An Innovative Trading Approach for Mercury Waste Management

Yogendra Shastri[†, *], Urmila Diwekar[†] and Sanjay Mehrotra[‡]
[†] Vishwamitra Research Institute
Center for Uncertain Systems: Tools for Optimization and Management (CUSTOM)
368 56th Street, Clarendon Hill, IL – 60514.
[‡] Department of Industrial Engineering and Management Sciences
Northwestern University
2145 North Sheridan Road, Evanston, IL – 60208.

ABSTRACT
This work proposes an innovative approach of watershed level mercury trading for sustainable management of mercury pollution. An optimization based decision-making framework has been developed to optimize the selection of mercury treatment technologies by industries in a watershed in the presence of nonlinearity and uncertainty in technology cost models. The impact of the regulation on technology selection by industries, often ignored in existing trading literature, has been quantified. A particularly novel contribution of this framework is the consideration of health care cost as an objective. The application of the framework to the Savannah River watershed case study in US emphasizes the importance of health care cost while evaluating the benefits of trading. Nonlinearity and uncertainty in the cost models is shown to significantly affect technology selection. The ecological perspective of innovation comes from the proposal of using water body liming to mitigate mercury bioaccumulation and concerns of mercury hotspots.

1. INTRODUCTION

Mercury has been recognized as a global threat to human health, aquatic and terrestrial biota, and the whole ecosystem. Consequently, sustainable management of mercury pollution is an important scientific and regulatory challenge [1, 2]. This task is challenging due to the complex mercury cycling, which includes majority emissions in the air followed by dry and wet deposition leading to bioaccumulation in aquatic food webs [3]. Innovative approach is therefore necessary to mitigate mercury pollution. Such an approach should be based on science of mercury fate and transportation. This work proposes pollutant (mercury) trading as a management alternative at the industrial sector level to balance the economic and ecological objectives, and formulates an optimization based decision making framework in the form of a mixed integer linear programming (MILP) problem. The linear deterministic formulation is then extended to incorporate nonlinearity and uncertainty in the model to study their impact on optimal decisions. A truly sustainable solution also accounts for the social dimension of the problem at hand, such as the adverse health impact due to mercury exposure. This is also often the most challenging aspect of sustainable management. This work proposes a novel approach to calculate the health care costs associated with mercury discharge and uses it to compare the efficiency of the trading approach over the traditional end of pipe treatment approach. This approach of formulating multi-objective optimization problems in pollutant trading is particularly innovative in this field. The usefulness of the proposed model is illustrated by applying it to the Savannah River watershed mercury waste management case study. Since the creation of hotspots in a watershed is one of the concerns related to pollutant trading, this work proposes to use water body liming for pH control in order to mitigate the creation of mercury hot-spots after trading has been implemented.

The article is arranged into several sections. The next section gives a brief overview of pollutant trading and outlines the proposed approach. The following section presents the different optimization model formulations. The case study details and the results are presented in the next two sections. The

* Current affiliation: Energy Biosciences Institute, University of Illinois at Urbana-Champaign

concept of water body liming as a management option is briefly discussed next. The article provides a summary and important conclusions in the end.

2. PROPOSED APPROACH FOR POLLUTANT TRADING

Pollutant trading is a market based approach which aims to achieve the same or better environmental performance with respect to pollution management at a lower overall cost. The relative success of this approach for air pollutants [4, 5, 6, 7], including the USEPA issued federal rule in 2005 allowing cap and trade policy to reduce mercury emissions from coal-fired power plants, has encouraged the introduction of watershed based pollutant trading [8, 9]. Trading is based on the fact that different firms in a watershed can face very different marginal costs to control the emission of the same pollutant. Trading program allows facilities facing higher pollution control costs to meet their regulatory obligations by purchasing environmentally equivalent (or superior) pollution reductions credits from another source at a lower cost. Facilities reducing pollutant discharge more than the required limit get credits for it which can be traded to another firm to gain monetary benefits or banked for future use, if that is a possibility. Some of the important parameters affecting the economics of trading include the trading ratio (how many units of pollutant reduction a source must purchase to receive credit for one unit of load reduction), transaction costs (expenses for trading participants that occur only as a result of trading), and the number of participants [8, 9].

The primary stakeholders in pollutant trading are: the polluters (industries) and the regulatory authority (which also represents the interests of the society). Since the primary motivation behind the concept of trading is to reduce the compliance cost for polluters, considerable focus has been given on understanding the economic implications of trading [10, 11, 12, 13]. However, work on the actual implementation of trading and its effect on industry decisions has been limited. Most of the literature, such as Hung & Shaw [14], considers marginal treatment costs for the industries to study the economic implications. Industries, however, cannot always decide using marginal costs since technology selection decisions can significantly alter their capital investments. This introduces discontinuity and integrality in the abatement costs which need to be captured in the trading mechanism. From the polluter's perspective, therefore, decisions such as if and how much to trade and which technology to implement from a set of alternatives become difficult.

From a regulatory perspective, trading is currently practiced mostly in a decentralized manner, where the role of the regulatory authority is restricted to setting up the basic trading mechanism (such as trading ratio) and overseeing the appropriateness of the trades. However, to balance the conventional economic goals of trading with environmental and social goals, the role of regulatory agency will be paramount [15]. The regulatory authorities (policy makers) must also consider industry capabilities and limitations, and leverage the regulatory tools to achieve this balance. Moreover, Oates et al. [16] and Atkinson & Tietenberg [17] have highlighted the importance of including emission level differences while comparing trading with the traditional command and control approaches.

These issues call for the formulation of an integrated decision making framework, which is the main contribution of the presented work. Use of systems theory based optimization technique offers a way to achieve this, where the cost minimization objective can be achieved while incorporating the watershed and pollutant specific details using constraints. Modeling is an important aspect for such an approach. Simplified linear models, while being computationally advantageous, may lead to gross qualitative and quantitative errors in the results. Nonlinear models on the other hand typically provide more accurate representation but result in computationally challenging problems. Inclusion of uncertainty, desirable for a robust solution, is also governed by a trade-off between accuracy and computational simplicity. Consequently, this work elaborates on these issues by performing a comparative study of the impact of various models on the framework and the optimal decisions. The next section describes the optimization model formulations.

3. TRADING OPTIMIZATION PROBLEM FORMULATION

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

D_i = Discharge quantity of polluted water from PS_i [volume/year]
c_i = Current pollutant concentration in discharge water from PS_i [mass/volume]
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 point source (PS) has the option of trading or implementing a particular waste reduction technology. Let $j = 1,\ldots,M$ be the set of waste reduction technologies available to the point sources. The technology specific parameters are:

$f_j(\phi_j, D_i)$ = Cost function for total plant cost for technology j [\$]
q_j = Pollution reduction possible from the implementation of technology j [mass/volume]

where, ϕ_j is the set of design parameters of technology j. Trading is possible between all point sources. For simplicity, a single trading policy exists between all possible pairs of point sources, and a single trading ratio r and transaction fee F (in \$/mass) is applicable to all the trades. The objective of the model is to achieve the desired TMDL at the *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.

3.1 Deterministic Model

The basic optimization model which assumes that all the information is deterministically known is formulated as:

Objective:

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

Constraints:

$$t_{ii} = 0 \qquad \forall i = 1,\ldots,N \tag{2}$$

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

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

The objective function gives the sum of the technology implementation costs for all point sources. Although each PS will also spend or gain from practicing trading, expense for one PS in a watershed is earning for one or more PS in the same watershed. As a result, for the complete watershed, trading does not contribute to the cost objective. The first set of constraints eliminates trading within the same PS. The second set of constraints ensures that all the regulations are satisfied, with or without trading. The trading ratio r is usually set higher than 1 to account for data uncertainty and provide a buffer [8]. Consequently, the PS accepting additional discharge reduction responsibility has to reduce the pollutant by an amount equal to the actual quantity traded (t_{ki}) times the trading ratio, as shown in Eq. 3. The last constraint ensures that the expenses incurred by each PS with trading are not more that those without trading. Since participation in trading is voluntary, a polluter will participate in trading only if there is a financial incentive, which is modeled by this constraint. The problem given by Eqs. 1-4 is a mixed integer linear/nonlinear programming problem. The decision variables in the problem are binary variables b_{ij} and continuous variables t_{ik}. It should be noted that the reduction capabilities of different treatment processes are considered to be fixed at q_j. Therefore, the selection of a technology by a PS to achieve reduction target red_i is a discrete process. For comparison, the optimization problem is also solved when the industries cannot trade, and hence have to implement a technology. For this case, the optimization model is constituted by Eqs. 1-3 and forcing t_{ik} and t_{ki} equal to zero. P_i in Eq. 4 for the trading model is provided by the solution of the optimization model without trading. The cost function $f_j\,(\phi_j, D_i)$ for technology j is a generalized representation. For a linear model, the cost function is given as:

$$f_j(\phi_j, D_i) = TC_i \times D_i \tag{5}$$

where, TC_j represents the cost per unit volume for technology j [\$/volume]. This leads to the formulation of a mixed integer linear programming (MILP) problem. For a nonlinear model, the cost function f_j is a nonlinear function of design parameters ϕ_j and volume D_i. This leads to the formulation of a mixed integer nonlinear programming (MINLP) problem.

3.2 Stochastic Model

There are various possible sources of uncertainty in this framework, such as discharge from individual point sources as well as the fate and transportation of mercury. Moreover, data related to many mercury treatment technologies can also be uncertain, either due to uncertain performance characteristics of the technology (e.g., conversion efficiency, catalyst life) or due to relatively scarce data about a new treatment technology. Considering this, the nonlinear deterministic model is extended by considering uncertainties in nonlinear technology cost functions. This results in the formulation of a stochastic programming problem as shown below:

Objective:

$$\text{Minimize} \quad E\left[\sum_{i=1}^{N}\sum_{j=1}^{M} f_j(\phi_j, D_i, u_j) \times b_{ij}\right] \tag{6}$$

Constraints:

$$t_{ii} = 0 \qquad \forall i = 1,\ldots,N \tag{7}$$

$$red_i \le \sum_{j=1}^{M} q_j \times D_i \times b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \qquad \forall i = 1,\ldots,N \tag{8}$$

$$P_i \ge \sum_{j=1}^{M} b_{ij} \times f_j(\phi_j, D_i, u_j) + F\left(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki}\right) \qquad \forall i = 1,\ldots,N \tag{9}$$

where, u_j is the set of uncertain parameters and E represents the expectation operator over the uncertain parameters u_j . The nonlinear cost functions f_j are now dependent on the 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 represents an additional set of decisions for the optimization model. This represents a stochastic nonlinear programming problem (SNLP) which is often computationally very difficult to solve. Problem decomposition is one of the proposed approaches in literature to solve such computationally demanding SNLP problems [18, 19], which is used in this work. Here, the given stochastic programming problem is decomposed into two or multiple stages. The first stage problem, known as the master problem, uses a linear approximation of the nonlinear recourse function to fix the first stage decision variables. The recourse function is exactly evaluated only as a sub-problem, referred to as the second stage problem.

For the trading model, linear approximations of the nonlinear technology models are given by TC_j which are used to formulate a linear deterministic problem discussed earlier. Technology selection

b_{ij} and trading amount t_{ik} represent the first stage decision variables. The first stage problem is represented as:

Objective:

$$\text{Minimize} \quad \theta \tag{10}$$

Constraints:

$$t_{ii} = 0 \qquad \forall i = 1, \ldots, N \tag{11}$$

$$red_i \leq \sum_{j=1}^{M} q_j \times D_i \times b_{ij} + \sum_{k=1}^{N} t_{ik} - r \sum_{k=1}^{N} t_{ki} \qquad \forall i = 1, \ldots, N \tag{12}$$

$$P_i \geq \sum_{j=1}^{M} b_{ij} \times TC_j \times D_i + F\left(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki}\right) \qquad \forall i = 1, \ldots, N \tag{13}$$

$$\theta \geq \sum_{i=1}^{N} \sum_{j=1}^{M} b_{ij} \times TC_j \times D_i \tag{14}$$

$$g \leq G \times \xi + \theta \tag{15}$$

where, θ represents the first stage objective function. Constraints represented by Eqs. 11-13 are explained earlier in the text. Eq. 14 puts a lower bound on the linear approximation of the nonlinear cost models, while Eq. 15 represents the optimality cut which is introduced after the solution of the second stage problem. This optimality cut includes the first stage decision variables b_{ij} and t_{ik} represented collectively here as ξ. The first stage decisions are passed on to the second stage where the recourse function is computed using nonlinear models. Here, the uncertain variables are sampled N_{samp} times and the second stage sub-problem is solved for each sample to calculate the expected value of the nonlinear recourse function. The second stage problem is thus given as:

Objective:

$$\text{Minimize} \quad \sum_{n=1}^{N_{samp}} \sum_{i=1}^{N} \sum_{j=1}^{M} C_j(n) \times b_{ij} \tag{16}$$

Constraints:

$$C_j(n) = f_j(n) \tag{17}$$

where, $C_j(n)$ represents the exact cost computed using the nonlinear cost models f_j for a particular sample n of the uncertain parameter set u_j. The solution of the second stage problem results in possible generation of optimality cut which is included in the subsequent master problem solution through the computation of G and g matrices. The details of problem solution using decomposition strategy are omitted for the sake of brevity and can be found in many stochastic programming textbooks such as Birge & Louveaux [18].

3.2 Health Care Cost Consideration

The discharge of mercury to the watershed, although below the TMDL limit, is still harmful to humans, particularly because of its bioaccumulative nature. It is, consequently, associated with some health care cost that must be considered along with the actual compliance cost for a true evaluation of the cost effectiveness of the trading mechanism. This is especially important since different geographical regions (such as states within a country) have different laws leading to differing effective health care costs (essentially different value of human life). Since trading can have implications on the locations of the industry, the understanding of this trade-off can contribute in sound policy making. This work, therefore, studies the implications of health care cost consideration on the trading decisions.

The health care costs are calculated using the $LC50$ (Lethal Concentration 50%) value of elemental mercury, where $LC50$ is defined as the concentration of a toxic substance such as mercury at which 50% of the population exposed to it dies within a certain time. First, the total mercury discharge in the watershed is correlated to the average mercury consumption by humans through contaminated food (primarily fishes). This value is then compared with the mercury consumption rate at which 50% population will die using the $LC50$ value. The comparison gives an approximate estimate of the human mortality rate due to the discharge of mercury in the watershed. The approximate heath care cost is calculated as:

$$\text{Health Cost } = \left(\frac{WQS_{final}}{WQS} \times Hg_{safe} \times F_{avg} \times \frac{1}{LC50 \times W_{avg}} \right) \times \left(\frac{P}{2} \right) \times C_{health} \tag{18}$$

where, WQS represents the water quality standard (mercury concentration in water in mass/volume) that leads to safe mercury concentration in fishes represented as Hg_{safe} (mass of Hg per unit mass of fish). WQS_{final} is the actual water quality standard after compliance, F_{avg} is the average fish consumption per person per day in the watershed, W_{avg} is the average water consumption per person per day, P is the population in the watershed affected by mercury pollution, and C_{health} is the health care compensation per mortality. If the $LC50$ value for humans is not available, the value for the fish being consumed by humans is used in the relationship. Although, there are various simplifying assumptions due to lack of sufficient data, the relationship should give an approximate estimate that can later be refined with the availability of new information.

The health care cost can be used to compare different optimization solutions, in which case the cost is calculated post-optimization. It is also possible to modify the optimization problems presented before by including the health care cost as a part of the objective function. Such a modified formulation is given by Eqs. 19-26 below.

Objective:

$$\text{Minimize} \quad \Psi + W_{health} \times Mortality \times C_{health} \tag{19}$$

Constraints:

$$t_{ii} = 0 \qquad \forall i = 1, \dots, N \tag{20}$$

$$red_i \leq \sum_{j=1}^{M} q_j \times D_i \times b_{ij} + \sum_{k=1}^{N} t_{ik} - r \sum_{k=1}^{N} t_{ki} \qquad \forall i = 1, \dots, N \tag{21}$$

$$P_i \geq \sum_{j=1}^{M} b_{ij} \times f_j + F \left(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki} \right) \qquad \forall i = 1, \dots, N \tag{22}$$

$$red_i^{final} = \sum_{j=1}^{M} q_j \times D_i \times b_{ij} + \sum_{k=1}^{N} t_{ik} - r \sum_{k=1}^{N} t_{ki} \qquad \forall i = 1, \dots, N \tag{23}$$

$$WQS_i = c_i - \frac{red_i^{final}}{D_i} \qquad \forall i = 1, \dots, N \tag{24}$$

$$WQS_{final} = \frac{\sum_{i=1}^{N} WQS_i \times D_i}{\sum_{i=1}^{N} D_i} \tag{25}$$

$$\text{Mortality } = \left(\frac{WQS_{final}}{WQS} \times Hg_{safe} \times F_{avg} \times \frac{1}{LC50 \times W_{avg}} \right) \times \left(\frac{P}{2} \right) \tag{26}$$

where, W_{health} represents the weight given to health care cost in the objective function, red_i^{final} represents the final reduction achieved by point source i, and WQS_i represents the final discharge concentration from PS i. All other symbols have their previously assigned meanings. The form of ψ changes depending on whether the problem is deterministic (linear or nonlinear) or stochastic. Such a formulation is appropriate under the centralized trading mechanism envisioned in this work. With this formulation, given the data such as industry willingness to spend on pollution abatement, available technologies and actual values of discharges, the regulators can evaluate different possible scenarios, considering various health care cost weights and TMDL values, and arrive at the optimal regulatory decisions. The next section discusses the application of the various models proposed in this section on a case study of mercury waste management in Savannah River basin.

4. SAVANNAH RIVER WATERSHED CASE STUDY

TMDL of 32.8 kilograms/year has been established by the USEPA for five contiguous segments of the Savannah River in the state of Georgia, US, leading to the applicable water quality standard (WQS) of 2.8 ng/l (parts per trillion) in the watershed [20]. Although only 1% of the allowable load (about 0.33 kg/year) is assigned to the wasteload allocation for point sources, the USEPA is still interested in regulating the point sources since reduction of air deposition will be a long term process while point source reduction is expected to give relatively more immediate results. Moreover, since mercury is a bioaccumulative and highly dangerous pollutant, USEPA has determined, as a matter of policy, that all point sources discharging mercury at a level higher than the regulation should reduce their loadings of mercury using appropriate, cost-effective mercury minimization measures [20].

In all, there are 29 significant point sources discharging mercury in the watershed, including 13 major municipal polluters, 12 major industrial polluters, 2 minor municipal polluters and 2 minor industrial polluters. The TMDL is implemented by applying the common WQS of 2.8 ng/l to all PS discharges across the watershed. The sum of the individual wasteload allocations was 0.001 kg/year, which was significantly less than 0.33 kg/year, the cumulative wasteload allocation provided to all PS [20]. This difference appears because there are 50 more point sources in the watershed that were ignored, either because the discharges were very small or not measurable with certainty. The overall reduction needed to achieve the TMDL was about 44% [20]. Since the current discharge concentrations for the 29 point sources were not reported in the literature, the individual discharge values were computed by taking 29 random samples so that the mean required reduction for the watershed based on the WQS is about 44%. Table 1 reports the information related to each of the 29 point sources and also gives the values of red_i (targeted reduction) and P_i (treatment cost without trading) for each PS at TMDL 32 kg/year. Three treatment technologies, available to all point sources for implementation, considered for this problem were: coagulation and filtration, activated carbon adsorption and ion exchange process. For the linear optimization model, the linear cost functions for the technologies were taken from USDOI [21]. The total plant cost, which included the capital as well as operating cost, was reported as a function of the waste volume [21]. Although the treatment efficiencies depend on numerous factors, a more efficient treatment is likely to be more expensive. This criterion, along with data given in [22], was used to decide the treatment efficiencies shown in table 2. The nonlinear cost functions reported in USDOI [23] were used. The uncertain parameters in coagulation and filtration process model were cost of membrane, electricity rate, cost of sodium hypochlorite, and membrane life; the uncertain parameters in granular activated carbon process model were the coefficients to compute the capital and operating costs; while uncertain parameters in the ion exchange process model were the resin price and two coefficients representing the slope and intercept to compute the tank total cost.

The trading ratio was fixed at 1.1 [24]. Since mercury trading in water has not been practiced yet, transaction fee was not easy to decide. However, an EPA document gave a hypothetical example of water quality trading [8] in which the transaction fee was taken to be in the range of the per kg treatment cost of the pollutant. This is also observed for SO_2 trading [25]. Accordingly for this work, the average treatment cost for the mercury in '\$/kg of mercury' for the considered technologies was first calculated, which led to a transaction cost of \$ 1.5 Million per kg. The values of the parameters required to calculate the heath care cost were: WQS = 2.8 ng/l; Hg_{safe} = 0.4 mg/kg; F_{avg} = 17.5 grams per person per day; and W_{avg} = 2 liters per person per day. The most common fish consumed in the Savannah watershed is largemouth bass with the mercury $LC50$ value of 50 μg/liter (from the Pesticide Action Network (PAN) database). P, the population affected by the consumption, was equal to 10000 based on the data reported for the basin for North Carolina by the North Carolina Department of Environment and Natural Resources. Since the watershed boundaries do not correspond with the political boundaries, this represents an approximation of the correct number. The compensation amount (C_{health}) was equal to \$ 3 Million per person based on the estimations by the USEPA [26] for slow bioaccumulative chemicals like mercury.

Table 1: Point source data for Savannah River basin

Industry	Total volumetric discharge (MGD- Million Gallons Per Day)	Current discharge concentration (ng/liter)	Targeted reduction (g/liter)	Treatment cost without trading (\$/year)
I_1	46.1	4.65	0.1149	1.68×10^7
I_2	1.5	3.7	0.0017	328,500
I_3	4.6	4.3	0.0092	1,679,000
I_4	1.5	3.4	0.0011	328,500
I_5	2.0	3.88	0.0028	730,000
I_6	2.24	3.7	0.0026	490,560
I_7	1.2	3.9	0.0017	438,000
I_8	27.0	4.83	0.0740	1.48×10^7
I_9	4.5	4.0	0.0072	1,642,500
I_{10}	1.0	3.1	0.00035	219,000
I_{11}	1.0	3.06	0.00029	219,000
I_{12}	1.0	3.22	0.00052	219,000
I_{13}	2.0	3.31	0.0013	438,000
I_{14}	3.765	4.8	0.0101	2,061,337
I_{15}	18.0	4.33	0.0369	6,570,000
I_{16}	7.2	5.1	0.0224	3,942,000
I_{17}	58.6	4.87	0.1639	3.21×10^7
I_{18}	23.0	4.52	0.0532	8,395,000
I_{19}	1.152	5.05	0.0035	630,720
I_{20}	0.362	4.14	0.00064	132,130
I_{21}	108.0	4.58	0.2588	3.94×10^7
I_{22}	4.68	5.2	0.0152	2,562,300
I_{23}	28.09	4.41	0.0607	1.02×10^7
I_{24}	1.921	3.9	0.0028	701,165
I_{25}	0.544	4.5	0.0012	198,560
I_{26}	0.5	3.95	0.0008	182,500
I_{27}	0.003	3.72	3.62×10^{-6}	657
I_{28}	1.246	4.1	0.0021	454,790
I_{29}	0.054	3.4	4.14×10^{-5}	11,826

Table 2: Data for the various treatment technologies

Process	Mercury reduction capability (ng/lit)	Capital requirement ($/1000 liters)
Activated carbon adsorption (A)	3	0.395
Coagulation and filtration (B)	2	0.268
Ion exchange (C)	1	0.158

5. SAVANAAH RIVER CASE STUDY: RESULTS

Following different studies were conducted for the Savannah River watershed:

- Quantification of trading impact on the compliance and health care costs
- Analysis of solution dependence on TMDL value

Moreover, the goal was also to quantify the effect of nonlinearity and uncertainty on the optimal decisions. In the subsequent text, analysis when trading was not permitted is referred to as 'technology option', while the analysis when trading was permitted is referred to as 'trading option'.

5.1 Linear Deterministic Model Results

Table 3 compares the optimal solutions for the technology and trading options for a TMDL of 32 kg/year. The results showed that the implementation of trading reduced the compliance cost by about 18% ($ 27 Million annually). However, the total mercury discharge for the trading option was higher by about 19%. The was due to the discrete nature of discharge reduction when technology j, with the pollutant reduction capability of q_j , was implemented by a PS i. If targeted reduction for industry i (red_i) was lower than q_j, then industry i overachieved the reduction target. However, when trading was permitted, the additional degree of freedom allowed the industries that overachieved the reduction to trade-out the additional reduction to another industry. Consequently, in the presence of trading, there was no over-achievement of the reduction targets leading to a higher total discharge, which was still within the TMDL regulation. Consequently, the health care costs associated with mercury discharge was higher by about 16% for the trading option ($ 0.16 Million). Thus, considering only the compliance costs, trading option appeared to be economically beneficial, but it might not be necessarily so in the wake of the ensuing health care costs. A comparison of the technology implementations for the two solutions showed a trend towards avoiding expensive technology options and satisfying part of the pollutant reduction through trading. When trading was allowed, 16 polluters traded all their reduction quantity to some other industry, while 5 polluters implemented technology and also traded some portion of their discharge. 9 industries accepted trades, thereby taking care of excess discharge from other industries. Total quantity of mercury traded was 0.06 g/year, which was about 7% of the desired reduction.

To analyze and compare the trading and technology options with respect to TMDL regulation, the models were solved for various integer TMDL values between 26 kg/year and 36 kg/year. The results, while confirming that compliance cost is always lower with trading, showed that the saving is not constant because the compliance cost for the technology option changed nonlinearly. This means that the exact benefits of trading depended on the TMDL value. This also led to situations where reductions in TMDL (stricter environmental regulation) were associated with a relatively smaller increase in the total cost. This observation was due to the integrality of decisions related to technology implementation (decision variables b_{ij}). For policy makers, such information can be valuable to extract maximum environmental benefits under given financial constraints.

Table 3: Comparison of results for trading and technology option

	Technology option	Trading option
Compliance cost (Million $)	145.94	118.74
Health care cost (Million $)	0.8735	1.0344
Total cost (Million $)	146.81	119.78
Total mercury discharge reduction (grams)	1.102	0.892
Number of technology A implemented	6	0
Number of technology B implemented	14	12
Number of technology C implemented	9	1

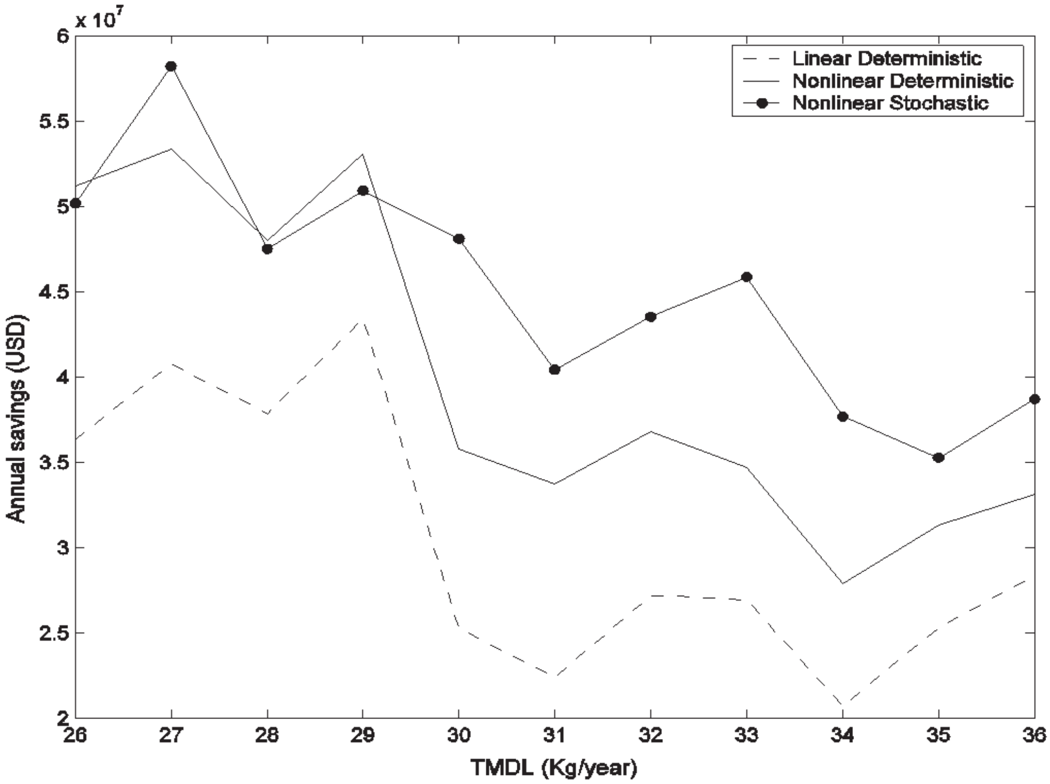

Figure 1: Effect of nonlinearity and uncertainty on annual savings due to trading

5.2 Effect of Nonlinearity and Uncertainty on Model Results

To understand the effect of nonlinearity and uncertainty, the nonlinear deterministic and nonlinear stochastic models were solved for the Savannah River case study for the TMDL range of 26 kg/year and 36 kg/year. The results were compared in terms of three different aspects: total annual savings, total quantity of mercury traded, and the technology selection decisions. For the stochastic model, the uncertain cost function parameters varied in the range of ±20% around the mean value with uniform distribution.

Fig. 1 plots the annual saving due to the implementation of trading for the considered TMDL range for the three models. It shows that the linear model significantly underestimated the annual savings as compared to the nonlinear deterministic model. The inclusion of uncertainty predicted even higher savings for most TMDL values. It should be noted here that trends in savings did not necessarily reflect the trends in overall cost. This was because the savings for a particular model were calculated over the technology option for the same model setting. Hence there was no common basic cost to compute the annual saving for the three models. The results highlighted the importance of considering model nonlinearity and uncertainty while assessing the benefits of trading.

Fig. 2 shows the implications of nonlinearity and uncertainty inclusion on technology selection for trading option. The figure shows the number of times each technology was implemented over the complete TMDL range (summation over all TMDL values). The results showed that with linear cost models, various small industries (i.e. industries with small volumetric discharge rates) implemented technologies along with the large industries (i.e. industries with large volumetric discharge rates). However, when nonlinear technology models were used, the large industries implemented most of the technologies and smaller industries satisfied the regulations by trading with these large industries. This increased the total quantity of mercury traded, as shown in Fig. 3. The distribution of technology selection is observed to be similar for both the deterministic models with coagulation and filtration being the most commonly implemented technology.

The inclusion of uncertainty in the model, however, had important implications on the distribution of technology selection. It can be seen from Fig. 2 that in the presence of uncertainty, granular activated

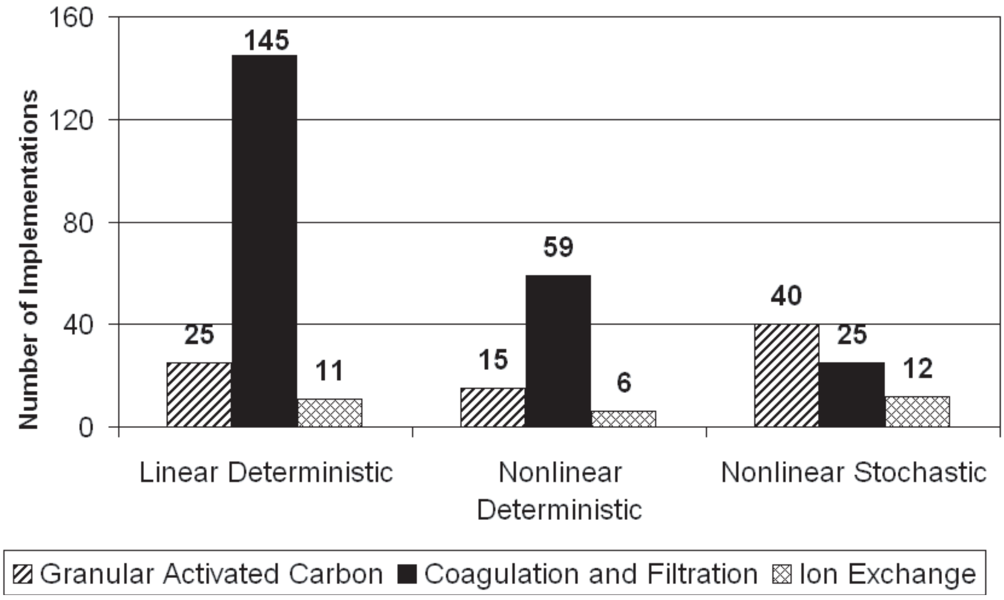

Figure 2: Effect of nonlinearity and uncertainty on technology implementation decision

carbon treatment was implemented most often. Since this treatment was the most efficient in terms of mercury removal capability, the total number of technology implementations correspondingly went down. The trend was again similar to the nonlinear deterministic case where most of the smaller industries preferred to trade with larger industries instead of installing technologies. The amount of mercury traded was much higher than the other two cases for most TMDL values (TMDL greater than 28 kg/year). This was because the most efficient technology was getting implemented more often, thereby creating a greater scope for trading. When the uncertainty range of the parameters was increased from ±20% to ±50%, it was observed that higher uncertainty discouraged the larger industries from investing in technology implementation. Consequently, it was optimal for the smaller industries to implement technologies while larger industries traded with them.

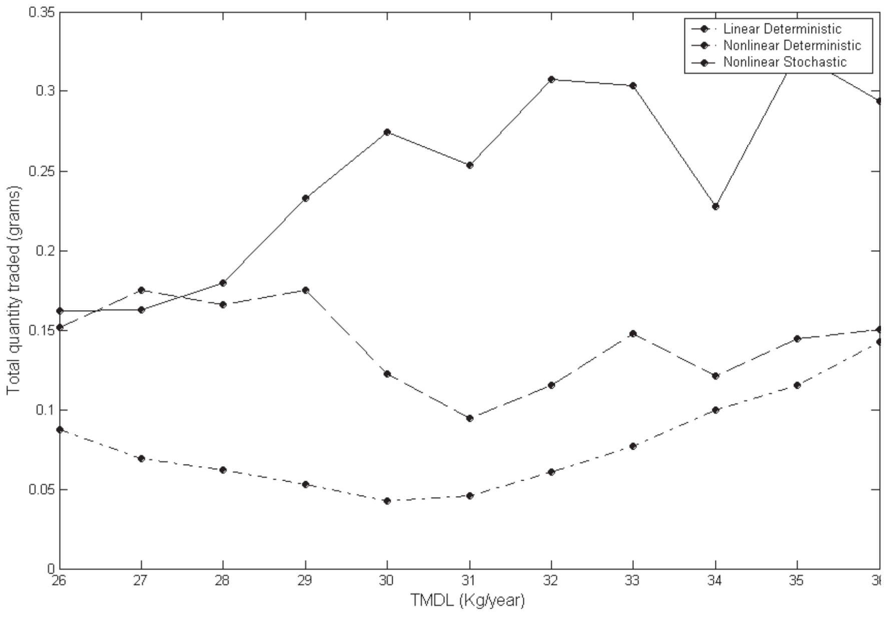

Figure 3: Effect of nonlinearity and uncertainty on quantity of mercury traded

5.3 Health Care Cost Consideration

The previous section reported the results when the optimization objective was the minimization of compliance cost (formulation A). The optimization model using health care cost as a part of the objective function (formulation B) was also solved for the Savannah River watershed. Since the health care cost calculation approach used here is based on various approximations, the problem was solved for different values of weighting coefficient W_{health} to study the effect of varying importance of health care. The results showed that at lower values of W_{health}, there was no difference in the overall cost for the two formulations since the health care costs were not significant enough to change the optimal decisions. However, for higher W_{health}, the optimization model minimized the mercury discharge and the point sources were forced to reduce more than their load allocations. The increased treatment costs were compensated for by reduced health care costs. Thus, it can be argued that for a successful trading mechanism, formulation B with health care cost as a part of the objective function is a better formulation.

6. ECOSYSTEM LEVEL MANAGEMENT: LAKE LIMING

Since mercury is a bioaccumulative chemical, concerns have been raised about allowing trading since trading can potentially lead to the creation of hotspots. A hotspot is defined as a place in the watershed where there is a high concentration of the pollutant (higher than the established regulation such as TMDL). However, it can be argued that the implementation of innovative management strategies such as liming at the ecosystem level can allay these concerns considerably. If trading mechanism is correlated with liming strategy to develop an integrated framework, significant scope exists to improve mercury pollution management. Liming is the addition of a base, such as limestone, to the water body to neutralize acid waters and soils and buffer them from rapid fluctuations in pH [27]. The proposal of water body liming to mitigate mercury bioaccumulation stems from the fact that acidic conditions aid mercury bioaccumulation [28]. Therefore, controlling the water body pH at potential mercury hotspots can minimize the impact of mercury. Liming has been successfully implemented in the past, particularly in the Scandinavian countries [29]. Shastri and Diwekar recently illustrated that efficient liming in the presence of uncertainty can be achieved by the use of appropriate uncertainty modeling techniques and optimal control theory [30]. The success should generate confidence in the proposed approach of linking mercury trading with liming to mitigate mercury pollution problems at the watershed level and using it as an integrated framework.

7. SUMMARY AND CONCLUSION

Growing concerns over mercury pollution have resulted in a significant research effort dedicated to effective pollution reduction and management. Sustainable management of mercury pollution will require innovation in science, engineering and management. Towards achieving that objective, this work proposed pollutant trading as an alternative and developed an optimization based framework for decision making. The basic linear and deterministic model was extended to understand the implications of model nonlinearity and uncertainty, while the effect of health care cost consideration on optimal decisions was also analyzed. The important conclusions from the application of the model to the Savannah River watershed case study are:

- Trading reduces the overall treatment cost for pollution reduction. However, this is accompanied by comparatively higher, although less than permitted, mercury emissions. This means that the advantages offered by reduced treatment cost with trading should be carefully weighed against increased risk of adverse health effects of mercury.
- Inclusion of nonlinearity and uncertainty has significant implications on total savings, quantity of mercury traded and technology selection decisions for the point sources.
- The importance given to human health can significantly alter the optimal pollutant trading decisions.

The work can be extended further by considering a larger watershed (scaling up) and including non-point sources in the analysis. Also important is the dry and wet deposition of mercury from the atmosphere to the watershed, which accounts for a substantial amount of mercury present in water bodies. The discussion in this article should, however, be looked at from a broader perspective, and not be restricted to the case of mercury waste. The proposed trading framework is valid for any pollutant. The specific aspects of the problem (such as liming for mercury pollution) should be incorporated in this general framework which should pave the way to achieve sustainable industrial waste management.

ACKNOWLEDGEMENTS

This work is funded by the NSF grant CTS-0406154 for first two authors and by NSF grant DMI-0200151 and ONR grant N00014-01-1-0048 for Prof. Sanjay Mehrotra.

REFERENCES

[1] USEPA. *Mercury study report to congress*. Report to congress: EPA-452/R-97-003, United States Environmental Protection Agency, 1997.

[2] USEPA. *Mercury research strategy*. Technical report: EPA/600/R-00/073, United States Environmental Protection Agency, Office of Research and Development, Washington DC 20460, 2000.

[3] R.E. DeSimone, M.W. Penley, L. Charbonneau, G.M. Smith, J.M. Wood, H.A.O. Hill, J.M. Pratt, S. Ridsdale, and R.J.P. Williams. The kinetics and mechanism of cobalamine-dependent methyl and ethyl transfer to mercuric ion. *Biochimica et Biophysica Acta*, 1973, 304, 851–863.

[4] C.L. Kling. Environmental benefits from marketable discharge permits or an ecological vs. economical perspective on marketable permits. *Ecological Economics*, 1994, 11, 57–64.

[5] D.R. Bohi and D. Burtraw. SO2 allowance trading: How experience and expectations measure up. *The Electricity Journal*, 1998, 10(7), 67–75.

[6] B. Solomon. Five years of interstate SO2 trading: Geographic patterns and potential cost savings. *The Electricity Journal*, 1998, 11(4), 58–70.

[7] A. Farrell. The NOx budget: A look at the first year. *The Electricity Journal*, 2000, 13(2), 83–93.

[8] USEPA. *Draft framework for watershed-based trading*. Technical report, EPA 800-R-96-001. Washington, DC: United States Environmental Protection Agency, Office of Water, 1996.

[9] USEPA. *Water quality trading policy*. Technical report, Office of Water, Washington, DC: United States Environmental Protection Agency, 2003.

[10] T. Tietenberg. Tradeable permits for pollution control when emission location matters: What have we learned? *Environmental and Resource Economics*, 1995, 5, 95–113.

[11] A. Kampas and B. White. Selecting permit allocation rules for agricultural pollution control: A bargaining solution. *Ecological Economics*, 2003, 47:135–147.

[12] T.N. Cason and L. Gangadharan. Transaction costs in tradable permit markets: An experimental study of pollution market design. *Journal of Regulatory Economics*, 2003, 23(2),145–165.

[13] R.G. Newell and R. Stavins. Cost heterogeneity and potential savings from market based policies. *Journal of Regulatory Economics*, 2003, 23(1), 43–59.

[14] M-F Hung and D. Shaw. A trading-ratio system for trading water pollution discharge permits. *Journal of Environmental Economics and Management*, 2005, 49, 83–102.

[15] USEPA. *Water quality trading assessment handbook*. Technical report, Washington, DC: United States Environmental Protection Agency, Office of Water, 2004.

[16] W.E. Oates, P.R. Portney, and A.M. McGartland. The net benefit of incentive based regulation: A case study of environmental standard setting. *The American Economics Review*, 1989, 79(5), 1233–1242.

[17] S. Atkinson and T.H. Tietenberg. The empirical properties of two classes of designs for transferable discharge permit markets. *Journal of Environmental Economics and Management*, 1982, 9, 101–121.

[18] J. Birge and F. Louveaux. *Introduction to Stochastic Programming*. Springer series in Operations Research, 1997.

[19] U.M. Diwekar. *Introduction to Applied Optimization*. Kluwer Academic Publishers, Dordrecht, 2003.

[20] USEPA. *Total maximum daily load (TMDL) for total mercury in fish tissue residue in the middle and lower savannah river watershed*. Report, United States Environmental Protection Agency, Region 4, 2001.

[21] USDOI. *Total plant costs: For contaminant fact sheets*. Technical report, U.S. Department of Interior, Bureau of Reclamation, Water treatment engineering and research group, Denver CO 80225, 2001.

[22] USEPA. *Capsule report: Aqueous mercury treatment*. Technical report: EPA/625/R-97/004, United States Environmental Protection Agency, Office of Research and Development, Washington DC 20460, 1997.

[23] USDOI. *Water treatment estimation routine WaTER user manual*. Water desalination research & development program report no. 43, U.S. Department of Interior, Bureau of Reclamation, Technical Service Center, Environmental Resources Services, Denver CO 80225, 1999.

[24] C. Marshall. *Results of water-based trading simulations: Final report*. Technical report, Phillip Services, Fort Washington, PA (generate for the U.S. Environmental Protection Agency), 1999.

[25] D. Burtraw, D. Evans, A. Krupnick, K. Palmer, and R. Toth. Economics of pollution trading for SO2 and NO*x*. *Annual Review and Environment and Resources*, 2005, 30, 253–289.

[26] USEPA. *Guidelines for preparing economic analysis*. Technical report: EPA 240-R-00-003, United States Environmental Protection Agency, 2000.

[27] T.A. Clair and A. Hindar. Liming for the mitigation of acid rain effects in freshwaters: A review of recent results. *Environmental Review*, 2005, 13(3), 91–128.

[28] M. R. Winfrey and J. W. M. Rudd. Environmental factors affecting the formation of methylmercury in low ph lakes. *Environmental Toxicology and Chemistry*, 1990, 9, 853–869.

[29] L. Henrikson and Y.W. Brodin. *Liming of acidified surface waters*. Springer, Berlin, 1995.

[30] Y. Shastri and U. Diwekar. Optimal control of lake ph for mercury bioaccumulation control. *Ecological Modelling*, 2008, 216, 1–17.