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Optimal Fleetwide Emissions Reductions for Passenger Ferries: An Application of a Mixed-Integer Nonlinear Programming Model for the New York–New Jersey Harbor

James J. Winebrake
Rochester Institute of Technology, Rochester, NY

James J. Corbett and Chengfeng Wang
University of Delaware, Newark, DE

Alexander E. Farrell
University of California, Berkeley, CA

Pippa Woods
Rutgers University, Newark, NJ

ABSTRACT
Emissions from passenger ferries operating in urban harbors may contribute significantly to emissions inventories and commuter exposure to air pollution. In particular, ferries are problematic because of high emissions of oxides of nitrogen (NO_x) and particulate matter (PM) from primarily unregulated diesel engines. This paper explores technical solutions to reduce pollution from passenger ferries operating in the New York–New Jersey Harbor. The paper discusses and demonstrates a mixed-integer, nonlinear programming model used to identify optimal control strategies for meeting NO_x and PM reduction targets for 45 privately owned commuter ferries in the harbor. Results from the model can be used by policy-makers to craft programs aimed at achieving least-cost reduction targets.

INTRODUCTION
Emissions from marine sources are a growing problem in urban coastal areas.[1-5] This problem is exacerbated by the increasing use of passenger ferries as an urban commuting option.[6-9] Passenger ferries provide a high-speed and comfortable alternative to automobiles, buses, trains, and subways, but unlike other mobile sources, passenger ferries are only recently becoming a regulated emissions source.[10] Thus, local air quality officials and transportation planners are faced with the challenge of reducing emissions from this important, but relatively dirty, commuting option.

IMPLICATIONS

This paper presents a model that can be used by decision-makers to identify least-cost emissions reduction strategies for passenger ferry operations in the New York–New Jersey Harbor. With the model, programs can be designed that capture maximum emissions reductions at least cost. The model can be easily generalized and applied in a variety of other harbor settings.

Ferry services play a particularly important role in the New York–New Jersey (NY/NJ) transportation network. Indeed, in 2000 alone, commuter ferries provided daily service to 85,000 commuters, shuttling them from terminal to terminal within the NY/NJ Harbor.[11] However, because emissions from these vessels are mostly unregulated, they also accounted for a significant proportion of regional emissions from commercial vessels operating in the harbor. For example, based on a recent emissions inventory report, ferries are estimated to contribute ~19% of nitrogen oxide (NO_x) emissions and ~12% of particulate matter (PM) emissions from commercial marine totals for the region, with ~92% of all PM emissions being $PM_{2.5}$.[11]

Reducing emissions from marine vessels in general, and ferries in particular, is important for several reasons. First, emissions reductions are needed to offset emissions from other commuter expansion or waterway transportation projects. Second, reductions in ferry emissions may enable economic growth in other sectors of the economy, while still allowing the region to conform to air quality requirements under the Clean Air Act. Third, ferry emissions reductions provide regional human health benefits resulting from reduced exposure to air pollution by commuters and noncommuters alike.[2,12]

Compared with other emissions sources, relatively little is known about maritime emissions and control strategies. However, initial analyses suggest that significant reductions in emissions from passenger ferries will be required to make ferries comparable to alternative landside commuting options.[13,14] These reductions may not come cheaply.[15]

Although some work has considered emissions reduction options on a vessel-by-vessel basis, no study has yet analyzed an entire fleet of vessels for the purpose of identifying least-cost strategies to meet fleetwide emissions reduction targets. This represents a major gap in our current understanding of commercial marine vessel emissions reduction potential because, as demonstrated in other sectors, considering emissions reductions across an entire group of pollution sources usually presents opportunities for deeper reductions at a lower cost.[16,17]

This paper discusses a model developed to identify least-cost strategies for emissions reductions in the private ferry vessel fleet operating in the NY/NJ Harbor. The paper focuses on the model design, its output, and its usefulness to policy-makers. Results from the model can be used to craft policies that could provide an incentive for private fleet operators to implement least-cost control strategies, while also meeting fleetwide emissions reduction targets.

MODELING FLEETWIDE SOLUTIONS

Optimization Models and Technology Choice

The use of optimization programming to explore cost and emissions tradeoffs in energy-related sectors has long been established. Specifically, least-cost optimization models focusing on energy technology choice have been discussed extensively in the literature. These types of models have been used to explore energy planning at both the national and local level.[18-24]

The scope of studies that model least-cost technology choice in the energy field ranges from modeling macroeconomic sectors to modeling at the firm level. In relation to our problem, optimization modeling has been used to understand specific technology choice decisions that meet energy service demands at least cost, often while also meeting environmental constraints. Sarimveis et al.[25] used such a model to explore energy management technologies in the pulp and paper industry, where least-cost solutions were found in meeting power needs at a paper mill. In another study, Gustafsson[26] applied a mixed-integer linear programming model to explore window and door replacements for a building. Lahdelma and Hakonen[27] applied a linear programming model to evaluate efficient energy production in a combined heat and power system (albeit without environmental constraints). Finally, we have been involved in studies that use linear programming optimization models to evaluate pollution control technology choices at the power plant level in the U.S. electric utility sector.[16,17,28]

Despite the use of optimization models in the energy field, as far as we know no one has yet applied such an approach to assess least-cost emissions reduction strategies for marine transportation. Our model takes an approach similar to past technology choice studies with emissions constraints; however, the model breaks new ground through the construction of an efficient nonlinear element that allows a suite of emissions control technologies to be pursued simultaneously. The model is discussed in detail in the following section.

The Marine Emissions Optimization Model (MEOM)

Model Summary. The MEOM is a mixed-integer nonlinear programming model that identifies least-cost emissions control strategies for a fleet of marine passenger ferries. The model is built and solved in the General Algebraic Modeling System (GAMS) software.[29]

In this study, we model a fleet of private passenger ferries operating in the NY/NJ Harbor. Recent data identified a total of 67 ferryboats and excursion vessels operating in the NY/NJ Harbor.[11] We focused on the 45 privately operated ferries providing passenger transportation services in the harbor. These are operated by three companies (35 operated by NY Waterway, 4 by Sea Streak, and 6 by NY Water Taxi). On the basis of engine characteristics, operating profiles, and emissions control options, the model determines how the ferry fleet can meet emissions reduction targets at least cost. Results of the model provide information to decision-makers interested in targeting policies and programs to assist ferry operators in meeting these targets.

The model is a nonlinear technology choice model with environmental constraints. Vessels are assigned the suite of technologies that will achieve user-defined fleetwide emissions reductions at least cost. There are two general types of technologies that can be used: (1) engine repowering, and (2) emissions control technologies.

Engine repowering as an emissions reduction tool is an important option for many ferry operators. In the past, vessels have used unregulated, mechanically controlled diesel engines that were tuned to provide optimal performance (with accompanying high levels of NO_x and PM emissions). However, most new engines are now electronically controlled, and beginning in 2004, all new engines for U.S. markets need to meet emissions standards (Tier I). After 2007, more stringent standards will be required (Tier II).[10,30,31] Thus, if a vessel's owner repowers the vessel's engines (a likely event for some vessels, even without environmental considerations), the existing dirty engines will likely be replaced with more efficient, cleaner engines.

The second type of option involves control technologies that are designed explicitly to reduce emissions.[15] In MEOM, we include the following options:

- diesel particulate filter (DPF);
- selective catalytic reduction (SCR);
- exhaust gas recirculation (EGR);
- intake air fumigation (IAF);
- emulsified diesel fuel (EMD);
- ultralow-sulfur diesel (ULSD);
- fuel injection equipment (FIE);
- low-NO_x catalyst (LNC); and
- diesel oxidation catalyst (DOC)

MEOM minimizes the costs of repowering and/or using combinations of control technologies while meeting a user-defined fleetwide emissions reduction target for both NO_x and PM. Conversely, MEOM can also be used to determine the maximum reductions in NO_x and PM that are possible given a budget constraint. Details about the model are found in the sections that follow.

Objective Function. For the remainder of this paper, we define the following sets. Set members can easily be added within our model:

- *V* (vessels): made up of the fleet of 45 vessels under analysis;
- *E* (engine types): made up of three engine types (existing, Tier I, Tier II). Several marine engine types are used in the existing fleet of vessels, including the Detroit Diesel Series 60, Cummins KTA50-M2, Caterpillar 3412, Caterpillar 3406, MTU 16V396, and Deutz 616V16;
- *K* (emissions control technology): made up of technology options (DPF, SCR, EGR, IAF, ULSD, FIE, LNC, DOC); and
- *P* (pollutants): made up of two pollutants (NO_x and PM).

The objective function for the model is defined as:

$$\min\left(\sum_{v}^{V}\sum_{e}^{E} BINE_{v,e}\cdot ETC_{v,e} + \sum_{v}^{V}\sum_{k}^{K} BINK_{v,k}\cdot KTC_{v,k}\right) \tag{1}$$

where $BINE_{v,e}$ and $BINK_{v,k}$ represent binary variables that dictate whether engine *e* and technology *k* are incorporated on vessel *v* (value of 0 if no, 1 if yes); and $ETC_{v,e}$ and $KTC_{v,k}$ represent the total annualized costs of incorporating engine *e* or technology *k* on vessel *v*. This total cost is determined as follows:

$$KTC_{v,k} = KCC_{v,k} + KOMC_{v,k} + KFC_{v,k} \tag{2}$$

$$ETC_{v,e} = ECC_{v,e} + EFC_{v,e} \tag{3}$$

where $ECC_{v,e}$ and $KCC_{v,k}$ represent the capital and installation cost of engine *e* and technology *k*, respectively, annualized over the lifetime of the engine or technology at a given discount rate (default rate of 10 years and 5%); $KOMC_{v,k}$ is the additional annual operation and maintenance costs (not counting fuel costs) for the new technology *k* (we assume no additional operation and maintenance costs for new engines); and $EFC_{v,e}$ and $KFC_{v,k}$ are additional annual fuel costs (or benefits) attributable to the new engine *e* or technology *k*. Readers should note that some control technologies require additional fuel consumption, and thus face fuel penalties, whereas new engine technologies may reduce fuel consumption through increased efficiency and thus have negative fuel costs. In our model, we assume a temporal relationship between the fuel efficiency gains of repowering and the age of the engine being replaced. This has been shown to be the case in several studies of older engines.[32,33] Finally, there are some installation cost benefits associated with installing certain control technologies in tandem on a particular vessel. Such synergistic effects are accounted for in the model where appropriate. Specific assumptions on emissions control technology characteristics for our analysis are found in Table 1.

Energy-Use Equations. Annual energy use per vessel is an important element of the model and is a function of operational characteristics and engine type. In MEOM, the annual kWh used by a ferry is calculated by considering both main engines and auxiliary engines.

Total energy used is determined by first multiplying the engine size (kW) by a composite power index (CPI) or load factor. The CPI is measured as a percentage of the rated power used by each vessel on an average route. For example, a CPI of 50% means that, on average, the vessel operates at 50% of its rated power during operation. It has been shown that vessels operating on longer routes tend to follow a load profile that has a higher CPI than vessels on shorter routes.[34,35] For our work, we use actual CPI data collected on a set of representative vessels from the harbor.[36]

Once we calculate an average rated load for each vessel (adjusted kW), we multiply by the number of hours the vessel operates annually. This is consistent with a similar approach used by others.[11,32] This allows us to determine the total annual kWh for each vessel. This approach is summarized in the following equation.

Table 1. Data for emissions control technologies.

Technology	Performance (% Reduction)		Costs ($/kW and $/kW-yr)		Fuel Penalty (%)
	NO_x	PM	Capital + Installation	O&M	
DPF	0	90	20	18	1
SCR	80	25	70	20	3
EGR	45	−10	20	0	4
IAF	25	−5	32	0.62	0
ULSD	0	8	0	0	0
FIE	20	−10	0	0.71	3
LNC	30	0	22	0	5
DOC	0	25	10	0	0

Notes: Data are from refs 32, 35, and 38; O&M = operating and maintenance.

$$KWH_v = KW_v \cdot CPI_v \cdot HR_v \tag{4}$$

where KWH_v is the annual kWh generated by the main engines for each vessel; KW_v is the rated power for each vessel's main engines; CPI_v is the composite power index described above; and HR_v is the annual hours of operation for each vessel. This result is added to the kWh generated by auxiliary engines based on auxiliary engine power, annual hours of operation, and a load factor for the auxiliary engines.

Emissions Limit Constraint. The base case emissions for each pollutant by vessel are calculated by multiplying an emissions factor for each existing engine type (in kg/kWh) by the total annual kWh for each vessel. Emissions factors are determined based on published data, emissions testing results from representative vessels, and emissions standards that will take effect in 2004 (Tier I) and 2007 (Tier II).[30] Separate emissions factors are used for the auxiliary engines based on emissions factors for uncontrolled diesel engines.

The determination of appropriate emissions factors is difficult because of limited measurements in the field. We have three data sources for our emissions factors: (1) data from engine manufacturers; (2) measurements in the field from a very small sample of vessels (four); and (3) standards published by the U.S. Environment Protection Agency or International Maritime Organization. For the model results presented in this paper, we used manufacturers' data when available in conjunction with data from other sources.[36,37] These data are consistent with field data obtained by others for these vessels.[36]

The emissions equations are given by

$$EM_{v,p} = EF_{e,p} \cdot KWH_v \tag{5}$$

and

$$AUXEM_{v,p} = EF_{AUX,p} \cdot AKWH_v \tag{6}$$

where $EM_{v,p}$ is the annual base case emissions from vessel v of pollutant p; $EF_{e,p}$ is the emissions factor in kg/kWh for the existing engine e and pollutant p; $AUXEM_{v,p}$ is the emissions from the auxiliary engines for vessel v and pollutant p; $EF_{AUX,p}$ is the emissions factor in kg/kWh for the auxiliary engines; and $AKWH_v$ is the annual kWh used by the auxiliary engines for vessel v.

We next establish an emissions limit by multiplying the base case emissions by a user-defined emissions reduction factor, as follows:

$$EMLIM_{v,p} = (EM_{v,p} + AUXEM_{v,p}) \cdot (ERF_p) \tag{7}$$

where $EMLIM_{v,p}$ is the emissions limit by vessel v and pollutant p; and ERF_p is an emissions reduction factor for pollutant p. Here, ERF_p represents the percentage of emissions that will be allowed under any new scenario run (from 0 to 100%). For example, for our Case 1 run (discussed later), we set ERF_{NOx} as 70%; the model will thus set a new emissions limit equal to 70% of the base case (i.e., requiring a 30% NO_x reduction). For Case 1, we set ERF_{PM} as 40% for PM, thus requiring a 60% PM reduction from the status quo.

The emission limit value is then incorporated into the final emissions constraint. In this case, the annual emissions from the fleet of vessels must be less than or equal to the emissions limit prescribed by the user. The emissions for each vessel are calculated based on vessels choosing both an engine type option (e) and a suite of control technologies (k). As mentioned in our discussion of the objective function, the decision variables ($BINE_{v,e}$ and $BINK_{v,k}$) are binary variables that identify what type of engine and what type of control technologies each vessel uses. The following equations demonstrate how the emissions constraint is handled:

$$\sum_{v}^{V}\left\{\left[\sum_{e}^{E} BINE_{v,e} \cdot EF_{e,p} \cdot KWH_v\right] \cdot \left[\prod_{k}^{K}(1 - BINK_{v,k} \cdot KEF_{k,p})\right] + AUXEM_{v,p}\right\} \leq \sum_{v}^{V} EMLIM_{v,p} \tag{8}$$

$$\sum_{e}^{E} BINE_{v,e} = 1 \tag{9}$$

where the only new variable introduced is $KEF_{k,p}$. This variable represents the percentage reduction of emissions of pollutant p obtained by use of control technology k (shown in Table 1). For example, suppose that SCR technology has demonstrated the ability to reduce NO_x emissions by 80% on marine vessels. For SCR technology, we set $KEF_{SCR,NOx} = 0.80$. If the model assigns this SCR technology, then the $BINK_{v,SCR}$ variable equals 1. Reviewing the equation once more, the reader will see that this has an effect of reducing the emissions from the main engines to(1 − [1][0.80]), or to 0.20 (20%) of the original NO_x emissions. In this way, we handle not only new engine repowering (e.g., moving from an existing engine to a new Tier I or Tier II engine), but also the application of various control technologies with that engine. Values for $KEF_{k,p}$ were determined from previous literature reviews that relied on manufacturers' data, as well as on in-field demonstrations and personal communications.[15,36,38]

Using the product factor, we can allow multiple control technologies. For example, the model may assign both SCR and FIE technology to a single vessel. In such a case, the emissions reductions are multiplicative. Therefore, if SCR reduces NO_x emissions by 80% and ITD reduces NO_x emissions by 20%, we have a cumulative emissions level of

$$\{1 - (1)(0.80)\} \times \{1 - (1)(0.20)\} = (0.20)(0.80) = (0.16) \tag{10}$$

or an equivalent reduction of (1 − 0.16) = 84%. Finally, for this constraint, auxiliary emissions are added, and the total is set to be equal to or less than the emissions limit identified earlier. In this equation, some vessels may remain at their existing configuration, whereas others will incorporate repowering and emissions control technologies more aggressively.

Temporal Aspects of the Model. The model was developed for an annual period, with capital costs annualized over a given equipment lifetime. It is possible to modify the model to evaluate emissions reductions and costs over shorter or longer periods of time; this activity is reserved for future work.

Technology Constraints. Other technology constraints can also be included in the model. For example, if a certain technology cannot physically be installed on a particular vessel (or whether we want to run the model for cases in which we force engine or technology choice), the decision variable ($BINE_{v,e}$ or $BINK_{v,k}$) for that vessel and technology can be set equal to 0 or 1.

A primary constraint we used for the series of runs reported in this paper is that ULSD is considered the status quo fuel. Given new regulations that will go into effect in the next several years, we believe that ULSD will ultimately be the fuel powering the NY/NJ ferries. However, it should be noted that the model can relax this optional constraint to determine technology strategies when ULSD is not the status quo fuel.

Other examples of technical constraints include a requirement that when EGR is selected, DPF must also be used (eq 11) and a requirement that DPF and DOC will not be used on the same vessel (eq 12). These equations are, respectively,

$$BINK_{v,DPF} - BINK_{v,EGR} \geq 0 \tag{11}$$

$$BINK_{v,DPF} \cdot BINK_{v,DOC} = 0 \tag{12}$$

Minimize Emissions with Budget Constraint. We can also turn the model upside-down by setting the left-hand side (LHS) of the emissions constraint as the objective function and setting the cost equation as the LHS of a budget constraint. This is useful if we want to explore the best way to spend limited dollars to reduce emissions. We explore this idea in Cases 5 and 6 below.

RESULTS AND USES OF THE MODEL

The model can be used for several different purposes. Here we discuss its usefulness for two purposes: (1) identifying least-cost fleetwide technology strategies to meet emissions goals; and (2) maximizing emissions reductions for a given budget constraint. Aside from technical configurations, the model can also identify average cost-effectiveness of emissions reductions ($/tonne), economic costs by vessel, emissions by vessel, and the distribution of costs among ferry operators.

Results from the model for a set of example cases are shown in Table 2. Table 3 includes specific technology choices for the vessels under Case 1 assumptions, and Table 4 includes similar results for Case 2. The cases are as follows:

- Base case: no reduction requirements; emissions represent the status quo;
- Case 1: minimize cost with 30% NO_x and 60% PM reductions;

Table 2. Summary of costs and emissions for cases.

	Cost[a] ($million)	NOx (tonne)	PM (tonne)	Vessels with Technology Installed[b] (*n*)											
				SQ	T1	T2	IAF	FIE	SCR	DPF	ULSD	EGR	EMD	LNC	DOC
Base case	–	2023	51.6	45	–	–	–	–	–	–	45	–	–	–	–
Case 1	1.64	1415	20.5	45	0	0	26	1	7	20	45	0	0	0	25
Case 2	0.57	1709	36.1	45	0	0	29	0	2	5	45	0	0	0	39
Case 3	1.02	2023	20.6	45	0	0	0	0	0	16	45	0	0	0	29
Case 4	0.63	1416	51.6	45	0	0	38	4	3	0	45	0	0	0	5
Case 5	–	1160	45.8	45	0	0	35	2	8	0	45	0	0	0	7
Case 6	–	2023	15.1	45	0	0	0	0	0	22	45	0	0	0	21

[a]For Cases 1–4, costs are annual costs; for Cases 5 and 6, costs are $10 million net present value; [b]Vessel counts add up to more than 45 because the owners/operators of some vessels install multiple technologies; SQ = status quo; T1 = Tier I engine; T2 = Tier II engine.

- Case 2: minimize cost with 15% NO_x and 30% PM reductions;
- Case 3: minimize cost with 60% PM reductions (no required NO_x reductions);
- Case 4: minimize cost with 30% NO_x reductions (no required PM reductions);
- Case 5: maximize PM reductions within a $10 million budget (net present value); and
- Case 6: maximize NO_x reductions within a $10 million budget (similar to Case 5).

As shown in Table 2, in no case does a vessel's owner/operator choose to repower with a Tier I or Tier II engine. This is because the engines of almost all the vessels in this particular fleet have repowered since 2000. Thus, the emissions from these engines in most cases meet Tier I standards as is (and even Tier II standards as well). Also shown in Table 2 is the negligible role that EGR, EMD, and LNC play in reducing emissions from a least-cost standpoint. None of these is chosen in any case.

The differences in technology choice by vessel for Cases 1 and 2 are shown in Tables 3 and 4, respectively. Case 1 (Table 3) represents an aggressive emissions reduction target (30% NO_x reductions and 60% PM reductions). Here, emissions reductions are met with IAF technology installed on almost two-thirds of the fleet (26 vessels), SCR technology installed on 7 vessels, and every vessel having some PM control technology installed (20 DPF and 25 DOC). In this case, six of the seven vessels with SCR installed also have DOC installed.

Case 2 (Table 4), on the other hand, represents a less aggressive target (15% NO_x reduction and 30% PM reduction). Here, although a few more vessels have IAF technology installed, only two have SCR installed. PM reductions are achieved through less reliance on DPF (installed on only 5 vessels) and more on DOC (installed on 39 vessels). For one vessel, nothing is done with respect to PM emissions.

Cases 3 and 4 demonstrate cases in which a reduction of only one pollutant is required. By dividing the total costs of control by the total emissions reductions for each pollutant, one can determine an average control cost ($/tonne) for each pollutant. For NO_x, the average is approximately $1040/tonne; for PM, the average is approximately $33,000/tonne. (Note that there are some minor PM reductions in the NO_x reduction case, and vice versa).

Finally, Cases 5 and 6 present a different kind of model run. Here, we take the LHS of the emissions constraint and set it as the objective function. We then take the original least-cost objective function and turn it into a budget constraint. We run the model to minimize emissions from the ferry fleet such that the net present value for emissions control costs is not greater than $10 million. (This would mimic a case in which a government agency desires to spend a sum of money on reducing emissions and wants to know how to spend that money most wisely.) We run the model minimizing NO_x emissions (Case 5) and PM emissions (Case 6). The results imply that for $10 million, we can reduce NO_x emissions by ~50% from the base case; whereas for $10 million we can reduce PM emissions by ~85% with no increase in NO_x emissions.

IMPLICATIONS

An important outcome of this research is the use of MEOM for developing emissions reduction programs. The model can be used to identify least-cost fleetwide technology choices to achieve emissions reduction targets. Policy-makers could use these results to craft programs aimed at achieving a similar technology mix.

Table 3. Emission control technology choice by vessel for Case 1.

Vessel ID	ULSD	IAF	FIE	SCR	EGR	LNC	EMD	DPF	DOC
1	●								●
2	●								●
3	●	●							●
4	●	●							●
5	●	●							●
6	●	●							●
7	●	●						●	
8	●								●
9	●	●						●	
10	●	●							●
11	●	●						●	
12	●	●						●	
13	●	●						●	
14	●	●						●	
15	●	●						●	
16	●			●					●
17	●			●					●
18	●			●					●
19	●	●							●
20	●	●						●	
21	●	●						●	
22	●	●						●	
23	●	●						●	
24	●	●						●	
25	●	●						●	
26	●	●						●	
27	●	●						●	
28	●	●						●	
29	●			●					●
30	●	●						●	
31	●			●					●
32	●			●					●
33	●	●						●	
34	●	●							●
35	●								●
36	●								●
37	●								●
38	●								●
39	●								●
40	●								●
41	●		●						●
42	●								●
43	●								●
44	●			●				●	
45	●	●						●	

Table 4. Emission control technology choice by vessel for Case 2.

Vessel ID	ULSD	IAF	FIE	SCR	EGR	LNC	EMD	DPF	DOC
1	●	●							●
2	●	●							●
3	●								●
4	●	●							●
5	●								●
6	●								●
7	●								●
8	●								●
9	●	●							●
10	●								●
11	●								●
12	●								●
13	●	●							●
14	●	●							●
15	●	●							●
16	●	●							●
17	●	●							●
18	●	●							●
19	●	●							●
20	●								●
21	●	●							●
22	●	●						●	
23	●	●						●	
24	●	●						●	
25	●	●							●
26	●	●						●	
27	●	●							●
28	●	●							●
29	●	●							●
30	●	●							●
31	●	●							●
32	●	●							●
33	●	●							●
34	●	●						●	
35	●								●
36	●								●
37	●								●
38	●	●		●					●
39	●								●
40	●								●
41	●	●		●					●
42	●								
43	●								●
44	●	●							●
45	●	●							●

From the cases explored here, the following regulatory question emerges: How does one get the owners/operators of key vessels to install expensive emissions control technology? One method is to provide the financial incentives that buy-down the upfront costs of these technologies to some reasonable level. This can be done through partial rebates, no-interest loans, or direct grants.

However, ensuring that these technology retrofits are installed on the most polluting vessels is another challenge. Regulators could set rebates and other financial incentives as a function of engine age or pollution levels. Such an approach is similar to the on-road vehicle rebate programs that have been tested in some states; in those programs, owners are offered financial incentives to turn in their old vehicles. Regulators could also fund only those vessels that exhibit the operational characteristics that make them a high-polluting vessel.

Taxes or emissions fees represent other mechanisms at the regulator's disposal for encouraging ferry operators to reduce emissions. Vessels could be charged a \$/tonne emissions fee, thus providing a disincentive to operating heavily polluting vessels. Of course, one of the many problems of an emissions fee system is determining the proper tax to set. Setting a tax too low will not create the important incentives to install emissions control technology, and setting a tax too high may cause ferry operators to overcontrol at a significant cost to them (and presumably their passengers).

Finally, another mechanism for achieving fleetwide emissions reductions at least cost is to implement some kind of market-based emissions trading program. For example, a cap-and-trade system in which vessels are allocated tradable emissions allowances could be considered. In such a system, vessels may receive allowances based on historic emissions levels (or some other measure). Vessel operators could then trade these allowances within their own operations or with other operators. In these systems, the regulatory body sets the initial level of allowances, the distribution method, and perhaps the market tools for efficient trading, whereas the vessel operators find the least-cost arrangement of allowance and technology retrofits to meet their limits cost-effectively. In this specific case, with only three operators managing 45 vessels, the market may not be competitive, although transaction costs are likely to be low.

All of these mechanisms should be considered systematically in light of the results of this model and the realities of vessel operation in the NY/NJ Harbor. Indeed, the next phase of this research is to help decision-makers develop policy mechanisms that would allow the private ferry fleet to achieve emissions reductions at least cost. Now that we understand what the technical configuration may be for that efficient solution, we can assist in devising the policy response.

CONCLUSIONS

This paper discussed the structure and uses of the MEOM model. This model will assist decision-makers in identifying optimal strategies for reducing emissions from private ferry vessels operating in the NY/NJ Harbor. MEOM is a flexible model that can be easily modified to include different vessel types, other pollutants, and a more diverse array of emissions control technologies. MEOM is also not relegated to study of the NY/NJ Harbor or to ferries: We expect that MEOM would be a useful tool for all coastal areas where vessel engine emissions are of particular concern.

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About the Authors

James J. Winebrake is an associate professor and chair of the STS/Public Policy Department at Rochester Institute of Technology; James J. Corbett is an assistant professor in the Marine Policy Studies Program at the University of Delaware; Chengfeng Wang is a graduate student in the Marine Policy Studies Program at University of Delaware; Alexander E. Farrell is an assistant professor in the Energy Resources Group at the University of California Berkeley; and Pippa Woods is with the Transportation Policy Institute at Rutgers University. Address correspondence to: James J. Winebrake, STS/Public Policy Department, Rochester Institute of Technology, Rochester, NY 14623; e-mail: jjwgpt@rit.edu.