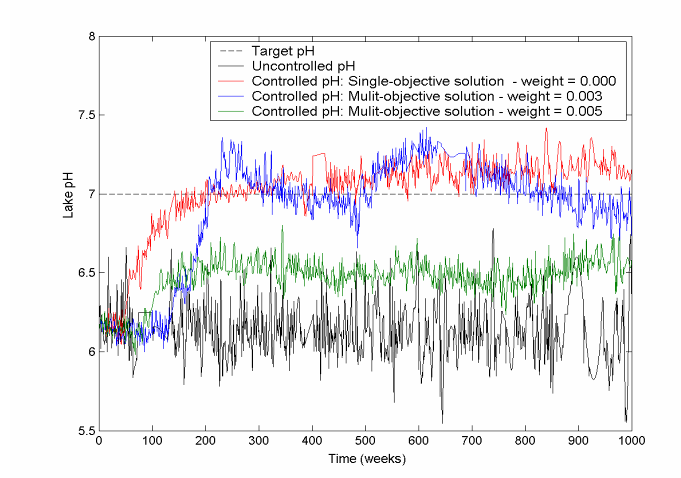

Figure 2. Lake liming results for multi-objective optimal control problem

Summary and Conclusions

The central idea proposed through this work is the application of systems theory based approaches for integrated pollution management, which has been illustrated using the case of mercury pollution management. Optimization has been used to economically achieve regulatory targets, while stochastic lake liming is used to further mitigate the harmful effects. The work should motivate more such application in environmental management, not only for mercury but also for other contaminants.

Acknowledgments

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References

Ottoson, F., Hakanson, L. (1997). Presentation and analysis of a model simulating the pH response of lake liming. *Ecol. Model.*,105, 89.

USDOI (2001). Total plant costs for contamination factsheets. Technical report, US Department of Interior, Bureau of Reclamation, Water treatment engineering and research group, Denver, CO.

USEPA (1996). Draft framework for watershed-based trading. Technical report EPA 800-R-96-001. USEPA, Office of Water, Washington DC.

USEPA (1997). Mercury study report to congress. Report to congress: EPA-452/R-97-003. USEPA.

USEPA (2001). Total Maximum Daily Load (TMDL) for total mercury in fish tissue residue in the middle and lower Savannah River watershed. Report, USEPA, Region 4.

Winfrey, M.R., Rudd, J.W.M. (1990). Environmental factors affecting the formation of methylmercuy in low pH lakes. *Environ. Toxicol. Chem.*, 9, 853.