Mercury Trading for Sustainable Industrial Waste Management

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Abstract

Effluent trading to manage water pollution holds considerable potential for industries and policy makers alike. This paper proposes an optimization based approach to assist decision making in pollutant trading which is beyond heuristics. The optimization model, formulated as an Mixed Integer Linear Programming (MILP) problem, allows decision makers to incorporate watershed and technology specific information in regulation development. The problem solution, as a consequence, suggests optimal approach to the industries to achieve the assigned load reduction targets. The basic model is extended to include health care costs to compare various decisions and also contribute towards decision making. The effect of uncertainty on the problem solutions is also analyzed by formulating a chance constrained programming problem as the extension of the original MILP problem. This ensures that no hotspots are created due to discharge uncertainty. The optimization model is implemented on a watershed level mercury pollution reduction case study. The results, indicating significant cost reductions due to trading, also emphasize the importance of considering watershed specific data in decision making. Health care cost is shown to be an important parameter for comparison and effects of uncertainty are observed to be more pronounced at tighter regulations.

1 Introduction

Pollutant trading is a market based strategy to economically achieve environmental resource management. The overall goal is to attain the same or better environmental performance with respect to pollution management at a lower overall cost. Since the U.S. Environmental Protection Agency (USEPA) issued its Emissions Trading Policy in 1986, the most frequent application of this approach has been in SOx trading [1]. The strategy has been found to achieve desirable cost reductions or environmental benefits in many applications [2, 3, 4]. On March 15, 2005, USEPA issued the federal rule allowing cap and trade policy to reduce mercury emissions from coal-fired power plants. This relative success of trading to deal with air pollutants has encouraged introduction of effluent trading concept for water pollution control as well. It is therefore prudent to systematically analyze this approach at this juncture. Pollutant trading adds flexibility and introduces new options to the policy makers and industries alike. A policy maker, while aiming for better environment and efficient waste management, has to understand the industry constraints, since the regulations need to be satisfied by the industries. With increasingly stringent environmental regulations, waste management has become an important financial consideration for industries. Trading offers these industries the options to satisfy the regulations at lesser costs. Individual industry level decisions are thus affecting the overall goal. Such decision are beyond heuristics and a systematic approach is called for.

This work uses optimization techniques to develop a decision making framework that will guide industries in taking optimal decisions in wake of the added flexibility due to trading. The model will also guide regulators in developing optimal regulations in different situations. Work in [5] presents one such analysis for NOx pollution and analyzes the effect of trading on overall cost, emission reductions and suggests industry level decisions. This work performs a similar analysis for mercury trading in watershed management. Compared to the model presented in [5], this model also takes health care costs, arising through pollutant exposure, into consideration for assessing the benefits of various decisions. For a watershed, the framework therefore helps develop efficient regulations such as TMDLs (Total Maximum Daily Load), given the watershed, industries and technology specific details, in the process optimizing the industry decisions as well. The model is then extended to include health care cost as objective in decision making, which further distinguishes it from the model in [5]. The effect of uncertainty, prevalent in most situations, on model solutions is also analyzed using chance constrained programming.

The proposed model is applied on a Savannah River watershed mercury waste management case study. Mercury is an important concern for environmentalists and its harmful effects on humans are well documented. It is opined that application of trading for mercury is not advisable since mercury cycle in environment is still not fully understood, partly due to its bioaccumulative potential and slow, long term effects. Consideration of human health care costs resulting from mercury exposure partially addresses this issue by quantifying the long term effects of mercury pollution. The problem formulation also ensures that the discharge conditions can not deteriorate over the existing ones and hence trading will not compromise the environment.

This work therefore might be viewed from two perspectives. The basic optimization model, applicable to any pollutant and media, is a step towards integrated policy making framework. Such a framework gives decision makers and industries the liberty to analyze various scenarios and opt for the best among them. The case study, on the other hand, sheds light on the possibility of using market based trades for mercury management. Consideration of aquatic mercury treatment technologies and health care costs at the watershed level helps better assess the perceived benefits of this technique for mercury.

The article is arranged as follows. The next section explains the basics and implementation aspects of watershed based pollutant trading. Section 3 formulates the basic optimization problem. Section 4 documents the case study details and is followed by section 5 presenting the results for the case study. Section 6 focuses on the health care cost, first including health cost as an objective to solve the case study and then conducting a sensitivity analysis for the health care cost. The model incorporating uncertainty is discussed in section 7 along with the solution method and case study results for the formulation. The article ends with conclusions presented in section 8.

2 Watershed based trading

2.1 Overview

Environmental credit 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. Early applications of trading were designed to provide greater flexibility for emission sources to meet air quality standards in a cost-effective manner [6]. Recently, Bush administration has approved a cap and trade policy for mercury air pollution in coal-fired power plants which aims to reduce mercury loading by about 70% by 2018. Following on the lines of air pollutant trading, trading principles have also been sanctioned by USEPA for water pollution problems on a limited basis since the early 1980s. USEPA has since then formalized the concept into a framework to guide effective implementation of water pollutant trading [7, 8]. Trading is based on the fact that sources in a watershed can face very different costs to control the emission of the same pollutant. 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 lower cost. Firms having financial capabilities and infrastructure to perform pollutant reduction below the required limit get credits for it that can be sold to another firm to gain monetary benefits or banked for future use if that is a possibility.

Pollutant dischargers are mainly classified as either point or non-point sources. Point sources are defined as the ones having direct and measurable emissions (e.g. industries, municipal waste treatment plants etc.) while non-point sources are the ones with diffused emissions that are difficult to measure (e.g. agricultural or storm-water runoffs). Amongst the various possibilities of carrying out trading, the one between point sources is thought to be simpler and achievable. This is owing to their measurable discharges in terms of quality and quantity and also due to the measurable assessment of pollution reduction techniques.

Point sources are regulated under the National Pollution Discharge Elimination System (NPDES) established under the Clean Water Act (CWA). Under NPDES, all facilities which discharge pollutants from any point source into waters of the United States are required to obtain a permit allowing them to discharge only a certain amount of pollutant. The permit provides two levels of control: technology-based limits (based on the ability of dischargers in the same industrial category to treat wastewater) and water quality-based limits (if technology-based limits are not sufficient to provide protection of the water body). The permits can be individual (specific to a company) or general (applicable to a group of companies). The existence of general water quality-based permits in a watershed is equivalent to the concept of Total Maximum Daily Load (TMDL) in the watershed. TMDL is established by state for waterbodies or watersheds where technology-based requirements alone are not sufficient to attain water quality goals. 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 nonpoint) sources.

EPA has proposed two possible trading mechanisms for point sources [7].

- Trades can occur in the context of individual point source permits. In this case, different point sources have individual (technology or water-quality based) pollutant permits and there is no common water quality based limit. Treatment cost differentials encourage trading between various point sources.

- Trades can also occur through the development of TMDL or other equivalent analytical framework. In this case, water quality-based limits, common to all the point sources in the watershed, are established. This provides a starting point to compare the costs of the baseline responsibilities necessary to achieve water quality goals with alternative allocations. Parties to the trade then negotiate within the loading capacity determined under the TMDL so as to satisfy the common discharge objective.

Various parameters that affect the economics of trading are 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), number of participants, availability of cost data and uncertainties related to continued industry participation and data availability.

2.2 Implementation perspective

Once the TMDL has been established, the point source is assigned a particular load allocation and may need to reduce its discharge to satisfy the allocation. It has two options to accomplish this:

- Implementation of advanced end of pipe treatment methods which entail certain capital and operating cost depending on the existing technology, the amount being treated and level of reduction being achieved, and varies for different point sources

- Trading a particular amount of pollutant to another point source in the watershed which is able to reduces its discharge more than that specified by the regulation

The major reason for pollutant trading being attractive is the flexibility it offers, not only for the polluters, but also for the policy makers. From the polluter's perspective, multiple waste treatment options are typically available for implementation. Therefore, in the presence of multiple polluters, multiple technologies and option of trading, decisions such as if and how much to trade become difficult for the polluters. For policy makers, trading opens up new avenues to achieve better environmental goals at lower overall cost for which the policy maker has various parameters like trading ratio, trading transaction costs, number of participants at his disposal. The policy maker, although driven by environmental objectives, must also consider industry capabilities and limitations. It is also important to understand the effect of trading on the final reductions. Whatever be the discharge level of a pollutant, even below the TMDL regulation, it adversely affects the environment and humans. Consideration of such effects is important in decision making. Finally, information about of the watershed and trading, if available while finalizing the regulation, might influence the regulation development itself. In this wake, a formal decision making framework that takes into account these aspects and guides the policy maker and polluters in decision making is desirable.

Use of optimization techniques offers a way to achieve this, where the objective of overall cost minimization can be achieved by incorporating the watershed and pollutant specific details through constraints. Once the modelling framework has been developed, it also opens up the option of exploring various scenarios to finalize the best settings. The next section explains a basic optimization model which is a step towards this objective.

3 Trading optimization problem formulation

The formulation considers that TMDL regulation has already been developed by the state in consultation with USEPA. This translates into specific load allocations for each point source.

Consider a set of point sources (PS$_i$), $i = 1, ..., N$, disposing pollutant 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]
c_i = Current pollutant discharge concentration for PS i [mass/volume]
a_i = Current pollutant discharge quantity for PS i [mass/year]
L_i = Load allocation to PS i based on TMDL regulation [mass/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.
Here, the value of red_i is given by

$$red_i = D_i.c_i - L_i = a_i - L_i \tag{1}$$

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:
TC_j= Total treatment plant cost [$/volume]
q_j = Pollution reduction possible from the process [mass/volume]

The total plant cost TC_j is the sum of the annualized capital cost and annual operating and maintenance cost. The annualized capital cost in turn depends on the total equipment and setup cost [9]. 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 and transaction fee is applicable to all the trades. 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 the desired TMDL goal at *minimum overall cost*.

Let b_{ij} be the binary variables representing the 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 problem is then formulated as follows:

$$\textbf{Objective}:$$

$$\text{Minimize} \qquad \sum_{i=1}^{N}\sum_{j=1}^{M} TC_j.D_i.\, b_{ij} \tag{2}$$

$$\textbf{Constraints}:$$

$$t_{ii} = 0 \qquad \forall i = 1, ..., N \tag{3}$$

$$red_i \leq \sum_{j=1}^{M} q_j.D_i.\, b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \qquad \forall i = 1, ..., N \tag{4}$$

$$P_i \geq \sum_{j=1}^{M} b_{ij}.TC_j.D_i + F\big(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki}\big) \qquad \forall i = 1, ..., N \tag{5}$$

The objective function gives the sum of the technology implementation cost for all point sources. Although each PS will also spend or gain from practising trading, expense of one PS in a watershed is gain 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. 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 the PS. The last constraint ensures that the expenses incurred by each PS with trading are not more that those without trading. This is because the trading framework by EPA mentions that no polluter can be forced to trade. As a result, a polluter is likely to participate in trading only if there is a financial incentive for it. The problem given by Eqs. 2-5 is a mixed integer linear programming problem (MILP). The decision variables in the problem are binary variables b_{ij} and continuous variables t_{ik}. In the subsequent text, this formulation is referred to as 'formulation A'.

The model in [5] for NOx budget is also a mixed integer problem with a similar objective of cost minimization for all sources. It selects the combination of control technologies for each plant to yield the lowest cost. However, there are a few differences in the two models. The NOx model takes decisions at individual boiler level while the proposed model takes decisions at the point source (company) level. The NOx model is a dynamic model and the decisions are made over a period of time to maximize the net present value. This permits the analysis of banking of trades over time. The proposed model on the other hand is not dynamic since the EPA framework does not mention any option of banking of trades for water effluent trading. The structure of the NOx model is such that, although emission goals over a period of time are achieved, there is a possibility of excessive emissions at localized space or time instants. This possibility does not exist in the proposed model, due to constraint 4. Further differences arise when the proposed model is extended to include health care cost, first for solution comparison and later in the objective function. Although [5] discuss various sources of uncertainty, the optimization model does not solve the problem considering uncertainty. The proposed model, on the other hand, is extended to systematically include uncertainty in decision making through chance constrained programming. These differences will become evident as the extended models are discussed later in the article.

The problem formulated above is quite general, applicable to any watershed and any pollutant. The next section discusses the application of the model on a case study of mercury waste management in Savannah River basin.

4 Mercury trading: Case study

Mercury is fast becoming a major concern for the environment due to better understanding of its harmful environmental and health impacts. Mercury can cycle in the environment in all media as part of both natural and anthropogenic activities. Mercury in water presents a grave danger not only to the aquatic communities but also to humans [10] through direct and indirect effects. Mercury, in the form of methylmercury, accumulates up the aquatic food chains so that organisms in higher trophic levels have higher mercury concentrations [11, 12]. As a result, contaminated fish consumption is the most predominant path of human exposure to mercury. The primary targets for toxicity of mercury and mercury compounds are the nervous system, kidney, and developing fetus. Other systems that may be affected include respiratory, cardiovascular, gastrointestinal, hematologic, immune, and reproductive systems [13]. This has resulted in fish consumption advisories at various water bodies throughout the US. Owing to its importance, the considered case study concerns with aquatic mercury waste management. It deals with management of mercury pollution in Savannah River basin in the state of Georgia, US.

4.1 Savannah river watershed details

TMDL has been established for five contiguous segments of the Savannah River. These segments are included in the list of impaired water bodies as the tissue mercury concentration in certain fish species exceeds the Georgia Department of Natural Resources (GDNR) Fish Consumption Guidelines. Although the mid-line of the Savannah River serves as the east-west boundary between the states of Georgia and South Carolina, the TMDL does not provide wasteload allocations to South Carolina NPDES facilities. This TMDL reflects assumption that concentrations of mercury in the South Carolina portion of Savannah River will meet the applicable Georgia water quality standards at the South Carolina-Georgia border. In order for TMDL to be developed, the applicable water quality standard must be determined, which gives the maximum safe concentration of mercury in water. EPA determined the applicable water quality standard for total mercury in the ambient water of the Savannah River Basin to be 2.8 ng/l (parts per trillion). At this concentration, or below, fish tissue residue concentrations of mercury will not exceed 0.4 mg/kg, which is protective of the general population from the consumption of freshwater fish. This interpretation of Georgia's water quality standard was based on site-specific data gathered for the Savannah River in 2000 specifically for the purpose of this TMDL. The loading of mercury from the watershed into the Savannah River was simulated using a Watershed Characterization System (WCS) model developed by EPA Region 4 [14]. The water quality model known as WASP5 [15] is used to simulate mercury fate and transport in Savannah River. The calculated allowable load of mercury that can come into the Savannah River without exceeding the applicable water quality standard of 2.8 ng/l as interpreted by EPA is 32.8 kilograms/year, which represents the TMDL for the watershed. Since about 99% of the mercury loading is through atmospheric sources, only 1% of the allowable load is assigned to the wasteload allocation for NPDES sources. This amounts to the allowable combined discharge of 0.33 Kg/year. Based on the current volumetric discharge of each of the NPDES sources, waste load allocation (permitted discharge of mercury by each source) is carried out.

In all, there are 29 significant point sources discharging mercury in the Savannah River watershed. The point sources represent a wide spectrum and include 13 major municipal polluters, 12 major industrial polluters, 2 minor municipal polluters and 2 minor industrial polluters. It should be noted that there are more point sources in the region. But the discharges from those are considered to be negligible owing to their relatively low discharge volumes. One of the options of implementing the TMDL is to apply a common WQS of 2.8 ng/lit to all the point source discharges across the watershed. Therefore, under this option, the wasteload allocation for each NPDES point source identified in this TMDL would be the product of 2.8 ng/l and its permitted or design flow rate. The sum of these individual wasteload allocations is 0.001 kg/year, which is significantly less than the 0.33 kg/year cumulative wasteload allocation provided to all NPDES facilities [16]. Current discharge concentrations for the 29 point sources are not reported in literature. For this case study, they are not considered to be related to their discharge quantities. The overall reduction needed to achieve the TMDL criteria is about 44% [16]. The targeted overall reduction for the PS is therefore taken to be 40% and individual discharge concentrations are adjusted accordingly. Further details about TMDL development can be found in [16].

Table 1 gives various parameter values related to the point sources. The table also gives values of red_i (targeted reduction) and P_i (treatment cost without trading) for each PS at TMDL 32 Kg/year, for which the problem is solved below.

Table 1: Point source data for the Savannah river basin

Industry	Total Volumetric Discharge (MGD-Million Gallons per Day)	Current Discharge concentrations (ng/lit)	Targeted reduction (g/year)	Treatment cost without trading ($/year))
I_1	46.1	4.65	0.1178	1.68×10^7
I_2	1.5	3.7	0.0018	355 875
I_3	4.6	4.3	0.0095	1679 000
I_4	1.5	3.4	0.0012	355 875
I_5	2.0	3.88	0.0029	730 000
I_6	2.24	3.7	0.0027	531 440
I_7	1.2	3.9	0.0018	438 000
I_8	27.0	4.83	0.0757	1.53×10^7
I_9	4.5	4.0	0.0075	1642 500
I_{10}	1.0	3.1	0.00041	237 250
I_{11}	1.0	3.06	0.00036	237 250
I_{12}	1.0	3.22	0.00058	237 250
I_{13}	2.0	3.31	0.0014	474 500
I_{14}	3.765	4.8	0.0104	2130 049
I_{15}	18.0	4.33	0.0381	6570 000
I_{16}	7.2	5.1	0.0229	4073 400
I_{17}	58.6	4.87	0.1676	3.32×10^7
I_{18}	23.0	4.52	0.0546	8395000
I_{19}	1.152	5.05	0.0036	651 744
I_{20}	0.362	4.14	0.00067	132 130
I_{21}	108.0	4.58	0.2656	3.94×10^7
I_{22}	4.68	5.2	0.0155	2647 710
I_{23}	28.09	4.41	0.0625	1.03×10^7
I_{24}	1.921	3.9	0.0029	701 165
I_{25}	0.544	4.5	0.0013	198 560
I_{26}	0.5	3.95	0.0008	182 500
I_{27}	0.003	3.72	3.81×10^{-6}	711.75
I_{28}	1.246	4.1	0.0022	454 790
I_{29}	0.054	3.4	4.47×10^{-5}	12 811.5

Table 2: Data for the various treatment technologies

Process	Mercury reduction capability (ng/lit)	Capital requirement ($/1000 gallons)
Coagulation and Filtration (A)	2.0	1.0
Activated carbon adsorption (B)	3.0	1.5
Ion exchange (C)	1.0	0.6

4.2 Technology details

Three treatment technologies are considered for this problem and they are available to all point sources for implementation. These include coagulation and filtration, activated carbon adsorption and ion exchange process. The capital requirement and reduction capability of any process is expected to be (nonlinearly) related to the capacity of the treatment plant and the form and concentration of the waste to be treated, amongst many other factors. For this analysis though, such complex relationships are ignored for simplicity and the treatment cost is only linearly related to the volume of the waste. Total plant cost data for the treatment methods is reported in [9] as a function of the waste volume. The total plant cost includes capital as well as annual operating cost per unit volume of waste treated, calculated as per the following equations [9]:

$$\begin{aligned}\text{Annualized capital cost} &= [\text{Total capital equipment cost} + \text{Project related} \\ &\quad + \text{spacial cost}] \times (\text{capital recovery factor for} \\ &\quad \text{30 years at 3.89\% real annual interest based} \\ &\quad \text{on lagged impact on interest = 0.057}) \qquad (6) \\ \text{Total annual cost}(TC) &= \text{Annualized capital cost+ Total annual} \\ &\quad \text{operations and maintenance cost} \qquad (7)\end{aligned}$$

Since waste volumes encountered in this case study are mostly greater that 1 MGD, asymptotic values reported in [9] are used. The treatment efficiencies depend on the waste composition and concentration. In general though, a more efficient treatment is likely to be more expensive. This criteria, along with data given in [17], is used to decide the treatment efficiencies. Table 2 gives the process data.

4.3 Trading details

Trading parameters needed for the problem solution are trading ratio and transaction cost. For a point source - point source trading, as considered in this problem, literature recommends a trading ratio between 1.1-1.25. For this problem, the ratio r is 1.1. Transaction fee is not easy to decide since mercury trading in water polluters has not been implemented so far. However an EPA document gives a hypothetical example of water quality trading [7] in which the transaction fee is taken to be in the range of per kg treatment cost of the pollutant. For this work, based on the average volumetric discharge of the industries and the average treatment costs of the processes, the average treatment cost in '$/Kg of mercury' is calculated. Accordingly the transaction cost is around 4.0×10^8 $/Kg.

4.4 Health care cost consideration

Discharge of mercury to the watershed, although below TMDL limit, is still harmful to humans and is consequently associated with some health care cost. In an ideal case, the discharge must be reduced to as low a level as possible. The problem considers health care cost to compare solutions obtained for various scenarios. The cost is not considered in the objective function for the optimization problem, rather it is added to the final cost.

The bioaccumulative nature of mercury and its slow dynamics make the long term effects of mercury exposure important. Hence it is important to account for such effects while quantifying health care costs. Majority of mercury accumulates in the food chain as methyl mercury. Hence quantification of health care cost based on methyl mercury concentration is most appropriate. IRIS (Integrated Risk Information System) database reports the methyl mercury reference dose for chronic oral exposure (RfD), which is the highest dose of methyl mercury without any harmful effects. But TMDL for the Savannah river is developed on the discharge of total mercury to the watershed, not only methyl mercury. Hence the problem needs a quantifying measure based on total mercury rather than methyl mercury. IRIS database does not report the RfD value for mercury (elemental).

Given these considerations, this work quantifies health care cost through the LC50 (Lethal Concentration 50%) value for mercury which quantifies harmful effects of long term exposure to mercury. The health care cost is a function of the final overall mercury discharge. This discharge value is used to calculate average mercury consumption by humans. When compared with the LC50 value, this gives the approximate mortality rate of humans. The parameters required to calculate this cost are:

LC50 value for mercury = LC50 = 350 μg/liter
Average fish consumption = F_{avg}= 17.5 grams per person per day,
Average water consumption = W_{avg}= 2 liters per person per day,
Safe concentration of mercury in fish = Hg_{safe}= 0.4 mg/Kg,
Population affected by the consumption = P = 10 000,
Compensation for the health cost = C_{health} = $ 1 Million per person, and
Final average water quality standard = WQS_{final}

Values of F_{avg}, W_{avg} and Hg_{safe} are taken from [16]. LC50 value is reported in the material and safety data sheet for mercury by Fisher Scientific. Compensation amount is based on the compensations received in road accident fatalities. Population is based on the data reported by US Census Bureau. The overall health care cost is then given as

$$\text{Health Cost} = \left(\frac{WQS_{final}.Hg_{safe}}{WQS} \frac{1000.F_{avg}.P}{2.LC50.W_{avg}} \right).C_{health} \tag{8}$$

where WQS is the targeted water quality standard resulting in safe desired level of mercury in fish and the term in brackets represents the mortality rate. The mortality rate is calculated by calculating the total amount of mercury consumed per day by a human and comparing it with the average per day mercury intake by a human through drinking, assuming that health effects due to drinking represents the long term effects quantified by the LC50 value.

5 Savannah case study: Results and discussion

The problem formulation is given by Eqs. 2-5. In the subsequent text, analysis when trading is not permitted is referred to as ‘technology option’ while the analysis when trading is allowed is referred to as ‘trading option’. Following different studies are conducted for the problem:

Table 3: Comparison of costs for two options

	Technology option	Trading option
Reduction cost (Million $)	147.99	121.10
Health care cost (Million $)	41.59	48.57
Total cost (Million $)	189.59	169.68
Total mercury discharge reduction (grams)	1.102	0.911

- Comparison between the solutions for technology option and trading option to quantify the impact of trading on the cost to satisfy regulations
- Dependence and comparison of the solutions for technology option and trading option on TMDL value to understand the effect of regulations on problem which will guide the policy makers

Next two sections report the results.

5.1 Comparison between trading and non-trading solutions

TMDL for this analysis is 32 Kg/year and the total mercury reduction target for all the point sources is 0.911 g/year.

A comparison of the solutions obtained for the two cases is given in Table 3. It can be seen that there is about 18% reduction in the treatment cost as a result of implementing trading, which amounts to around 27 Million $ annually. This supports the expected result that trading will reduce the overall expenditure. However, while satisfying TMDL, the total mercury discharge for the trading option is higher by about 17%. This becomes significant when one considers the health care costs associated with the mercury discharge. A comparison of the health care costs shows that the cost for technology option is about 14% less than that for trading option, a difference of 7 Million $. Thus, considering only the reduction costs, trading option appears to be economically beneficial but it is not necessarily so in the wake of ensuing health care costs.

The technology only solution results in the implementation of technology A by 14 polluters, technology B by 6 polluters and technology C by 9 polluters. In comparison, when trading is available, 14 industries implement technology A while technology B and C are not implemented at all. 15 polluters trade all their reduction quantity to some other industry while 6 polluters implement technology and also trade some portion of their discharge. Total quantity of mercury traded is 0.053 g/year, which is about 5% of the desired reduction. The results show a trend towards avoiding expensive technology options and satisfying part of the pollutant reduction through trading. Also observed is a significant preference towards one technology (technology A) after trading is allowed.

5.2 Solution dependence on the TMDL regulation

To analyze and compare trading and technology options with respect to TMDL regulation, the problem is solved for various TMDL values between 23 Kg/year and 40 Kg/year. Plots showing the treatment, health care and total costs for both options as a function of TMDL are shown in figure 1.

The plots reveal a familiar trend with respect to the reduction costs i.e. reduction costs with trading are always lower than those without trading. But the variation in these costs, particulary the technology option costs, is not linear leading to varying differences in the reduction costs for trading and technology options. This means that the exact benefits of trading depend on the TMDL value. It can also be observed that the health care costs for trading option are always higher due to lesser discharge reductions. The relationship and variation between the technology and trading option for the total cost is similar to that for the reduction cost, but the difference is reduced due to the opposite trend in health care cost. The advantages offered by trading option are therefore subject to the correct relative evaluation of these two opposing trends. For this problem, with the given considerations, it can be concluded that trading becomes economically attractive, even after considering health care costs, at lower TMDL values. In future, regulations are expected to get more stringent making trading more beneficial.

Another important aspect to consider in figure 1 is the nature of variation of different plots. The nonlinearity of these variations puts forth certain points where reductions in TMDL are associated with relatively smaller increase in the total cost. This observation is quite pronounced for technology option where the integrality of decisions related to technology implementation (decision variables b_{ij}) make a strong impact. For policy makers, such information can be invaluable to extract maximum environmental benefits under given financial constraints. For trading option, although these effects are observed, they are considerably reduced due to the flexibility in decision making offered by trading.

Figure 2 plots the reductions achieved by both options as a function of TMDL. It can seen that technology option always achieves higher reductions and trading option is able to exactly achieve the desired reductions on many occasions. But the difference between the reductions and subsequent environmental benefits for technology option over trading option varies, depending on the TMDL value.

6 Health care cost consideration

The previous formulation minimized the discharge reduction cost while considering health care cost only for comparison and indicated that this cost affects the overall cost trends. This section therefore studies the impact of health care cost on problem solution more extensively. First, a sensitivity analysis for the health care cost is carried out for the model. Health care cost depends on mortality and monetary compensation per affected person, both of which are approximated here. The mortality is a function of LC50 value which is assumed to model the long term effects of mercury contamination. The monetary compensation puts a value on human life and can be a difficult parameter to estimate, being dependent on region, country, and policies. The sensitivity analysis accounts for some of these unknown factors to a certain extent. Then, formulation A is modified to include health care cost as a part of the objective function, the new objective being minimization of total (reduction and health care) cost. The new formulation is solved for various cases and sensitivity analysis for it is also performed.

Next two sections discuss these cases.

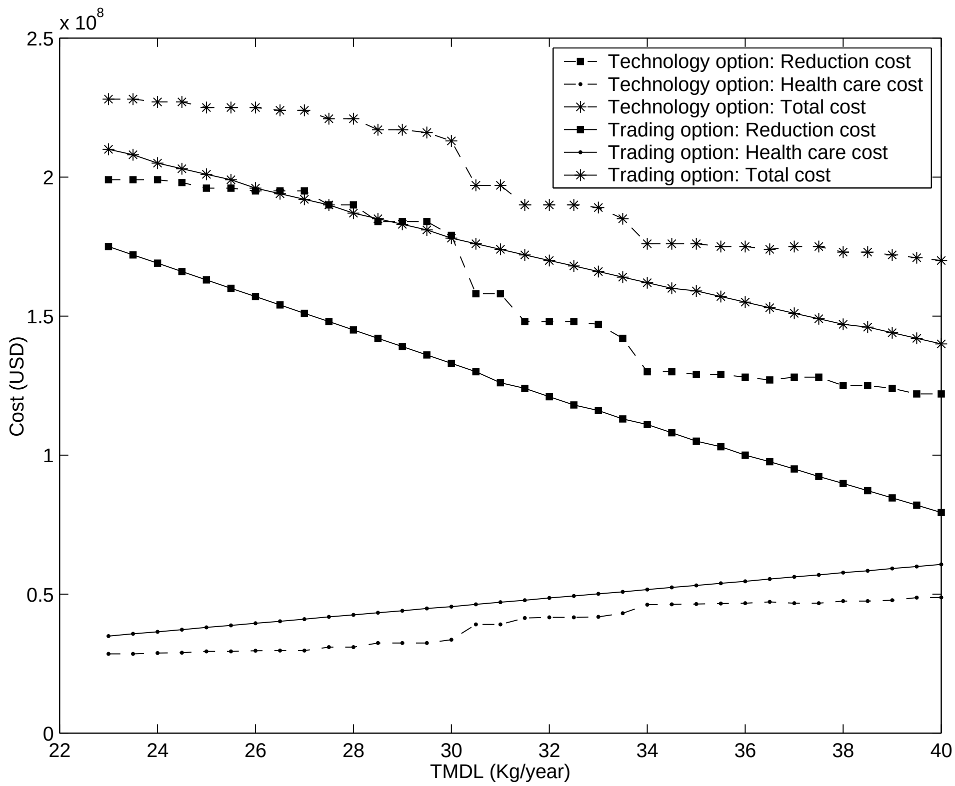

Figure 1: Cost variations with TMDL for the two solution options

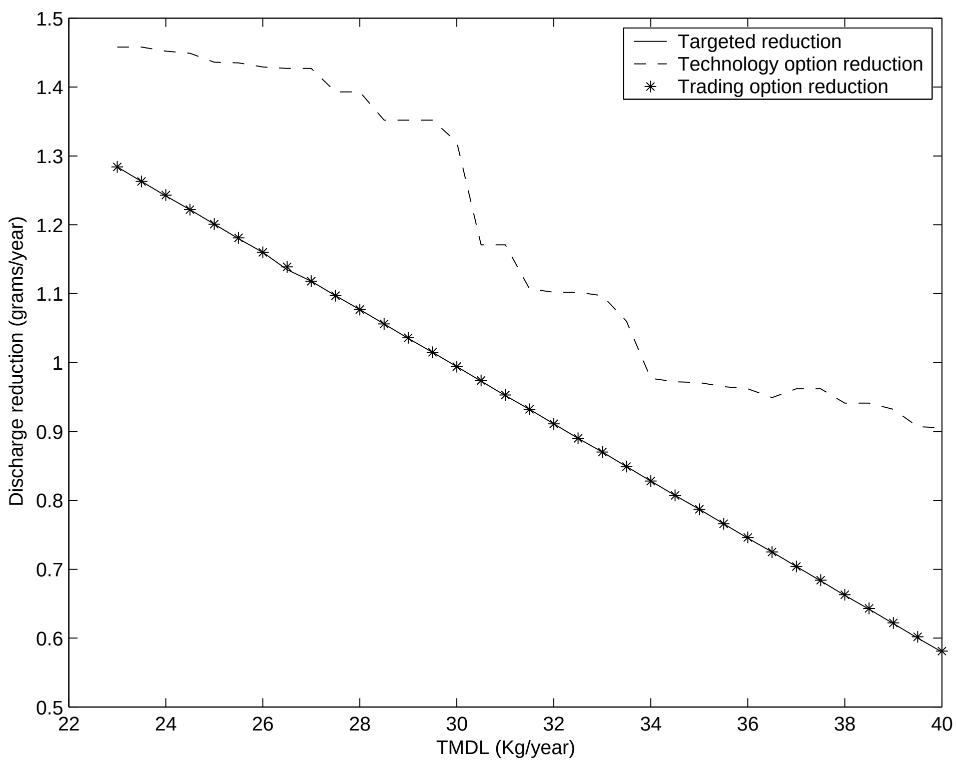

Figure 2: Final discharge reduction variation with TMDL for the two solution options

6.1 Sensitivity analysis for health care cost

The sensitivity analysis is conducted by varying the compensation per affected person (C_{health}) in formulation A, given by Eqs. 2-5. Previously reported results considered C_{health} to be 1 Million $. The problem is now solved for two more values of C_{health}, 3 Million $ and 5 Million $.

Results are shown in figure 3, which plots the total costs for various cases. The plots shown that increase in health care cost increases the total cost at any TMDL. But more important is the dependence of these costs on TMDL at various compensation values. For C_{health}=1 Million $, increase in TMDL reduces the total cost and hence higher TMDL appears to be more optimal. Since the reduction costs are also decreasing with increasing TMDL, while the health care costs are simultaneously increasing, this means that health care costs are not as significant as the reduction costs. But this trend is seen to be changing when C_{health} is increased to 3 Million and 5 Million $. For C_{health}= 3 Million $, the plots are almost flat, meaning that increase in health care costs is equivalent to decrease in reduction costs as TMDL is increased. When C_{health}= 5 Million $, the overall cost increases with increasing TMDL. The health care costs become more prominent than the reduction costs, thereby dominating the trend in overall cost. Thus, at C_{health} = 5 Million $, a lower TMDL appears to be more optimal. It should be noted that since the health care cost is not an objective, the decisions do not change. Changes in the overall cost trends are therefore a results of the varying significance of health care costs in the problem. Since the parameter C_{health} quantifies the value of human life in some sense, the results point that economies which value human life more (signified by higher value of C_{health}), will be putting stricter regulations in place (lower TMDL). The contrary holds true for economies putting lesser value on human life. One can also analyze these trends in conjuncture with the current TMDL for Savannah river basin set by USEPA. The current approved TMDL is 32.8 Kg/year. Assuming that USEPA has set this regulation optimally (through consideration of other parameters like safe fish tissue mercury concentration), one can get a crude estimate on the value that has been put on human life. For this case, this will come out to be around 3 Million $ per affected person. Another interesting observation from figure 3 is that at lower C_{health} values, trading option is more economical than technology option. But as C_{health} values are increased, the advantages diminish and ultimately technology option becomes more economical than trading option. Simulations reveal that the trends change at the compensation value of 3.75 Million $. At this C_{health} value, the trading option is more economical at lower TMLDs but expensive at higher TMDLs. This change in trend can be linked to the higher reductions achieved by technology option than trading option and the increasing importance of these higher reductions with increasing C_{health} values.

The results of sensitivity analysis for the health care cost have thus thrown light on some interesting aspects of the optimization problem, most importantly emphasizing the role of valuation of human life in regulation development.

6.2 Modified problem formulation

The new problem formulation, referred hereafter as ‘formulation B’, with health care cost as a part of the objective, is given by Eqs. 9-16. Formulation A has been appended to include the health care cost as the function of mortality rate in Eq. 9. Additional equations are added to the problem to calculate the mortality rate. red_i^{final} is the final reduction achieved by point source i. All other

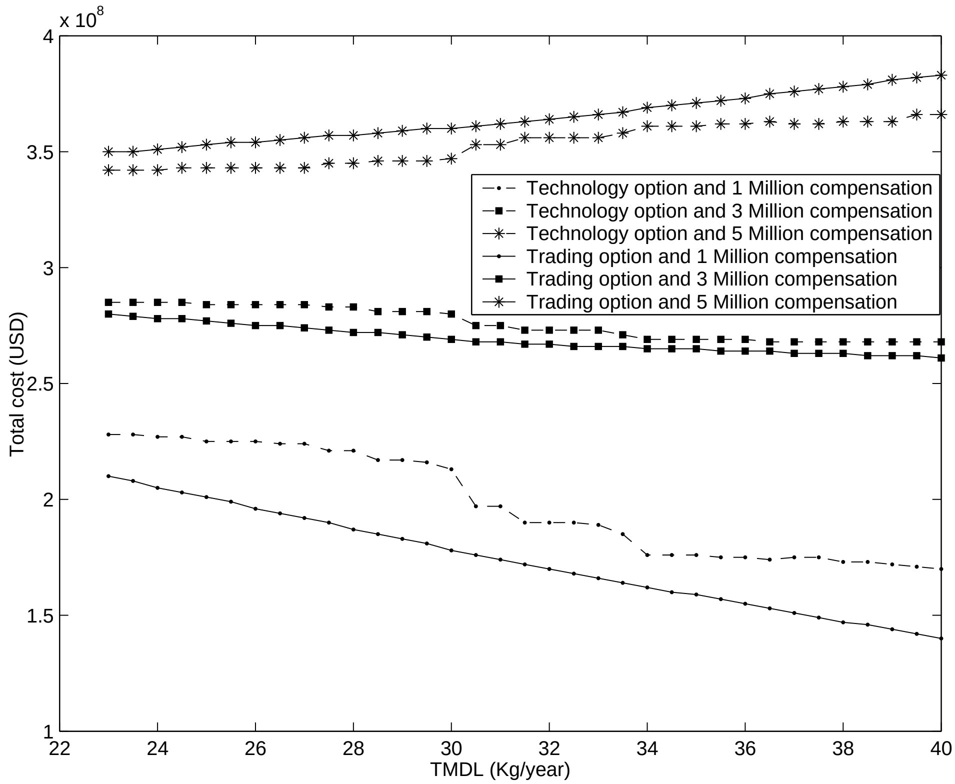

Figure 3: Total cost variations with TMDL for different health care compensations for original problem formulation

symbols have their previously assigned meanings.

$$\textbf{Objective}:$$

$$\text{Minimize} \qquad \sum_{i=1}^{N}\sum_{j=1}^{M} TC_j.D_i.\ b_{ij} + \text{Mortality}.C_{health} \tag{9}$$

$$\textbf{Constraints}:$$

$$t_{ii} = 0 \qquad \forall i = 1,...,N \tag{10}$$

$$red_i \leq \sum_{j=1}^{M} q_j.D_i.\ b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \qquad \forall i = 1,...,N \tag{11}$$

$$P_i \geq \sum_{j=1}^{M} b_{ij}.TC_j.D_i + F\Big(\sum_{k=1}^{N} t_{ik} - \sum_{k=1}^{N} t_{ki}\Big) \qquad \forall i = 1,...,N \tag{12}$$

$$red_i^{final} = \sum_{j=1}^{M} q_j.D_i.\ b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \qquad \forall i = 1,...,N \tag{13}$$

$$WQS_i = \frac{(red_i - red_i^{final})}{D_i} \qquad \forall i = 1,...,N \tag{14}$$

$$WQS_{final} = \frac{\sum_{i=1}^{N} WQS_i.D_i}{\sum_{i=1}^{N} WQS_i} \tag{15}$$

$$\text{Mortality} = \left(\frac{WQS_{final}.Hg_{safe}}{WQS}\frac{1000.F_{avg}.P}{2.LC50.W_{avg}}\right) \tag{16}$$

Consideration of health care cost in the objective function enables one to account for the pollution effects in decision making. Next section gives the results for the modified problem.

6.3 Model results: Savannah River basin

The model is applied to the previously analyzed case study of mercury waste management in Savannah River basin. Data reported in Tables 1 and 2 is applicable here and the problem studies variation in reduction, health care and total cost with TMDL. The problem is solved for various TMDL values between 23 Kg/year and 40 Kg/year.

Variation of total cost with TMDL is shown in figure 4 for trading option. For comparison variation of formulation A results is also shown. It can be seen that at 1 Million \$ compensation (C_{health}), there is little to no difference in the overall cost for the two formulations. Analysis of the results indicates that health care costs are not significant enough to change the optimal decisions when these costs are included in the objective. To determine the dependence of these trends on the health care compensation, simulations were carried out for different C_{health} of 3 Million \$ and 5 Million \$, the results for which are also plotted in figure 4. While the results at C_{health}=3 Million \$ are the same as those at 1 Million \$, there is a significant difference in the results for C_{health}=5 Million \$. At this compensation value, health care costs in the objective become more significant than the reduction costs. As a result, the optimization model tries to minimize the mercury discharge under the given constraints creating a difference in the optimal solutions of formulations A and B. It is also seen that the optimal solution in this case is independent of TMDL. Analysis of technology allocations and pollutant trading reveals that point sources are made to reduce more than their load allocations. This reflects in increased treatment costs which are compensated for by reduced health care costs leading to reduced total costs. It is possible that these results might change when one considers the financial constraints (availability of limited funds) on individual point source. Such a constraint will reduce the possible options with each point source thereby affecting the overall problem solution.

Table 4 compares the results for formulations A and B at TMDL of 32 Kg/year for C_{health}=5 Million \$. A preference towards more efficient and expensive technologies and consequent reduction in the health care and overall cost is evident from the tabulated results. This further emphasizes the importance of health care cost in decision making.

The results for sensitivity analysis of formulation B (Eqs. 9-16) are shown in figure 5. As for formulation A, one can see that at every TMDL, increase in health care cost increases the total cost. But here the trends in the variation of the total cost with TMDL do not change with C_{health} value. The slope of the curves reduces as C_{health} is increased, as was observed for formulation A, and the optimal values for the technology and trading option approach each other. At C_{health}=5 Million \$, the solutions are identical and no pollutant is traded. One can also see that the trading option is never expensive than technology option, contrary to the results for formulation A, because in this case the total cost is optimized as compared to only the reduction cost in formulation A.

Figure 6 plots the variations in the total cost for different problem formulations and both technology and trading options. These plots are for C_{health} value of 3.75 Million \$. For formulation A, trading option is economical at lower TMDL (below 33 Kg/year) but becomes uneconomical above this TMDL. When variations for formulation B are plotted though, trading option is economical at all TMDL values. Moreover, the total costs for formulation B with trading option are the least amongst all. It can therefore be argued that considering health care cost in the objective of trading option is

Table 4: Solution comparison with and without health care cost as objective

	Formulation A	Formulation B
Reduction cost (Million $)	121.10	281.15
Health care cost (Million $)	242.88	53.46
Total cost (Million $)	363.98	334.61
Total mercury discharge reduction (Kg)	0.911	1.945
No. of Technology A implemented	14	3
No. of Technology B implemented	0	29
No. of Technology C implemented	0	13
No. of companies with multiple technologies	0	16

important to accurately assess the relative economy of the two options.

7 Chance Constrained Formulation and Analysis

The previous two formulations, given by equations 2-5 and by equations 9-16, assumed that data is known deterministically, without any uncertainty. But in many cases data is known only in terms of parameter ranges and sometimes their distributions. One has to work with the available data to arrive at optimal decisions.

For the problem of pollutant trading, there are various sources of uncertainty, starting from the bioaccumulation data resulting in uncertain regulations, to plant discharge concentrations, creating problems in load allocations. In this work, the current discharge of mercury by each industry (a_i) is considered to be uncertain, normally distributed around a mean value. As explained before, once the TMDL has been developed, each industry is assigned a specific load reduction target based on the current discharge levels. Since the current discharge values are uncertain, load allocations and subsequent decisions are affected by the uncertainty. This converts the optimization problem from deterministic to stochastic, a class of optimization problems dealing with uncertainty. Next section explains the model for this stochastic case and suggests a solution strategy.

7.1 Problem formulation

The formulation is an extension of formulation A given by Eqs. 2-5, and does not consider health care costs in the objective function. Eqs. 2-5 again constitute the stochastic problem, the difference being that in stochastic case parameter red_i is uncertain. Since TMDL value is fixed and red_i is a linear function of TMDL and a_i, red_i and a_i have the same distribution. a_i is considered to be normally distributed with standard deviation σ_i and value used in previous deterministic analysis as mean. This means that parameter red_i in Eq. 4 is also normally distributed.

Different solution techniques are available to solve stochastic programming problems, such as chance constrained programming, decomposition techniques, various sampling based techniques etc. [18, 19]. Since the constraint represented by Eq. 4 is linear and the distribution of uncertain parameter red_i is stable (normal), chance constrained method is used in this work to solve the stochastic programming problem [20].

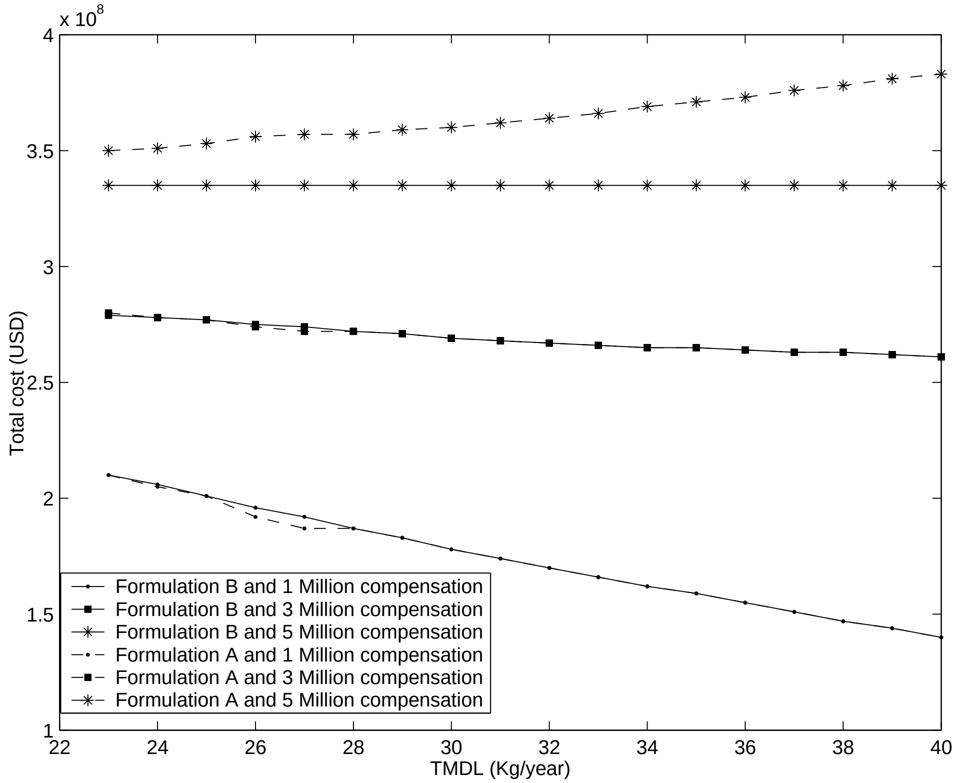

Figure 4: Cost variations with TMDL for objectives with and without health cost

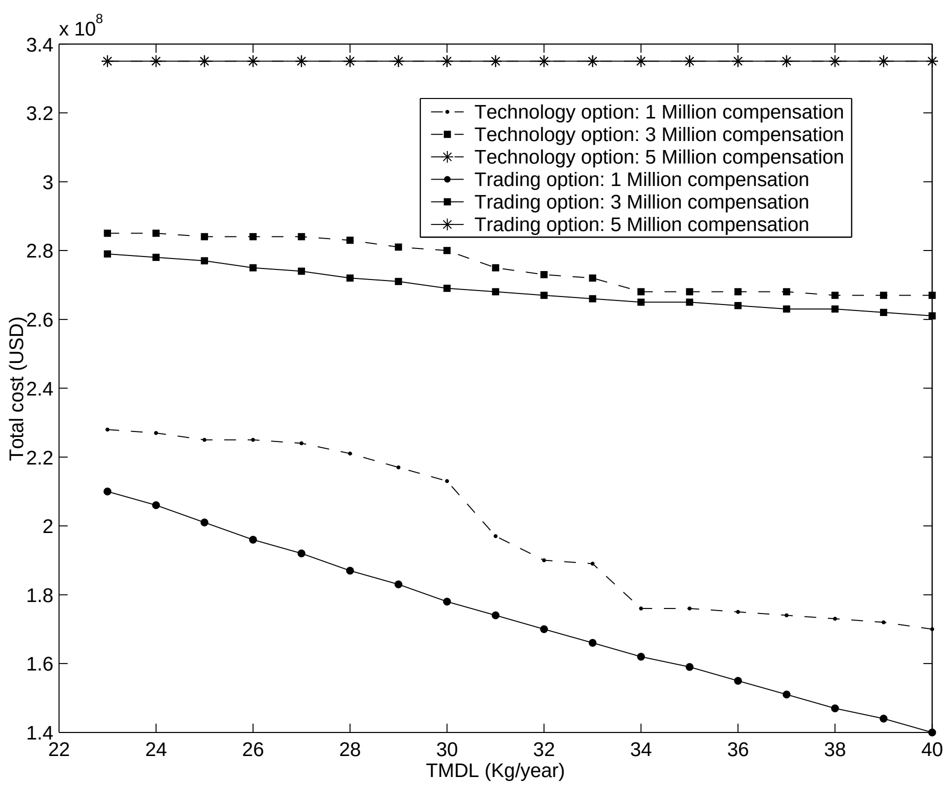

Figure 5: Total cost variations with TMDL for different health care compensations for modified problem formulation

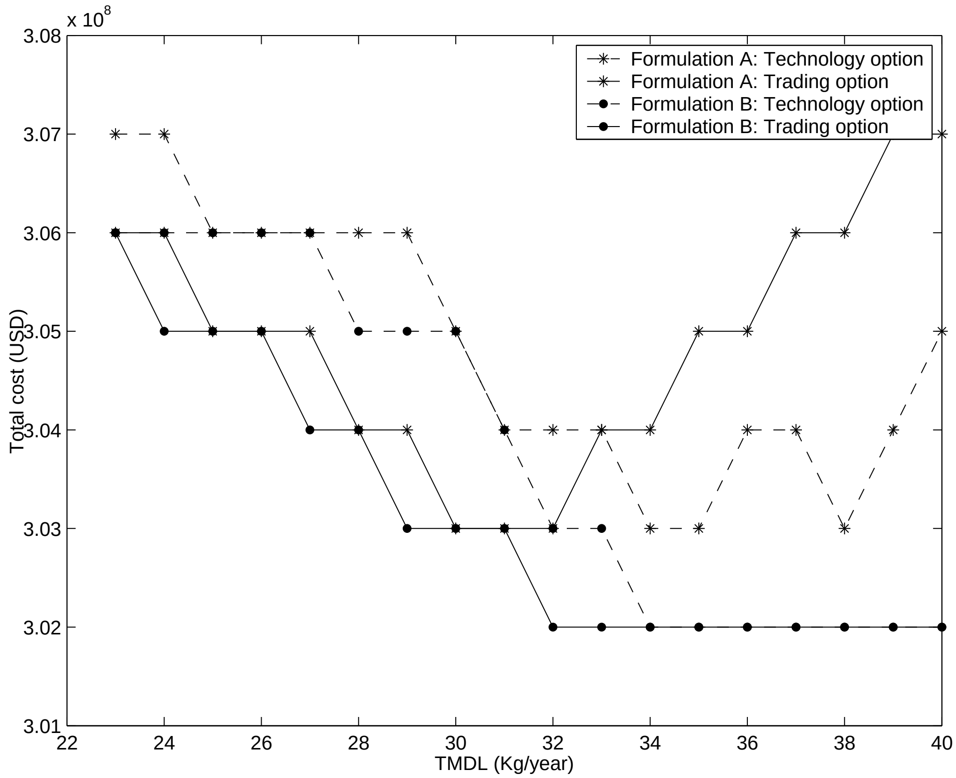

Figure 6: Total cost variations with TMDL for different formulations for C_{health}=3.75 Million $

In chance constrained programming, some of the constraints are to be satisfied with a certain probability which allows conversion of the problem into a deterministic equivalent. Consider the constraint given by equation

$$P(g(x) \geq u) \geq \alpha \tag{17}$$

Here u is the uncertain variable with cumulative distribution function F and $g(x) \geq u$ is the constraint that is to be satisfied with a probability of α, which corresponds to Eq. 4 in trading problem formulation (Eqs. 2-5). $g(x)$ and u are the right hand side and left hand side of Eq. 4, respectively. Then the deterministic equivalent of constraint (17), due to chance constrained programming, is

$$g(x) \geq F^{-1}(\alpha) \tag{18}$$

The chance constrained formulation of (4) is therefore given as

$$\sum_{j=1}^{M} q_j.D_i.\, b_{ij} + \sum_{k=1}^{N} t_{ik} - r\sum_{k=1}^{N} t_{ki} \geq F_i^{-1}(\alpha) \qquad \forall i = 1, ..., N \tag{19}$$

Here, F_i is the cumulative distribution function of uncertain variable red_i with mean red_i^* and standard deviation σ_i. The actual required reductions red_i for various point sources might not be correlated. But incorporating constraint (19) for all the point sources ensures that the worst case scenario under the given constraint satisfaction probability (α) is accounted for. This will guarantee that there are not localized “hotspots” due to discharge uncertainties.

Constraint represented by (19) is used in deterministic optimization techniques to solve the chance constrained problem, results of which are reported in the next section.

Table 5: Solution comparison for different levels of uncertainty

	$\sigma_i = 5\%$	$\sigma_i = 16.67\%$
Total cost (Million $)	184.52	219.81
Total mercury discharge reduction (Kg)	1.051	1.378
No. of Technology A implemented	17	17
No. of Technology B implemented	4	9
No. of Technology C implemented	3	0

7.2 Model results: Savannah river basin

The desired reduction red_i has a constant standard deviation of 5% for all the point sources i.e. $\sigma_i = 0.05(red_i^*)$. This simulates $\pm 15\%$ uncertainty in discharge concentration. The problem is solved for various values of α, the probability of constraint satisfaction. The values of α used in this problem are 0.5, 0.9 and 1.0. The problem solution (i.e. technology selection and trading policy) is then used to estimate the actual health care costs by taking into consideration the uncertain mercury discharge values. Since technology decisions are already made, expected values of the health care costs are directly calculated for each TMDL. The analysis is performed for various values of TMDL, ranging from 23 Kg/year to 40 Kg/year, to explore the dependence of the results on regulation.

The variations in total cost for different values of α are plotted in figure 7 while those for the health care costs are plotted in figure 8. The plots indicate that higher values of α increase the constraint satisfaction probability and reduce the health care costs. This increases the total costs due to increased reduction costs. The total cost fluctuates a little for $\alpha = 0.5$, but is almost linear for α=0.9 and 1.0. Since the flexibility offered by trading diminishes the integrality effects as discussed before, these results indicate that trading becomes more important at larger uncertainties. The non-linearity in the trends also puts forth certain interesting points such as the TMDL of 35 Kg/year. At this TMDL, cost difference in 50% and 90% constraint satisfaction is relatively small as compared to other TMDLs. This can be explained from the variation of reduction cost for this range in figure 1. The reduction cost does not increase appreciably for the TMDL between 35 Kg/year and 33 Kg/year. This means that the solutions obtained for TMDL 35 Kg/year can also satisfy lower TMDLs. The solutions are therefore overachieving the targets in this region and hence can take care of some uncertainties, resulting in smaller differences in the cost for 50% and 90% constraint satisfaction. Such results help in finding the TMDL values for which the solution is more robust.

To analyze the effect of degree of uncertainty on problem solution, chance constrained analysis is carried out for 16.67% standard deviation, i.e. $\sigma_i = 0.167(red_i^*)$, which simulates $\pm 50\%$ uncertainty in the current discharge concentrations, for various values of α. The results indicate that increase in uncertainty increases the total cost. Table 5 compares the solutions for the two cases of uncertainty, using previously defined σ_i, for 90% constraint satisfaction ($\alpha = 0.9$) at TMDL 32 Kg/year. It can be seen that cost increase is also accompanied by higher discharge reduction and additional implementation of expensive technology (technology B). Simulations also showed that when $\sigma_i = 16.67\%$ and point sources can not implement more that one technology, possibly due to internal financial constraints, the problem is infeasible below TMDL 30 Kg/year, even if trading is an option. These results show that presence of uncertainty causes additional cost burden to ensure load reduction satisfaction.

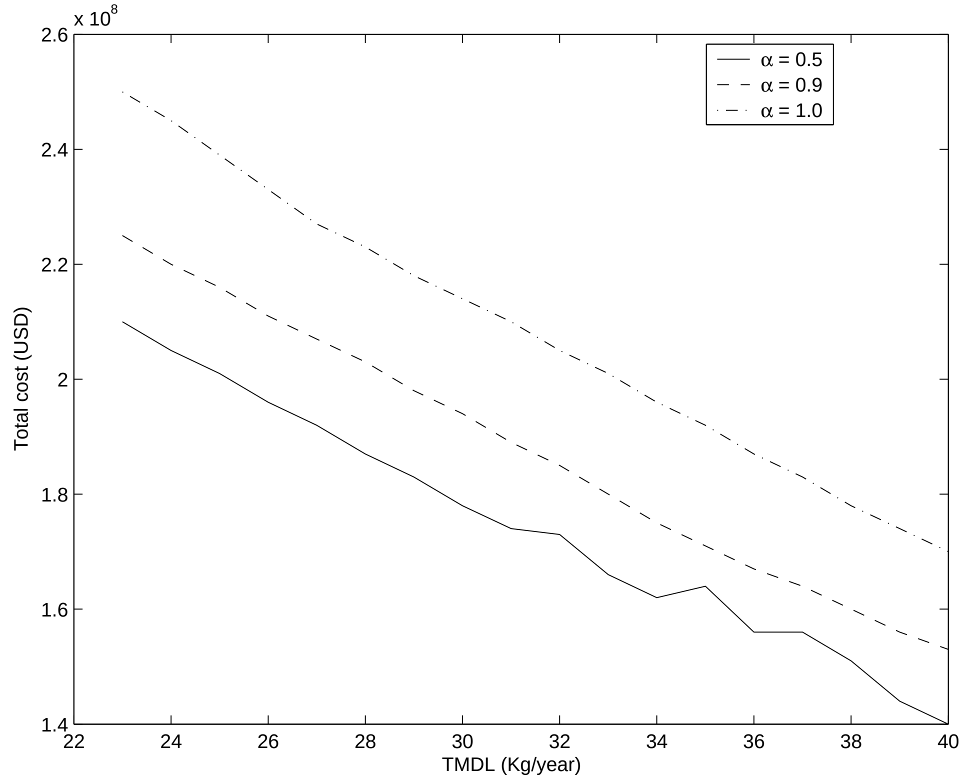

Figure 7: Total cost variation of the stochastic problem using chance constrained programming

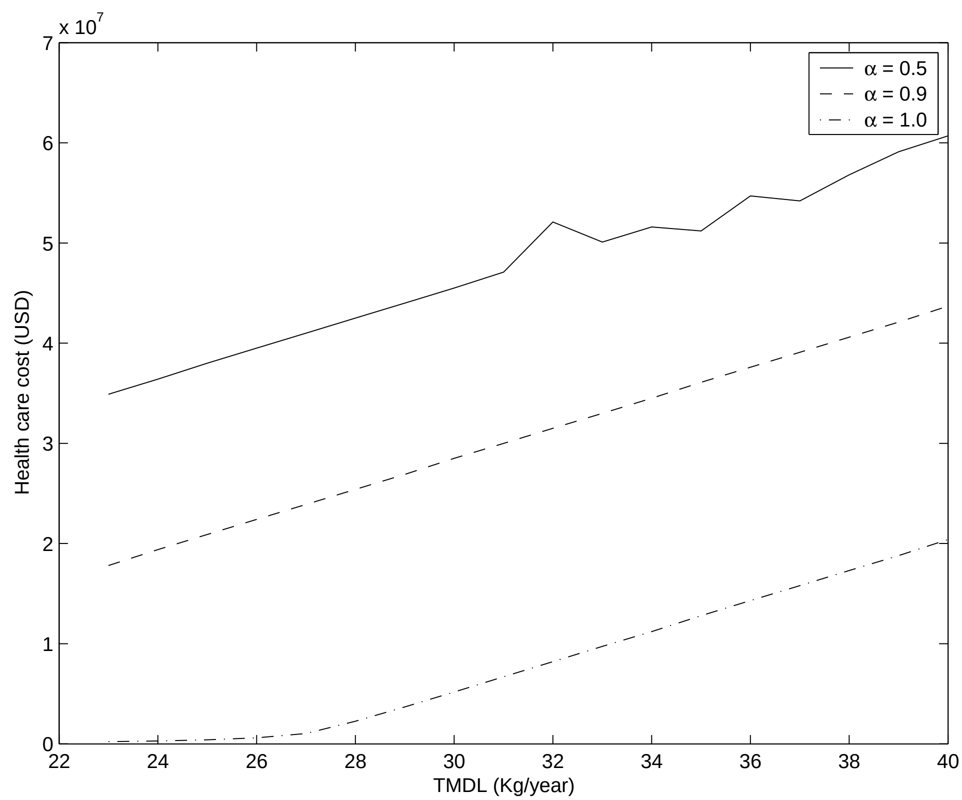

Figure 8: Health care cost variation of the stochastic problem using chance constrained programming

8 Discussion and Conclusion

Work presented in this article analyzed water pollutant trading, an option to achieve industrial symbiosis at watershed level. The option of trading to achieve better environmental targets complicates the matter for the policy makers and polluters alike. Policy maker has to take optimal decisions, such as regulations, considering industry constraints while the industries also have to make their own decisions regarding the course of action to take to satisfy those regulations. To effectively carry out this task, an optimization model was formulated which minimized the overall cost taking into account the watershed and technology specific aspects. The model formulation suggests optimal decisions to individual polluters and allows one to take optimal policy decisions as well. The proposed optimization model was applied to the case study of mercury waste management in Savannah River basin.

Based on the results reported in this article, following conclusions can be drawn.

- Trading reduces overall treatment cost for pollution reduction. But 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.
- Results after the inclusion of health care cost in the objective of minimization depend on the significance of health care cost. For high compensation values, higher emission reductions are achieved offsetting the increased treatment costs, thereby arriving at lower overall costs.
- Sensitivity analysis for the health care cost highlights the importance of correct valuation of human life in regulation development. It suggest that higher valuation will typically lead to stricter regulations.
- Analysis of the problem in presence of uncertainty indicates that impact of uncertainty is more pronounced as the regulations become stricter.
- When the dependence of the solutions on TMDL regulation was analyzed, a nonlinear variation was observed in all cases. This indicates that consideration of trading and watershed specific details during regulation development might help develop better regulations, achieving an effective tradeoff between cost and reductions. For this particular problem of Savannah river basin, trading became more attractive with more stringent regulations.

When these results are compared with the results presented in [5] for NOx, one observes that the effect of trading on overall cost is more for mercury waste management. This difference is particularly obvious for the total reductions achieved with and without trading, the difference being larger for the case of mercury.

The work can be extended further by considering a larger watershed (scaling up) and including non-point sources in the analysis. Non-point sources are believed to have considerable potential for pollution reduction [21] but also complicate the problem as they are associated with uncertainties, static as well as time dependent (e.g. seasonal variations). Techniques such as stochastic programming will need to be used for such cases. As regards to mercury, better characterization of mercury cycling and its harmful effects is needed to generate confidence in trading. Bioconcentration factors (BCF) and bioaccumulation factors (BAF) are possible options. Lack of reliable models have restricted their use in such situations. Better characterization of their uncertainties can resolve some of the issues and would be looked into in future.

Acknowledgements

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