

PROCESS DESIGN AND CONTROL

Market-Based Pollution Abatement Strategies: Risk Management Using Emission Option Contracts

Anshuman Gupta and Costas D. Maranas*

*Department of Chemical Engineering, The Pennsylvania State University,
University Park, Pennsylvania 16802*

In this work, a model for incorporating market-based pollution abatement instruments in the technology selection decision of a firm is developed. Multistage stochastic programming is used to model emission and market uncertainties while accounting for the availability of derivative instruments such as emission option contracts. The model quantifies the benefits of the flexibility offered by these instruments in minimizing total pollution abatement costs and helps in predicting the environmental liability faced by a firm in terms of the probability of meeting both compliance requirements in the future and the resulting noncompliance penalties. Management of environmental and financial risks is also addressed by linking the optimization model with basic statistical and probabilistic techniques.

1. Introduction

The past decade has witnessed a significant increase in the attention given by both policy makers and regulators to market-based environmental policy instruments. These policy instruments have emerged as a more cost-effective alternative to the conventional “command-and-control” standards that had dominated the previous 2 decades of environmental law and regulation.^{1,2} The basics of a tradeable emission permits program are as follows.³ Facilities are issued tradeable permits (credits) denominated in units of a specific pollutant (e.g., pounds or tons of SO₂) in amounts equivalent to their allowable emissions over a given period of time (e.g., a year). All permits are transferable so if a facility can generate excess permits by reducing emissions below its allocated levels, then it can sell these extra credits to other facilities. At regular intervals, facilities submit emission reports for the compliance period which may range anywhere from 3 months to 1 year. At that time, facilities must own sufficient permits to cover emissions. This implies that each facility must hold at least as many credits valid during the compliance period as its emissions during the same period. Having been used to cover emissions, those credits are then “retired” from the regulatory compliance system, preventing subsequent use or transfer. The compliance date marks the end of each period for which a facility has to file an emissions report, which is due on the certification date. The period between the compliance date and the certification date, which is typically around 30–60 days, is known as the reconciliation period during which facilities may adjust their accounts by buying/selling permits in the open market.

The most sophisticated use of such a market-based program for pollution control to date has been the Acid

Rain Program (see <http://www.epa.gov/airmarkets/>) launched by the U.S. Environmental Protection Agency (EPA). Title IV of the Clean Air Act set a goal of reducing annual SO₂ emissions by 10 million tons below 1980 levels. To achieve these reductions, the law required a two-phase tightening of the restrictions placed on fossil-fuel-fired power plants. Phase I began in 1995 and affected 110 coal-burning electric utility plants located in 21 eastern and midwestern states. The emission limits in this phase were set at 2.4 pounds of SO₂/1 million British thermal units (MMBtu). Subsequently, phase II, which began in the year 2000, tightened the annual emissions limits to 1.2 pounds of SO₂/MMBtu imposed on these large, higher emitting plants and also set restrictions on smaller, cleaner plants fired by coal, oil, and gas. The program affected all existing utility units with an output capacity greater than 25 MW and all new utility units. The Act also called for a 2 million ton reduction in NO_x emissions by the year 2000.

Another implementation of an emissions market is the Regional Clean Air Incentives Market (RECLAIM) developed by the South Coast Air Quality Management District for the Los Angeles Basin (see <http://www.aqmd.gov/reclaim/reclaim.html>). Under RECLAIM, each of the 400 participating industrial polluters is allocated an annual pollution limit for nitrogen and sulfur oxides that decreases by 5–8% each year for the next decade. When the polluters are allowed to meet the regulatory requirements in a more flexible market setting, the burden of identifying the appropriate control technology is shifted from the control authority to the polluting firm.

Market-based approaches such as the Acid Rain Program and RECLAIM can, in principle, minimize the overall cost of a given environmental target by equalizing marginal abatement costs across sources.⁴ As a representative example of how that is achieved, consider a simplified setting consisting of two paper mills, each

* To whom all correspondence should be addressed. E-mail: costas@psu.edu. Phone: 814-863-9958. Fax: 814-865-7846.

Table 1. Abatement Costs for Low-Cost and High-Cost Firms

waste (gpd)	production cost (\$/day)		waste (gpd)	production cost (\$/day)	
	low cost	high cost		low cost	high cost
5	60	60	2	71	112
4	61	67	1	86	172
3	64	82	0	116	300

generating 5 gallons/day (gpd) of waste. One paper mill can control pollution at a relatively low cost, while the other has relatively high abatement cost. The production costs for the two paper mills at varying emission levels are listed in Table 1. Note that lower emission levels are achieved at higher production costs, with the difference in production costs between two emission levels corresponding to the marginal cost of emission reduction. Next, suppose the government decides to decrease the volume of waste from 10 to 8 gpd. To achieve this regulatory goal, the government issues four marketable permits to both firms. Each permit gives the owner of the permit the right to emit 1 gallon of waste/day, implying that if a firm wants to generate 5 gpd of waste, then it must buy a fifth permit. Consequently, the firm that sells that one permit can then generate only 3 gpd of waste.

In a command-and-control regulatory framework, where both firms are forced to reduce the emissions to 4 gpd, the total abatement cost incurred is \$8/day (\$1/day for the low-cost firm and \$7/day for the high-cost firm). Because the daily marginal abatement cost for reducing the emission level from 5 to 4 gpd is \$7 for the high-cost firm, it is willing to pay up to \$7 for acquiring an additional permit. The low-cost firm, on the other hand, is willing to accept any amount above \$3 because if the low-cost firm gives up one permit, it can generate only 3 gallons of waste and consequently its production cost increases by \$3 (from \$61 to \$64). Based on these individual valuations of the price of an additional permit by the two firms, any price lying between the minimum ask price of the low-cost firm (\$3) and the maximum bid price of the high-cost firm (\$7) would be acceptable to both firms and would result in the transfer of the permit from the low-cost firm to the high-cost firm. Thus, as a result of this trade, the total abatement cost to the industries would be reduced from \$8/day to \$4/day.

In addition to cost efficiency, a number of potential advantages of emission trading programs compared to command-and-control allocation of emission targets can be identified.⁵ A tradeable emission permits program accommodates growth, even in nonattainment areas, by allowing new firms to bid permits away from existing firms. Moreover, the program generates a clear price signal which guides firms in developing and evaluating new, more efficient pollution control technologies. From a political perspective, emission trading programs are perceived as fairer and thus more acceptable than other forms of environmental regulation because they promote decentralized decision making.

2. Literature Review

The very first reference to market-based techniques for dealing with pollution problems can be found in the seminal work by Dales⁶ in the context of water pollution. When the pollution abatement problem is viewed within an economic, cost-benefit framework in conjunction with a property rights standpoint, this "economic-legal"

essay proposes the basic idea of tradeable emission permits. Utilizing the ideas proposed by Dales,⁶ Montgomery⁷ provides a rigorous theoretical justification of how a market-based approach leads to the efficient allocation of abatement costs across the various polluting sources. Necessary and sufficient conditions for market equilibrium and efficiency are derived given the setting of multiple profit-maximizing firms attempting to minimize total compliance costs. More recently, Hahn and Noll⁸ have identified a number of desirable attributes that are key for the efficient functioning of an emissions market. These include (i) appropriate incentives for firms to operate within the allowance system, (ii) minimum restrictions on allowable trades, (iii) low transaction costs, and (iv) strict enforcement of non-compliance penalties. The authors claim that market structures with these characteristics enable firms to incorporate the emission trading activities into their long-term capital investment planning initiatives.

It has been widely accepted by both policy makers and academics that the success of any emission trading program depends heavily on the details of its design. The various design issues involved in implementing market-based pollution abatement programs are discussed by Hahn,¹⁰ Carlson and Sholtz,³ Andersson,¹¹ Hagem and Westskog¹² and Tietenberg.^{9,13} Some of the questions that need to be answered in the design of any emission trading program include the following:

1. What is the basis used for setting the pollution targets? Two potential alternatives are (a) aggregate emissions emitted in a receiving medium^{12,14,15} and (b) concentration levels measured at specific receptor locations.^{7,16,17} The advantage of an aggregate emission-based market lies in the associated administrative simplicity in monitoring and assessing the contribution of each emitter to the total pollutant output. The disadvantage, however, is that, for a number of local pollutants, the damage caused is more directly related to their concentration within the environmental medium than to the aggregate total amount. In such instances, a concentration-based program is more applicable.

2. Should the permits be "grandfathered" or auctioned while initiating a market-based pollution abatement program? Grandfathering refers to the practice in which permits are initially allocated to the market participants based on their historical emission profiles.⁹ This approach has great political appeal, particularly from the perspective of existing firms because the monetary benefits of pollution abatement stay with them and are not transferred to the general public.⁴ Consequently, to reduce this welfare cost incurred by society, the practice of auctioning is gaining popularity for the initial allocation of emission credits.^{18,19} In particular, this is achieved by utilizing the revenue generated from the auctioning of permits to reduce taxes.

3. Should borrowing/banking of permits be allowed? Banking allows firms to save emission reductions for future use while borrowing entails using permits issued for the future for meeting current emission requirements.^{10,12} Increased flexibility and lower transaction costs, both translating into lower overall abatement costs, are the widely claimed benefits of allowing banking and borrowing.^{15,20,21} From a regulators perspective, however, these benefits come at the expense of the loss of control of temporal emission patterns which could potentially lead to the creation of seasonal "hot-spots"

in pollution levels causing irreparable damage to the environment.⁹

In addition to the above-described market characteristics, another key factor that affects market efficiency and performance is the inherent uncertainty associated with almost all emission levels.^{3,22} Several technical, commercial, and operational factors contribute to the observed uncertainty in emission levels. These include uncertainty in the demand for a firm's goods/services resulting in variation in production activity levels, measurement and monitoring uncertainty, variability in the quality of fuel and other inputs utilized, and randomness in weather and other environmental factors.¹⁴

This imperfect information regarding emission levels typically leads to either the facilities ending up short or in excess of emission permits. Both of these are highly undesirable scenarios because the former results in excessive emissions in the environment in conjunction with high violation penalties for the facilities while the latter represents unrealized productive and/or market value for the firm.³ As a result of the occurrence of either the "short" or the "long" scenario, facilities are forced to participate in the market in order to reconcile their emission credit accounts by either selling or buying permits. However, as in any market setting, the supply and demand are never perfectly matched because the quantity of permits demanded by the short facilities is never exactly equal to the permits available for sale by the long facilities. This mismatch of supply and demand translates into significant market volatility in both the price and the quantity of permits available for trading. For instance, if the aggregate market is short, then permit prices could potentially rise to the level of compliance penalties. Alternately, an excessively long market could cause the permit price to decline to zero. Consequently, failure to recognize emission uncertainty and the resulting market volatility can pose severe financial, operational, and political challenges for the firm. In view of this, the incorporation of emission and market uncertainties within the technology investment planning framework for pollution abatement is pursued in this work as described next.

3. Basic Emission Trading (BET) Model

The basic problem addressed in this work can be stated as follows:

Given a set of candidate technologies characterized by their respective emission levels, fixed capital investment and variable production costs, current market price and availability of emission permits, and future demand and market scenarios, determine the optimal technology-permit portfolio that minimizes the total expected cost.

The detailed model formulation is based on the following notation.

Sets

$\mathcal{J} = \{j\}$ = set of available technologies

$\mathcal{H}_1 = \{k_1\}$ = set of demand scenarios

$\mathcal{H}_2 = \{k_2\}$ = set of market scenarios

Parameters

c_j^{fx} = fixed investment cost for acquiring technology j

c_j^{var} = variable production cost of technology j

c^{nc} = emission noncompliance penalty

p^0 = current permit price

β_j = emission coefficient for technology j

θ_{k_1} = demand in scenario k_1

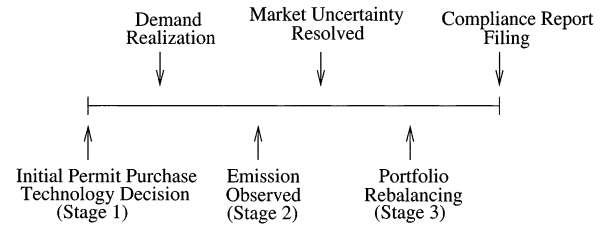


Figure 1. Schematic representation of the three decision stages.

$\omega_{k_1}^0$ = probability of demand scenario k_1

p_{k_2} = future permit price in market scenario k_2

$\omega_{k_2}^m$ = probability of market scenario k_2

\hat{N}^0 = maximum number of permits available initially

$\hat{N}_{k_1 k_2}^p / \hat{N}_{k_1 k_2}^s$ = maximum number of permits purchased/sold in emission scenario k_1 and market scenario k_2

Variables

Y_j = 1 if technology j is acquired; 0 otherwise

N^0 = number of permits purchased initially

E_{k_1} = emission in demand scenario k_1

$N_{k_1 k_2}^p / N_{k_1 k_2}^s$ = number of permits purchased/sold in demand scenario k_1 and market scenario k_2

$E_{k_1 k_2}^{\text{exs}}$ = excess emission in demand scenario k_1 and market scenario k_2

Utilizing the above-described notation, the BET model is formulated as follows.

(BET)

$$\min p^0 N^0 + \sum_j c_j^{\text{fx}} Y_j + \sum_{k_1} \omega_{k_1}^0 \left[\sum_j c_j^{\text{var}} Y_j \theta_{k_1} + \sum_{k_2} \omega_{k_2}^m [p_{k_2} (N_{k_1 k_2}^p - N_{k_1 k_2}^s) + c^{\text{nc}} E_{k_1 k_2}^{\text{exs}}] \right]$$

subject to

$$\sum_j Y_j = 1 \quad (1)$$

$$0 \leq N^0 \leq \hat{N}^0 \quad (2)$$

$$E_{k_1} = \sum_j \beta_j Y_j \theta_{k_1} \quad \forall k_1 \quad (3)$$

$$0 \leq N_{k_1 k_2}^p \leq \hat{N}_{k_1 k_2}^p \quad \forall k_1, k_2 \quad (4)$$

$$0 \leq N_{k_1 k_2}^s \leq \min(N^0, \hat{N}_{k_1 k_2}^s) \quad \forall k_1, k_2 \quad (5)$$

$$E_{k_1 k_2}^{\text{exs}} = \max(0, E_{k_1} - N^0 - N_{k_1 k_2}^p + N_{k_1 k_2}^s) \quad \forall k_1, k_2 \quad (6)$$

Incorporation of demand and market uncertainties within the technology selection decision process, as described in the BET model, utilizes the *multistage stochastic programming* framework.^{23,24} In this approach, a *stage* corresponds to the description of the system, in terms of the variables and constraints, between two points of uncertainty resolution. In particular, three decision stages are implied by model BET as schematically represented in Figure 1. The first stage corresponds to the start of the planning horizon where the "here-and-now" decisions corresponding to technology selection (Y_j) and initial permit purchase (N^0) are made. The costs incurred in this stage include the initial permit investment (first term in the objective function) and the fixed capital investment required for acquiring

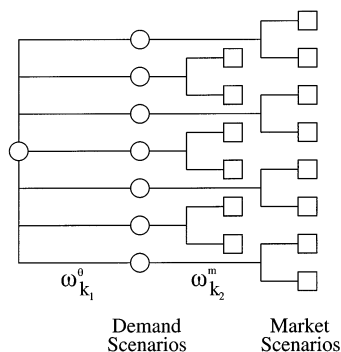


Figure 2. Scenario tree representation of demand and market uncertainty.

the chosen technology (second term). Investment in exactly one technology from the pool of available candidate technologies is ensured by eq 1, while the bound on the number of permits available for purchase initially is enforced through eq 2. After the initial formulation of the firm's technology-permit portfolio, the first level of uncertainty is resolved as the demand for the firm's product is realized. Uncertainty in product demand translates into uncertainty in emission levels (E_{k_1}), as captured by eq 3. Demand uncertainty also affects the bottom line of the firm through variable production charges, as accounted for by the third term in the objective function. Once emission uncertainty is resolved and prior to the filing of the compliance report to the regulatory authority, the firm rebalances its permit portfolio in the reconciliation phase of the planning period. Based on the price realized for the permit and the quantity of permits available for buying/selling in the reconciliation phase, "wait-and-see" permit purchase ($N_{k_1 k_2}^p$) and selling ($N_{k_1 k_2}^s$) decisions are made. Resolution of trading quantity uncertainty impacts the reconciliation phase trading decisions through eqs 4 and 5, while resolution of price uncertainty affects the total cost through the fourth term in the objective function. Finally, the excess emissions ($E_{k_1 k_2}^{exs}$), if any, are determined through eq 6, and the resulting noncompliance penalties are taken into account through the last term in the objective function.

A scenario-based description of both demand and market uncertainty forms the basis of model BET. The *nonanticipative*²⁴ resolution of these uncertainties can be represented through a *scenario tree* as shown in Figure 2. Nonanticipativity implies that an inner stage decision is contingent on the *actual* values realized by *all* uncertain parameters preceding that decision. This corresponds to the inner stage decision variables depending on the entire history of the uncertainty resolution process. For instance, the excess emission realized in the third stage of model BET depends on both the demand realized in stage two and the market scenario observed in stage three. This nonanticipative characteristic is captured by the diverging structure of the scenario tree representing the exponential increase in the number of overall scenarios with the number of uncertain parameters. Each node where branching occurs represents a stage, while each branch of the tree corresponds to a particular realization of both demand and market uncertainty. A different cost is realized for each branch through the tree, resulting in a distribution of the total cost at the end of the planning horizon. Minimization of the expected value of this cost distribution, where the expectation is evaluated using the

demand and market scenario probabilities ($\omega_{k_1}^0$ and $\omega_{k_2}^m$, respectively), is achieved through the objective function of the BET model.

The proposed model provides an effective tool for assessing the risk exposure of a firm's pollution abatement initiatives by quantifying the effect of emission and market uncertainties on the total cost incurred by the firm. As formulated, the BET model represents an *adaptive* strategic "posture" on the firm's behalf in its attempt to combat these various sources of uncertainty. By making recourse trading decisions during the reconciliation period, the firm either minimizes its environmental liability or maximizes its financial returns. In addition to these adaptive decisions, a facility may also adopt a more aggressive *shaper* position in the face of uncertainty by actively managing the risk exposure of its assets. Unlike the adaptive approach, in which no attempt is made to influence the uncertainties affecting the system, the shaper or risk management approach tries to restructure the various distributions so that the downside risk is limited while the upside potential is retained. From an operational perspective, this can be achieved through specially designed contracts such as *options*.²⁵ The use of such contracts in the context of emission trading is explored next.

4. Emission Trading with Option Contracts

Options are legally binding and negotiable contracts that give the holder the right, but not the obligation, to purchase a certain quantity of an agricultural, industrial, or financial product at a specified price and time for a one-time, upfront premium payment. They are also known as *derivative securities* or *contingent claims* because they derive their value from other more basic *underlying* variables such as stock and commodity prices. From a risk management perspective, the key feature of an option is its asymmetrical payoff. Because the contract does not imply any obligation to buy the underlying product, the holder of the contract profits from favorable price changes while being protected from adverse ones. In return for this downside protection, the option holder has to pay a *premium* to the option-issuing authority. Buying an option is similar to purchasing insurance where the "insured" pays an insurance premium to the insurance company in order to avoid losses.

Option contracts are popular for managing price risk for a variety of commodities. These include agricultural products such as corn, wheat, and soybean, metals such as gold, platinum, and copper (see the Chicago Board of Trade and Chicago Board Options Exchange websites at www.cbot.com and www.cboe.com respectively), and energy products such as heating oil, crude oil, natural gas,^{26,27} and electricity. Borrowing from the risk management practices for the above-mentioned commodities, the incorporation of emission options within the BET model framework is proposed based on the following additional notation.

Sets

$\mathcal{I} = \{i\}$ = set of available option contracts

Parameters

q_i = premium for option i

K_i = strike price for option i

\hat{C}_i^0 = maximum number of options of type i available

Variables

- C_i^0 = number of options of type i purchased initially
 $C_{ik_1k_2}$ = number of options of type i exercised in demand scenario k_1 and market scenario k_2
 $C_{ik_1k_2}^c/C_{ik_1k_2}^s$ = number of options of type i exercised for compliance/speculation in demand scenario k_1 and market scenario k_2

Using the above notation, the BET model with options (BETO) is formulated as

(BETO)

$$\min p^0 N^0 + \sum_i q_i C_i^0 + \sum_j c_j^{\text{fx}} Y_j + \sum_{k_1} \omega_{k_1}^\theta \sum_j c_j^{\text{var}} Y_j \theta_{k_1} + \sum_{k_1} \omega_{k_1}^\theta \left[\sum_{k_2} \omega_{k_2}^m \left[\sum_i K_i C_{ik_1k_2} + p_{k_2} (N_{k_1k_2}^p - N_{k_1k_2}^s - \sum_i C_{ik_1k_2}^s) + c^{\text{nc}} E_{k_1k_2}^{\text{exs}} \right] \right]$$

subject to

equations 1–4

$$0 \leq C_i^0 \leq \hat{C}_i^0 \quad \forall i \quad (7)$$

$$0 \leq C_{ik_1k_2} \leq C_i^0 \quad \forall i, k_1, k_2 \quad (8)$$

$$C_{ik_1k_2} = C_{ik_1k_2}^c + C_{ik_1k_2}^s \quad \forall i, k_1, k_2 \quad (9)$$

$$0 \leq N_{k_1k_2}^s \leq N_0 \quad \forall k_1, k_2 \quad (10)$$

$$0 \leq N_{k_1k_2}^s + \sum_i C_{ik_1k_2}^s \leq \hat{N}_{k_1k_2}^s \quad \forall k_1, k_2 \quad (11)$$

$$E_{k_1k_2}^{\text{exs}} = \max(0, E_{k_1} - N_0 - N_{k_1k_2}^p + N_{k_1k_2}^s - \sum_i C_{ik_1k_2}^c) \quad \forall k_1, k_2 \quad (12)$$

In addition to the technology selection and the initial permit purchase decisions, the first-stage decisions in the BETO model also include the number and type of options purchased (C_i^0). The total premium paid for getting into these contracts is accounted for by the second term in the objective function, while the bounds on the maximum availability of these contracts are enforced through eq 7. Equation 8 models the exercise of these options in the reconciliation phase. Note that the inequality form of eq 8 implies that the firm is not obliged to exercise any/all of its options. The total options exercise cost, which depends on the number ($C_{ik_1k_2}$) and the strike price (K_i) of the options exercised, is given by the fifth term in the objective function. Subsequently, the permits obtained as a result of exercising the options may be used for either compliance ($C_{ik_1k_2}^c$) or speculation ($C_{ik_1k_2}^s$) purposes, as represented by eq 9. Speculation corresponds to the use of the acquired permits as purely financial instruments whereby they are sold in the open market at a price higher than the strike price. The bounds on the number of permits that can be sold in the reconciliation phase are given by eqs 10 and 11. Finally, based on these portfolio rebalancing decisions, the excess emission is defined by eq 12. The BETO model, thus, establishes the optimal technology–permits–options portfolio for the firm's pollution abatement initiatives.

Derivative financial instruments, such as options, *implicitly* facilitate the management of a company's risk exposure. This, as mentioned previously, is due to the asymmetric payoff associated with options, which provides the firm with an opportunity to limit its downside risk while allowing for profits on the upside. In addition to the use of these exchange or over-the-counter-traded contracts, a more actively managed risk control strategy can be formulated through which the dispersion of the unexpected future outcomes is *explicitly* shaped in accordance with the firm's risk-bearing inclination/capacity.^{28–30} In the present setting, this corresponds to tailoring the total cost probability distribution as discussed in the following section.

5. Risk Management

The central idea underlying any risk management and control initiative is the incorporation of the classic tradeoff between risk and return within the decision-making process. As formulated, both the BET and BETO models capture only the returns component of this tradeoff through minimization of the total expected cost in the objective function. Also, by taking a purely expected cost-minimization perspective, these models assume that the firm is *risk neutral* or indifferent to cost variability. This is clearly not the case because most firms (and individuals), in general, are *risk averse*, implying that they prefer lower, as opposed to high, variability for a given level of return. Consequently, the importance of controlling variability is well recognized in the financial community especially with regards to portfolio management applications.^{29,31} To this end, the most popular metric for quantifying variability has been the *variance* in returns of a given portfolio. This metric, which captures the difference between the actual and expected returns on any investment, is widely used in financial decision making in both Wall Street and corporate policy formulation settings.²⁸

Borrowing from portfolio optimization theory, the first risk management approach considered is variance control. Let TC denote the random variable representing the total cost incurred over the entire planning horizon. Also, let $\hat{\sigma}^2$ be the maximum acceptable level of variability in terms of the variance of the probability distribution associated with TC. Enforcement of this maximum acceptable limit is achieved through the inclusion of the following constraint in the BETO model.

$$\text{Var}[\text{TC}] \leq \hat{\sigma}^2 \quad (13)$$

The variance in eq 13 is defined as

$$\text{Var}[\text{TC}] = E_{\theta,m}[\text{TC}^2] - E_{\theta,m}[\text{TC}]^2 \quad (14)$$

according to basic probability theory, with $E_{\theta,m}[\cdot]$ denoting the expectation operator with respect to the demand and market uncertainties. The two terms in eq 14 are given by

$$E_{\theta,m}[\text{TC}^2] = \sum_{k_1,k_2} \omega_{k_1}^\theta \omega_{k_2}^m \text{TC}_{k_1k_2}^2 \quad (15)$$

$$E_{\theta,m}[\text{TC}] = \sum_{k_1,k_2} \omega_{k_1}^\theta \omega_{k_2}^m \text{TC}_{k_1k_2} \quad (16)$$

where

$$TC_{k_1 k_2} = p^0 N^0 + \sum_i q_i C_i^0 + \sum_j c_j^{fx} Y_j + \sum_j c_j^{var} Y_j \theta_{k_1} + \sum_i K_i C_{ik_1 k_2} + p_{k_2} (N_{k_1 k_2}^p - N_{k_1 k_2}^s - \sum_i C_{ik_1 k_2}^s) + c^{nc} E_{k_1 k_2}^{exs} \quad (17)$$

is the total cost incurred in demand scenario k_1 and market scenario k_2 .

Two potential drawbacks of the variance control approach to risk management can be identified as listed below.

1. Because variance is a symmetric measure of the dispersion of the actual cost outcomes around the expected value, a reduction in its value not only limits downside risk but also adversely affects the upside potential. This implies that, in addition to eliminating some of the excessively high cost scenarios, this approach also eliminates some of the favorable, excessively low cost scenarios in an attempt to reduce the spread of these values around the mean. Also, even the downside risk is only reduced and not completely eliminated because it is still possible that, under high-uncertainty conditions, the decision maker may run into a specific realization of the uncertain parameters that results in unacceptably high recourse costs.

2. Inclusion of eq 13 within the multistage stochastic programming framework introduces nonlinearities into the model. This results in an increase in the computational intractability of these already difficult to solve models.

In view of these limitations of the variance control methodology, an alternate probabilistic approach can be formulated which corresponds to the addition of the following constraint in the model description.

$$\Pr(TC \geq \hat{TC}) \leq \alpha \quad (18)$$

Equation 18 ensures that the probability of the total cost (TC) exceeding some maximum cost (\hat{TC}) is less than some specified probability level (α). Note that, through eq 18, only the downside risk, as represented by the high-cost scenarios, is directly affected. Incorporation of this asymmetric, probabilistic constraint within the modeling framework requires an additional binary variable defined as follows.

$$Z_{k_1 k_2} = \begin{cases} 1 & \text{if } TC_{k_1 k_2} \geq \hat{TC} \\ 0 & \text{if } TC_{k_1 k_2} \leq \hat{TC} \end{cases} \quad (19)$$

Subsequently, addition of the following set of constraints enforces eq 18

$$\hat{TC} Z_{k_1 k_2} - M(1 - Z_{k_1 k_2}) \leq TC_{k_1 k_2} \leq \hat{TC}(1 - Z_{k_1 k_2}) + MZ_{k_1 k_2} \quad (20)$$

$$\sum_{k_1, k_2} \omega_{k_1}^\theta \omega_{k_2}^m Z_{k_1 k_2} \leq \alpha \quad (21)$$

where M is an upper bound on the total cost TC.

The probabilistic approach described above only partially mitigates the two challenges presented by the variance control approach because (i) the probability of the occurrence of excessively high cost scenarios, though reduced, is not completely eliminated and (ii) the computational challenge presented by nonlinearities is replaced by the combinatorial complexity associated with additional binary variables. In light of these

Table 2. Technology Parameter Values

j	c_j^{fx} (RMU)	c_j^{var} (RMU)	β_j (RWU of pollutant/WU of product)
1	100	10	0.700
2	200	20	0.600
3	300	30	0.550
4	400	40	0.500
5	500	50	0.475
6	600	60	0.450

Table 3. Market Parameter Values

parameter	value
c^{nc} (RMU)	200
p^0 (RMU)	120
p (RMU)	uniform (0, 200)
θ (RWU)	uniform (50, 100)
\hat{N}^p (#)	uniform (0, 50)
\hat{N}^s (#)	uniform (0, 50)
\hat{N}^0 (#, permits only)	100
\hat{N}^0 (#, permits and options)	50
\hat{C}_i^0 (#, options only)	10
\hat{C}_i^0 (#, permits and options)	5

observations, a more computationally tractable approach which targets the worst-case cost scenario can be implemented through the incorporation of the following constraint.

$$\left(\max_{k_1 k_2} TC_{k_1 k_2} \right) \leq \hat{TC} \Rightarrow TC_{k_1 k_2} \leq \hat{TC} \quad (22)$$

Through this approach, thus, both the computational tractability and risk elimination criterion are met. It is important to note that, in a real-life, practical setting, any/all of the above-described approaches may be used to formulate an integrated risk management program for the firm. To illustrate how these various approaches may impact the risk–return profile of a firm's pollution abatement initiatives, they are applied to a representative planning case study as described in the following section.

6. Case Study

A manufacturing firm that is planning its pollution abatement activities has six potential technology candidates under consideration for meeting the demand of its products/services. The parameters characterizing each technology, which are the fixed investment cost, variable production charges, and the emission coefficient, are listed in Table 2. Note that all cost parameters are assumed to be in relative monetary units (RMU) while demand/emission levels are in relative weight units (RWU). Technologies 1–6 span the entire spectrum of cost-emission possibilities, ranging from the low cost–high emission extreme (technology 1) to the high cost–low emission alternative (technology 6). Also, note that the technology parameter values in Table 2 are in accordance with the classic law of diminishing returns as reflected by the decrease in the marginal effectiveness of the pollution abatement potential of the technologies with increasing cost.

The various parameters describing the current and future market settings are listed in Table 3. Each emission permit can be used to cover 1 RWU of emission. These permits are currently available at a 40% discount over the noncompliance penalty implying a slightly long aggregate market. The future permit price is assumed to be uniformly distributed between zero and the noncompliance penalty. Both of these extreme

Table 4. Parameter Values for Option Contracts

	<i>i</i> value									
	1	2	3	4	5	6	7	8	9	10
K_i (RMU)	150	145	140	135	130	125	120	115	110	100
q_i (RMU)	10	12	14	16	18	20	22	24	26	28

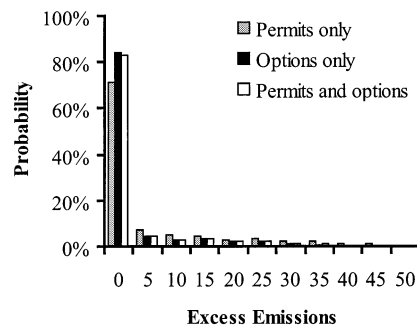
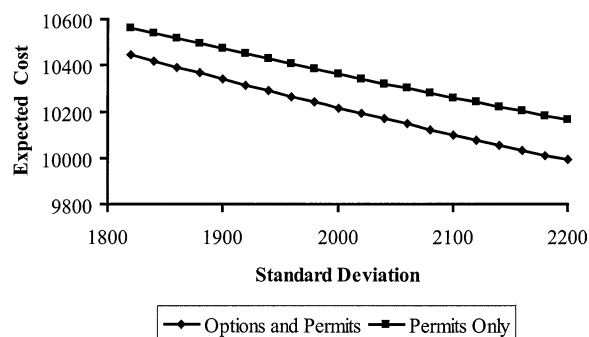
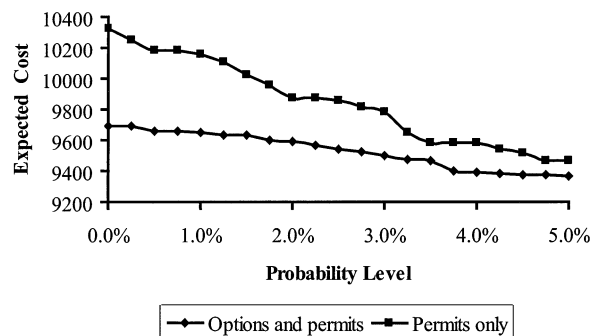
Table 5. Cost Analysis for the Three Market Settings

cost component	permits and options (RMU)		
	permits (RMU)	options (RMU)	permits and options (RMU)
initial permit investment	5717.2	0.0	4507.3
option premium	0.0	1279.9	441.7
fixed capital investment	200.0	200.0	200.0
variable production cost	1977.1	1977.1	1977.1
net permit trading cost	693.0	1823.1	816.4
noncompliance penalty	874.4	417.8	429.4
option exercise cost	0.0	4735.8	1231.9
option trading cost	0.0	-733.3	-233.9
total expected cost	9461.7	9700.4	9369.9

price scenarios are assumed to occur with equal probability, which, in general, may not be true because the chances of a severely "glutted" or "squeezed" market may vary with the degree to which business activity is correlated. Uniform distributions are also assumed to describe the other sources of uncertainty such as the demand and reconciliation period trading limits as indicated in Table 3.

Three alternative market environments, based on the type of contracts made available initially to the firm by the regulatory authority, are considered within the proposed modeling framework. Specifically, the three settings considered differ based on whether (i) permits only, (ii) options only, or (iii) both permits and options are made available to the firm for setting up its initial compliance portfolio. The number of compliance instruments made available in each of these three scenarios are listed in Table 3. Note that a total of 100 instruments are made available in each of the three market settings. The strike prices and premiums charged for the available options are given in Table 4. To capture the tradeoff between present costs and future gains, an inverse relationship is assumed to exist between the strike price and the premium. This reflects the willingness of the firm to pay a higher premium initially in exchange for obtaining the future right to purchase an emission permit at a lower cost.

When the data given in Tables 2–4 are utilized, the BETO model is solved for the three alternative market settings using the CPLEX 7.0 solver accessed via GAMS.³² The resulting model (see Table 6 for model statistics) is solved on an IBM RISC 6000 machine in approximately 5 CPU s. The resulting optimal expected costs are listed in Table 5 along with their breakdown in terms of the various constitutive components. As illustrated by the results in Table 5, a minimum total cost is incurred when both permits and options are made available to the firm. The flexibility provided by the availability of both types of compliance instruments translates into expected cost savings of 1% and 3.5% respectively over the permits-only and options-only settings. The cost analysis presented in Table 5 provides valuable insights into the sources of these observed savings. The savings over the options only result from the reduction in recourse permit trading costs while, for the permits-only case, the savings realized can be primarily attributed to the reduction in noncompliance penalties. These expected savings in noncompliance

**Figure 3.** Excess emission distributions.**Figure 4.** Expected cost–standard deviation tradeoff curve.**Figure 5.** Variation of the total expected cost with the probability level.

charges can be traced back to the reduction of the excess emissions as illustrated through Figure 3. As this figure indicates, the probability of adequately meeting emission requirements is increased from approximately 70% with permits only to around 80% through the inclusion of option contracts. Aside from the tangible cost savings realized from this increased chance of regulatory compliance, the firm also gains considerable political and social capital by being perceived as an environmentally conscious organization.

Next, the impact of the proposed risk management techniques on the risk profile of the firm's pollution abatement activities is investigated. The results obtained for the variance control, probabilistic, and worst-case approaches are presented in Figures 4–6, respectively. The tradeoff curves shown in these figures are obtained by first appending the corresponding risk management constraints to the BETO model followed by parametrically varying the appropriate risk metric. The resulting optimization models (model statistics summarized in Table 6) are then solved, and the optimal expected costs are plotted against the risk metric. These figures indicate that the inclusion of options in the compliance portfolio leads to more effective risk management. This conclusion is based on the observation

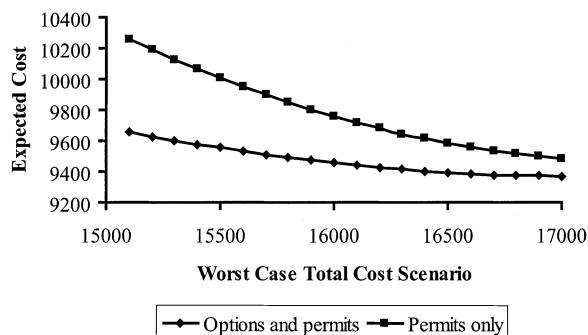


Figure 6. Variation of the total expected cost with the worst-case total cost scenario.

Table 6. Model Statistics

model	no. of constraints	no. of variables	no. of discrete variables
BETO	13 238	9 623	6
BETO + variance control	13 638	10 024	6
BETO + probabilistic control	14 038	10 824	406
BETO + worst-case control	13 638	10 423	6

that, in all three figures, the curve corresponding to the permits-only portfolio lies entirely above the permits and options portfolio. This implies that, for a given level of risk, lower cost is incurred by holding an options and permits portfolio as opposed to a purely permits portfolio. In addition to reducing the absolute level of risk for a specified level of return, option contracts also reduce the *risk premium* paid by the firm for its risk management initiatives. The risk premium corresponds to the amount of upside potential that a firm has to sacrifice in exchange for a specified amount of downside protection. In the current setting, this corresponds to the marginal increase in the total cost for a unit decrease in the firm's risk exposure as captured by the slope of the risk–return curves in Figures 4–6.

7. Summary

In this work, the technology selection problem faced by a firm undertaking a market-based pollution abatement initiative was addressed. In particular, this research focused on the incorporation of the following three issues in the planning process: (1) inclusion of demand and market uncertainties; (2) use of market-priced option contracts; (3) risk assessment and control.

A multistage stochastic programming approach was utilized to incorporate demand and market uncertainties in the decision-making process. The partitioning of the decisions into the upfront, “here-and-now” decisions and the recourse, “wait-and-see” decisions provided the appropriate structure for a multistage stochastic programming formulation. More specifically, the technology selection and initial permit purchase decisions were made prior to the resolution of the system uncertainties. Subsequently, contingent on these decisions and the particular realizations of the demand and market parameters, the reconciliatory trading decisions were made in order to optimize in the face of uncertainty.

In addition to using decision postponement techniques as modeled through the multistage approach, the use of option contracts was also explored for the purpose of combating uncertainty. Borrowing from finance theory, the BET model was extended to incorporate these derivative compliance instruments that were defined as

contracts that provide the holder the right without the associated obligation of purchasing a permit in the future at a predetermined price in return for an upfront premium payment. The impact of this asymmetric payoff on the bottom line was studied by providing the firm with the choice of including these contracts in its pollution abatement portfolio.

The issue of actively managing the risk exposure of the firm, which entails limiting downside risk while maintaining upside potential, was also raised in this work. To this end, three alternative approaches that could potentially be embedded within the proposed modeling framework for capturing the tradeoff between risk and return were defined. These were (i) variance control, (ii) probabilistic analysis, and (iii) worst-case analysis. The advantages and disadvantages of these approaches were provided from both a computational and a decision-making perspective.

To highlight the effectiveness of the proposed model as a decision-making tool, it was applied to a planning case study. Three alternative market settings were considered based on what type of instruments were made available to the firm for setting up its initial compliance portfolio. The availability of *both* permits and options, as opposed to *only* permits or options, was shown to be financially beneficial for the firm, resulting in the achievement of its pollution abatement objectives at minimum cost. The option contracts were also shown to be highly effective risk management instruments because their inclusion resulted in a significant reduction in the risk premium observed by the firm.

In conclusion, future work on the problem addressed in this work could proceed in several different directions. The model could be extended to a multiperiod setting where some/all of the permits for the planning horizon are allocated initially and decisions regarding borrowing and banking of permits over time need to be made. Additional complexity could also be introduced in the form of multiple production facilities emitting several different classes of related/independent pollutants. Interpollutant and intersite trading opportunities that would arise as a result of the presence of multiple pollutants/sites could then be investigated. Finally, the proposed model could also be integrated with option pricing models to aid the design and structuring of over-the-counter-purchased option contracts.

Acknowledgment

The authors gratefully acknowledge financial support by NSF-GOALI Grant CTS-9907123.

Literature Cited

- (1) Stavins, R. N. Transaction Costs and Tradeable Permits. *J. Environ. Econ. Manage.* **1995**, *29*, 133.
- (2) Coggins, J. S.; Swinton, J. R. The Price of Pollution: A Dual Approach to Valuing SO₂ Allowances. *J. Environ. Econ. Manage.* **1996**, *30*, 58.
- (3) Carlson, D. A.; Sholtz, A. M. Designing Pollution Market Instruments: Cases of Uncertainty. *Contemp. Econ. Policy* **1994**, *12*, 114.
- (4) Jensen, J.; Rasmussen, T. N. Allocation of CO₂ Emission Permits: A General Equilibrium Analysis of Policy Instruments. *J. Environ. Econ. Manage.* **2000**, *40*, 111.
- (5) Muller, R. A.; Mestelman, S. Emission Trading with Shares and Coupons. *Energy J.* **1994**, *15*, 185.
- (6) Dales, J. H. *Pollution, Property and Prices*; University of Toronto Press: Toronto, Canada, 1968.

- (7) Montgomery, W. D. Markets in Licenses and Efficient Pollution Control Programs. *J. Econ. Theory* **1972**, *5*, 395.
- (8) Hahn, R. W.; Noll, R. G. Environmental Markets in the Year 2000. *J. Risk Uncertainty* **1990**, *3*, 351.
- (9) Tietenberg, T. Transferable Discharge Permits and the Control of Stationary Source Air Pollution. *Land Econ.* **1980**, *5*, 391.
- (10) Hahn, R. W. Economic Prescriptions for Environmental Problems: How the Patient Followed the Doctor's Orders. *J. Econ. Perspect.* **1989**, *3*, 95.
- (11) Andersson, F. Small Pollution Markets: Tradeable Permits versus Revelation Mechanisms. *J. Environ. Econ. Manage.* **1997**, *32*, 38.
- (12) Hagem, C.; Westskog, H. The Design of a Dynamic Tradeable Quota System under Market Imperfections. *J. Environ. Econ. Manage.* **1998**, *36*, 89.
- (13) Tietenberg, T. *Environmental and Natural Resource Economics*; Addison-Wesley Longman Inc.: Reading, MA, 2000.
- (14) Hennessy, D. A.; Roosen, J. Stochastic Pollution, Permits and Merger Incentives. *J. Environ. Econ. Manage.* **1999**, *37*, 211.
- (15) Cronshaw, M. B.; Kruse, J. B. Regulated Firms in Pollution Permit Markets With Banking. *J. Regul. Econ.* **1996**, *9*, 179.
- (16) Krupnick, A. J.; Oates, W. E.; Verg, E. V. D. On Marketable Air-Pollution Permits: The Case for a System of Pollution Offsets. *J. Environ. Econ. Manage.* **1983**, *10*, 233.
- (17) McGartland, A. M.; Oates, W. E. Marketable Permits for the prevention of Environmental Deterioration. *J. Environ. Econ. Manage.* **1985**, *23*, 207.
- (18) Cason, T. N.; Plott, C. R. EPA's New Emissions Trading Mechanism: A Laboratory Evaluation. *J. Environ. Econ. Manage.* **1996**, *30*, 133.
- (19) Dijkstra, B. R.; Haan, M. Sellers Hedging Incentives at EPA's Emission Trading Auction. *J. Environ. Econ. Manage.* **2001**, *41*, 286.
- (20) Rubin, J. A Model of Intertemporal Emission Trading, Banking and Borrowing. *J. Environ. Econ. Manage.* **1996**, *31*, 269.
- (21) Yates, A. J.; Cronshaw, M. B. Pollution Permit Markets with Intertemporal Trading and Asymmetric Information. *J. Environ. Econ. Manage.* **2001**, *42*, 104.
- (22) Godby, R. W.; Mestelman, S.; Muller, R. A.; Welland, J. D. Emissions Trading with Shares and Coupons when Control over Discharges is Uncertain. *J. Environ. Econ. Manage.* **1997**, *32*, 359.
- (23) Dantzig, G. B. Linear Programming Under Uncertainty. *Manage. Sci.* **1955**, *1*, 197.
- (24) Birge, J. R.; Louveaux, F. *Introduction to Stochastic Programming*; Springer: New York, 1997.
- (25) Hull, J. C. *Options, Futures and Other Derivatives*; Prentice Hall: Upper Saddle River, NJ, 1997.
- (26) Clubley, S. *Trading in Oil Futures and Options*; Woodhead Publishing Ltd.: Cambridge, London, 1998.
- (27) Errera, S.; Brown, S. L. *Fundamentals of Trading Energy Futures and Options*; PennWell: Tulsa, OK, 1999.
- (28) Damodaran, A. *Corporate Finance: Theory and Practice*; John Wiley: New York, 1997.
- (29) Luenberger, D. G. *Investment Science*; Oxford University Press: New York, 1998.
- (30) Triantis, A. J. Real Options and Corporate Risk Management. *J. Appl. Corporate Finance* **2000**, *13*, 64.
- (31) Sharpe, W. F. *Portfolio Theory and Capital Markets*; McGraw-Hill: New York, 1970.
- (32) Brooke, A.; Kendrick, D.; Meeraus, A. *GAMS: A User's Guide*; Scientific Press: Palo Alto, CA, 1988.

Received for review June 20, 2002

Accepted December 6, 2002

IE020467D