Joint Environmental and Cost Efficiency Analysis of the Electricity Production Industry: Applying the Materials Balance Condition

Eric W. Welch
Darold T. Barnum

Great Cities Institute
College of Urban Planning and Public Affairs
University of Illinois at Chicago

Great Cities Institute Publication Number: GCP-09-03

A Great Cities Institute Working Paper

February 2009

GREAT Cities
UIC'S METROPOLITAN COMMITMENT

UIC

The Great Cities Institute
The Great Cities Institute is an interdisciplinary, applied urban research unit within the College of Urban Planning and Public Affairs at the University of Illinois at Chicago (UIC). Its mission is to create, disseminate, and apply interdisciplinary knowledge on urban areas. Faculty from UIC and elsewhere work collaboratively on urban issues through interdisciplinary research, outreach and education projects.

About the Author

Eric W. Welch
Graduate Program in Public Administration
College of Urban Planning and Public Affairs
University of Illinois at Chicago

Darold T. Barnum
Department of Managerial Studies
Department of Information & Decision Sciences
Great Cities Institute
University of Illinois at Chicago

Great Cities Institute Publication Number: GCP-09-03

Great Cities Institute (MC 107)
College of Urban Planning and Public Affairs
University of Illinois at Chicago
412 S. Peoria Street, Suite 400
Chicago IL 60607-7067
Phone: 312-996-8700
Fax: 312-996-8933
http://www.uic.edu/cuppa/gci

Joint Environmental and Cost Efficiency Analysis of the Electricity Production Industry: Applying the Materials Balance Condition

Abstract

The electricity generation industry produces a substantial proportion of the greenhouse gases that contribute to climate change in the United States and globally. Yet, little research has been done to examine what the economic and environmental tradeoffs currently are for electric power plants. This paper demonstrates a new method, developed by Coelli, Lauwers, and Van Huylenbroeck [4,1,3], to calculate the optimal allocation of carbon containing fuel inputs and consideration of economic costs of electricity production. Using EIA 906 and FERC 423 data, the paper estimates cost/carbon tradeoffs facing two sets of plants: those that use coal and gas inputs and those that use coal, gas and oil inputs. Findings show that for the three input case, there is a 78.9% percent increase in cost for moving from the cost efficient point to the carbon efficient point, while there is a 38% increase in carbon to move from the carbon efficient point to the cost efficient point. These findings, while based only on a subset of electric power plants, indicates that the policy gap between efficient cost and environmental production is wide and will require substantial government and market incentives, as well as restructuring of the industry before it can be narrowed. The paper also identifies some plants that are super inefficient: they can improve both cost and carbon efficiency by changing their mixture of carbon inputs.

Keywords: Electricity generation, cost and environmental efficiency, data envelopment analysis, DEA, carbon

INTRODUCTION

During the past four decades, environment pollution from economic activities has increasingly been recognized as a critical problem, and pollution from electricity generation has been no exception. The Environmental Protection Agency (EPA) calculates that electricity generation contributes approximately 39% of all human related emissions of carbon dioxide in the United States (http://epa.gov/climatechange/emissions/co2_human.html#fossil). As policy actions that seek solutions to climate change become imminent, new methods for identifying incentives can that simultaneously reduce costs and carbon emissions provide valuable contributions to the electricity production industry and society alike.

One line of research has applied non-parametric efficiency analysis techniques to produce performance measures that recognize the range of economic and environmental inputs and outputs of manufacturers in various industries (e.g., see reviews by [10,13]. In most of this research, pollution is included in the efficiency model as either an additional input or a negatively scaled additional output of the production process [1,5,8,9,11]. With respect to the energy industry, Fare et al. was early to incorporate the consideration of a weak disposable environmental output (pollution) variable into data envelopment analysis (DEA) analysis of electric utilities (1996). This and other analyses have incorporated both sulfur dioxide and nitrogen oxides into efficiency analysis of US coal fired electric power plants [6] and productivity changes among Taiwanese power plants [2]. Research to date on electricity industry has not sought to integrate carbon dioxide, one of the main contributors to climate change and easily calculable from material input quantities.

Past approaches have a number of shortcomings, however. First, they have no economic interpretation—if a firm's technical efficiency declines (or increases) when a pollution variable is added, the change provides no information about the economic cost (or benefit) of this outcome. For example, even though it is possible to show that an electricity generation plant using only natural gas will emit lower pollution but have higher cost per unit of electricity produced than a plant using only low-grade coal, traditional approaches cannot determine whether the trade-off is economically sound or not. The solution is indeterminate because of the method's inability to estimate an economic cost of pollution. A second limitation of prior efficiency research is the focus on the technical efficiency of the production process has generally treated select pollutants as byproducts. From the perspective of material balance, this approach obviates the fundamental material connection between inputs and outputs; traditional approaches do not consider the optimal allocation of inputs based on their contents, such that waste can be reduced. In the case of carbon emissions in electric generation industry, an efficiency analysis that also considers the carbon content of different fuel inputs can help identify appropriate environmental tradeoffs.

In their seminal working paper and article, Coelli, Lauwers, and Van Huylenbroeck [4,3] introduced a new methodological approach that avoids the preceding shortcomings of conventional models, and applied it to Belgium pig-finishing operations. The new method is much more closely tied to economic methodology than past approaches, thereby increasing its usefulness when both physical productivity and costs are of concern. This article uses the Coelli et al. method to examine both the optimal allocation of carbon containing fuel inputs and consideration of economic costs of electricity production.

THE COELLI-LAUWERS-VAN HUYLENBROECK METHOD

Suppose a utility wishes to produce a given amount of electricity with two types of input – coal and gas. These two fuels are substitutes, of course, but they are not perfect substitutes because the boiler fuel configuration is fixed in the short term. That is, boilers have decreasing returns to scale, so the more electricity that must be produced based on the energy from an individual boiler, the last unit of electricity produced will require more fuel input the previous unit [14]. This fact results in imperfect factor substitutability between the amounts of coal and gas inputs needed by a technically efficient utility to produce a given amount of electricity, such as the one illustrated in Figure 1 by the dotted line (a piece-wise isoquant). For example, a technically efficient utility could generate a fixed amount of electricity with about 4.25 BTUs of gas and 0.75 BTUs of coal, with about 1.75 BTUs of each, or with about 0.75 BTUs of gas and 4.25 BTUs of coal.

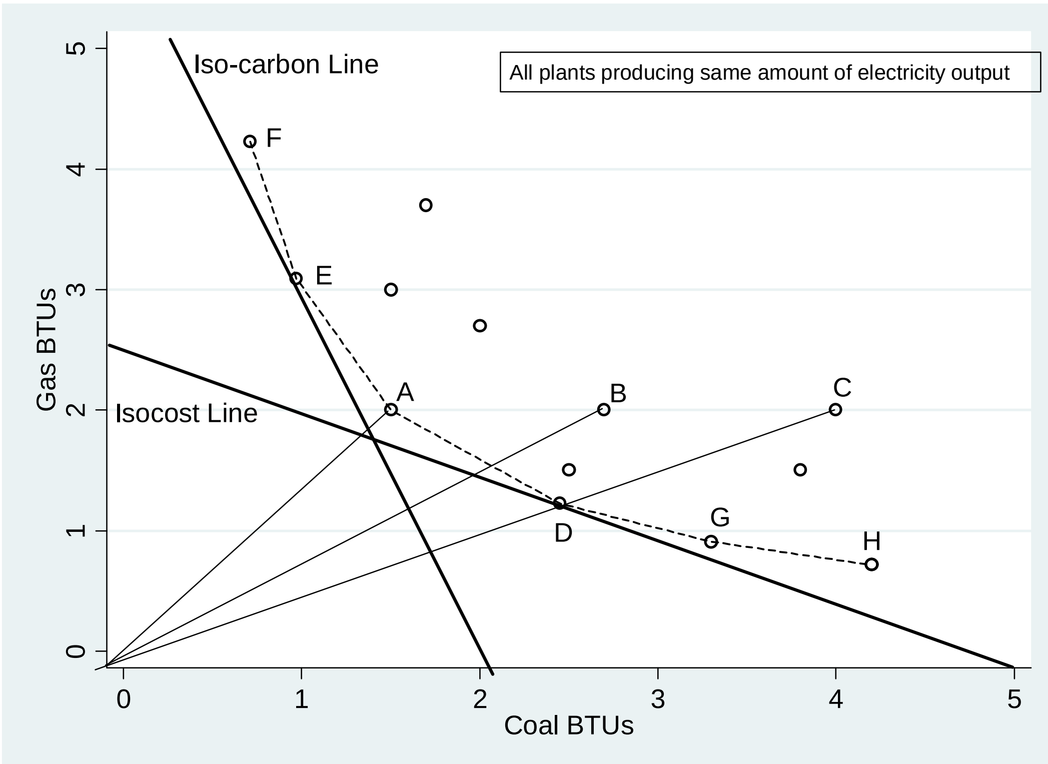
The isoquant, that is the efficient frontier, is defined by those plants using the lowest amount of one input for a given amount of the other. Any plant on the line is technically efficient, and any plant using more input is technically inefficient. In the illustration, plants A and D are technically efficient and plants B and C are technically inefficient

Although a plant will be technically efficient with any input combination on the isoquant, the place it should be on the isoquant depends on input prices if it wishes to minimize total cost. To determine this point, we need to draw an isocost line, with each point on the line representing the combination of inputs available for a given sum. For the line as it is drawn in Figure 1, for a given amount of money a buyer can purchase, for example, 5 BTU equivalents of coal and no gas, no coal and 2.5 BTU equivalents of gas, or about 2.5 BTU equivalents of coal and 1.25 BTU equivalents of gas. If the entire line is moved downward, the amount of money required for the reduced quantities will drop, and if it is moved upward the amount of money required for the increased quantities will rise. Because a technically efficient plant must purchase enough inputs to be on the isoquant, the minimum cost will occur where the isoquant and isocost lines are tangent, which in the example is the input usage of plant D. Note that although plant A is technically efficient, it is not cost efficient because the line (and therefore total cost) has to move further up in order to pay for A's input combination.

Finally, we come to the insight introduced by Coelli, Lauwers, and Van Huylenbroeck [4,3]. The amount of pollution per BTU can be considered the “price” of that pollution. So, just as we did with the prices we had to pay for inputs, we can just substitute the price of pollution, construct an isopollution line, and use it to find the technically efficient combination of inputs that will minimize pollution. For example, for the isocarbon line in Figure 1, all of the preceding comments about cost efficiency apply to carbon efficiency. With this new pollution indicator, we can compare plants based on their relative contribution to pollution.

There is more. Now we can compare the input ratios of a cost-efficient point on the isoquant and a pollution-efficient point on the isoquant. For our illustration in Figure 1, an isopollution line for carbon emissions would have a slope of 2.55/1.43, which would mean that it would obtain tangency with the isoquant where the ratio of gas to coal BTUs is about 3 to 1, as represented by the next to highest technically efficient DMU. Knowing this information would allow us to estimate the cost per unit minimizing pollution with the current technology and input characteristics, which would be the cost of moving from the cost-efficient point represented by plant D to the pollution-efficient point represented by plant E. We could use this information as a basis for setting the size of a pollution tax on the worst-polluting input and/or the size of an anti-pollution subsidy for the least-polluting input, in order to encourage plants to change their input combinations to the one that minimizes total pollution. In some cases, as noted by Coelli, Lauwers, and Van Huylenbroeck [4], a technically efficient but cost inefficient plant might actually lower its total costs as well as total pollution by moving toward the pollution-minimizing position. In our illustration, this would be true for plants F, G and H.

Figure 1. Cost and Environmental Efficiency Illustration



Application to U.S. Electrical Plants and Utilities

This analysis takes advantage of two publicly available Energy Information Agency (EIA) datasets that record the consumption and production of electric power plants in the United States. The Federal Energy Regulatory Commission (FERC) Form 423 dataset contains monthly cost and quality of fuels for approximately 600 regulated electric utility plants. These data are collected on a monthly basis by FERC for all fuel types used either for steam turbine or combined-cycle gas and steam turbine for plants generating 50 or more megawatts. These data have been collected for more than three decades such that the reporting procedures, data cleaning, and disclosure activities are well understood and standardized (EIA, 2008). Data included in the FERC Form 423 include fuel type, quantity, BTU content, sulfur content, ash content, cost, as well as contract information, origin and destination information. The EIA 906 dataset contains monthly plant level data on fuel type, BTU consumption, electricity generation, and heat content collected from just under 4,300 utilities and non-utilities that generate at least one megawatt. Prior to 2004, the EIA 906 data included combined heat and power plants, but since 2004 those data are collected in a different form.

The resulting data includes all regulated electric power plants of one megawatt or larger for four years from 2002 through 2005. Fuel type and cost data (cents per million BTUs) from FERC 423 and fuel type, BTU content of fuel consumed (million BTUs and calculated metric tons of carbon) and electricity generation data (megawatt hours) from EIA 906 are used in the analysis. All data are accessible at the EIA website http://www.eia.doe.gov/cneaf/electricity/page/data.html.

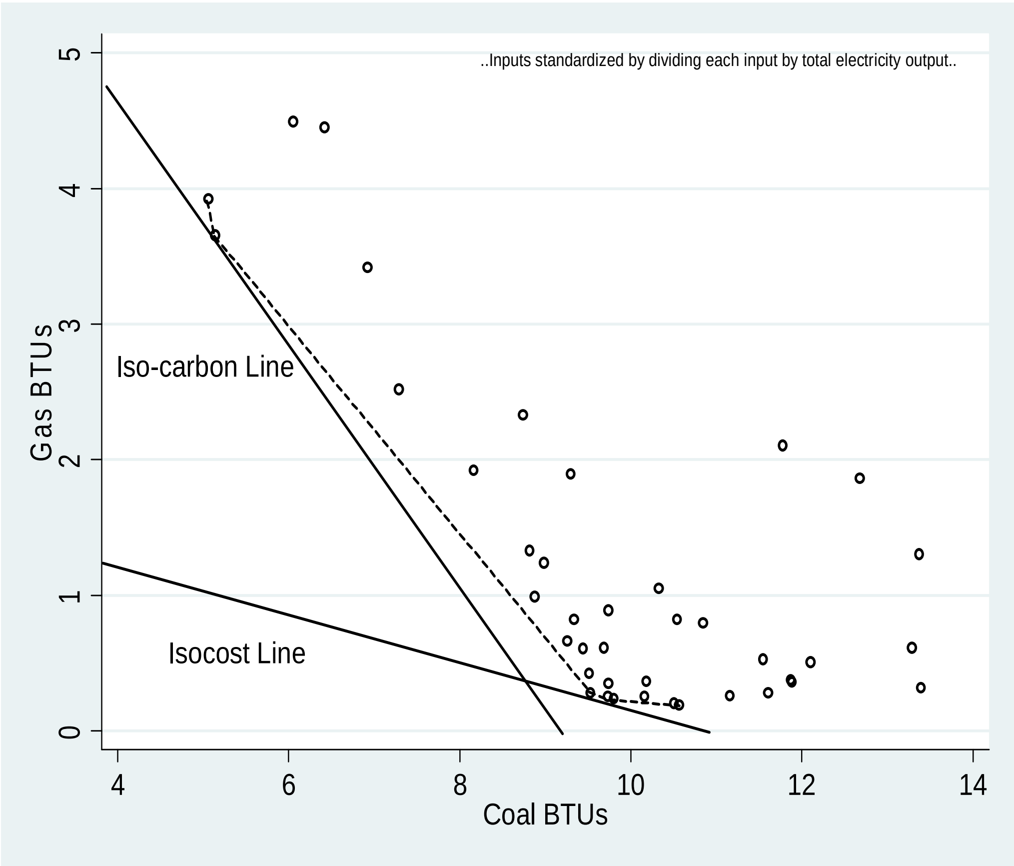
We apply the preceding methodology to two samples of U.S. electricity generation plants, using mean values for the period 2002-2005. Although the procedure can accommodate any number of pollutants, input types, and desirable outputs, in order to more clearly demonstrate the procedure we consider only carbon pollutants. For our first illustration we consider, coal and gas inputs, and MM Kilowatts of Electricity output, and for our second illustration we add oil inputs. Further, for the first sample of plants, we limited ourselves to those plants that produced at least one percent of their electricity from gas and at least one percent from coal, and, for the second sample, we included all plants that used some of each of the three inputs, but with no more than 97 percent of the electricity was generated from coal. This was done because the plants had to have sufficient boilers using each type of fuel to make it possible to substitute one for the other to at least some degree.

In total, our first plant sample consisted of 40 plants with four years of data for each, and our second sample consisted of 30 plants with four years of data for each. In order to minimize random errors we aggregated the plant data over the four years, resulting in 40 data points for the first sample and 30 for the second. We illustrate the first sample graphically and the second using DEA linear programming models.

It should be noted that the full impact of changing rates of technical substitution between the fuels cannot be estimated from our data, because we do not control for the boiler capacity available in each plant for each fuel. For example, we would expect plants with the most gas boiler capacity to use the most gas, and those with the most oil boiler capacity to use the most oil. Therefore we would expect the observed rates of technical substitution to be more linear than would be the case if all plants had the same proportions of boiler capacity available.

However, the methodology applies even if the rate of technical substitution is completely linear over its entire range, with the only consequence being that the isocost and isopollution lines will intersect with the isoquant at one or the other of its end points rather than tangents closer to its middle. As can be observed in Figure 2, as would be expected the isoquant is linear over much of its range. However, the rate of technical substitution does change before reaching the endpoints, which may indicate that those plants with the highest proportions of gas and coal capacities overuse their favored fuels and as a consequence face declining returns from them. Another possibility could be that the plants with the highest usages of each fuel type may have a relative price ratio which favors their favorite fuel by more than the average price ratio for all plants studied. This would shift the isocost for such plants in a way that might make the fuel ratio chosen economically justified. However, identifying the reasons for a plant's particular choice is beyond the scope of this paper, and, in all illustrations, the methodology is valid.

Figure 2. First Sample Plant



<u>Graphical Analysis: the First Plant Sample</u>

Plant data from the first sample are shown in Table 1. We can show the relationship between inputs, holding the output constant, by dividing each input by the output. These relationships are graphed in Figure 2, which also illustrates the isoquant, isocarbon and the isocost lines, with all based on four-year averages.

Table 1. First Plant Sample Data

PLANT NAME	PLANT CODE	UTILITY NAME	STATE	Ave Gen Electricity	Ave BTUs of Coal Consumed	Ave BTUs of Gas Consumed
A B Brown	6137	Southern Indiana Gas & Elec Co	IN	6,163,066	30,294,398	790,320
Apache Station	160	Arizona Electric Pwr Coop Inc	AZ	5,517,537	27,926,967	2,550,636
Asheville	2706	Carolina Power & Light Company	NC	4,529,376	21,986,752	1,410,674
B C Cobb	1695	Consumers Energy Co	MI	4,226,319	20,947,899	508,244
Bay Front	3982	Northern States Power Co	WI	357,821	2,502,618	244,302
Black Dog	1904	Northern States Power Co	MN	3,441,034	15,856,662	3,725,422
Blount Street	3992	Madison Gas & Electric Co	WI	838,061	5,325,384	951,687
Blue Valley	2132	Independence (City of)	MO	520,966	3,536,185	163,373
Chesterfield	3797	Virginia Electric & Power Co	VA	16,597,123	78,253,149	8,748,091
Dan E Karn	1702	Consumers Energy Co	MI	6,859,350	33,231,640	2,909,784
Deerhaven	663	Gainesville Regional Util	FL	2,697,559	13,606,948	2,770,980
Greene County	10	Alabama Power Co	AL	7,389,720	35,122,303	2,509,806
Hamilton	2917	Hamilton (City of)	OH	585,718	3,966,695	93,407
Hawthorn	2079	Kansas City Power & Light Co	MO	8,103,708	40,586,506	2,569,911
Irvington	126	Tucson Electric Power Company	AZ	1,726,362	6,854,478	4,753,060
Jack Watson	2049	Mississippi Power Co	MS	7,796,611	37,629,418	1,666,149
Kraft	733	Savannah Electric & Power Co	GA	2,329,365	12,728,829	987,059
Lansing Smith	643	Gulf Power Company	FL	5,972,656	20,492,696	14,586,950
Lon Wright	2240	Fremont City of	NE	934,960	5,487,513	132,764
McIntosh	6124	Savannah Electric & Power Co	GA	2,022,710	10,851,116	1,101,141
Muskogee	2952	Oklahoma Gas & Electric Co	OK	19,957,230	105,792,226	2,044,087
Neil Simpson II	7504	Black Hills Power & Light Co	WY	1,450,209	8,194,842	600,839
Northeastern	2963	Public Service Co of Oklahoma	OK	16,090,651	68,427,176	23,656,034
Northside	667	JEA	FL	2,006,228	7,672,278	5,699,362
O H Hutchings	2848	Dayton Power & Light Co	OH	1,437,523	8,669,126	272,008
Polk	7242	Tampa Electric Co	FL	2,871,141	13,640,274	1,885,875
Quindaro	1295	Kansas City (City of)	KS	1,673,766	9,429,930	218,790
R S Nelson	1393	Gulf States Utilities Co	LA	9,143,283	37,642,747	18,584,254
Rawhide	6761	Platte River Power Authority	CO	4,258,193	21,833,538	540,271
River Rouge	1740	Detroit Edison Company	MI	5,324,570	25,605,350	749,231
Riverside	1081	MidAmerican Energy Company	IA	1,354,643	8,354,412	349,435
Rodemacher	6190	Central Louisiana Electric Co	LA	6,899,953	33,651,611	8,964,868
S A Carlson	2682	Jamestown (City of)	NY	356,438	2,498,037	367,034
Silver Lake	2008	Rochester (City of)	MN	558,636	3,297,863	150,411
Sutherland	1077	IES Utilities Inc	IA	1,683,701	10,158,074	306,901
Trimble County	6071	Louisville Gas & Electric Co	KY	7,954,439	39,376,529	1,396,389
Urquhart	3295	South Carolina Elec & Gas Co	SC	1,707,941	5,719,220	4,435,170
Wabash River	1010	PSI Energy, Inc	IN	9,513,163	45,426,084	6,839,605
Weston	4078	Wisconsin Public Service Corp	WI	6,750,844	35,898,099	648,762
Yates	728	Georgia Power Co	GA	11,941,318	61,873,256	2,203,385

Note: For this sample, mean 2002-2005 costs per BTU were \$0.016 for coal and \$0.050 for gas. Mean carbon per BTU is 25.5 units for coal and 15.3 units for gas.

Note that a declining rate of technical substitution (RTS) between the inputs only sets in at the extremes of the isoquant, with a large portion of the middle section representing a constant RTS. Also of interest is that some plants are substantially more efficient than others, and some do not appear to be mixing inputs such that they will be cost efficient. Also, it is notable but not surprising that the points of tangency with the isoquant are different for the isocost and isocarbon lines, with the two points occurring at the opposite ends of the constant RTS section of the isoquant. This would mean that taxes on coal and or subsidies for gas would have to be relatively high in order to induce utilities to change their fuel proportions for economic reasons.

More observations can be made from Figure 2. First, most facilities are located near the isocost-isoquant tangent point, a result that provides some face validity to the analysis. Second, the figure shows that most of the plants are not technically efficient, and they could reduce both their costs and carbon outputs by becoming more technically efficient. Third, there are a substantial number of plants – including some of the technically efficient plants – that could reduce both their costs and carbon outputs by substituting gas for coal. These include the four technically efficient plants to the right of the isocost tangency point with the isoquant as well as the inefficient plants to their right that are using about the same amount of gas but far more coal. Finally, the technically efficient plant using the most gas could also decrease its costs and carbon output by using less gas and more coal. In short, there are a substantial number of plants that could lower both costs and carbon output, a no-lose situation for all concerned.

DEA Models and Procedures

We do not attempt to illustrate the second sample graphically, because its three inputs make it difficult to show graphically. We therefore use formal DEA analysis for the sample.

Our DEA model to measure technical efficiency (1-4) is input oriented and reflects constant returns to scale. For both of our samples, the relationship between electricity output and BTU input was linear, which is not surprising because it would be expected that utilities would match capital and fuel inputs to maintain constant returns to scale. All DEAs were conducted with Tone's DEA-Solver software [12]. For each observation $j = 1,...,J$ there are data on

$n = 1,...,N$ inputs and on $m = 1,...,M$ outputs, where $x^j = (x_{j1},...,x_{jN}) \in \mathbb{R}_+^N$ and $y^j = (y_{j1},...,y_{jM}) \in \mathbb{R}_+^M$. For both samples, *m* = 1; for the first sample, *n* =2 and for the second sample *n* = 3. The DEA score θ estimates the technical efficiency of the target DMU *k*.

$$\min_{\boldsymbol{\lambda}} \theta \tag{1}$$

subject to

$$\sum_{j=1}^{J} x_{jn}\lambda_j \le \theta x_{kn} \qquad n = 1,...,N \tag{2}$$

$$\sum_{j=1}^{J} y_{jm}\lambda_j \ge y_{km} \qquad m = 1,...,M \tag{3}$$

$$\lambda_j \ge 0 \qquad j = 1,...J \tag{4}$$

Our DEA model to measure cost efficiency and environmental efficiency (5-8) also is input oriented and reflects constant returns to scale. We show it in vector form.

$$\mathbf{cx}^* = \min_{x\lambda} \mathbf{cx} \tag{5}$$

subject to

$$\mathbf{x} \le \mathbf{X}\boldsymbol{\lambda} \tag{6}$$

$$\mathbf{y}_0 \ge \mathbf{Y}\boldsymbol{\lambda} \tag{7}$$

$$\boldsymbol{\lambda} \ge 0 \tag{8}$$

In this case, $\mathbf{c}$ is the vector of “prices,” which we assume are common for all observations, and $\mathbf{x}$ is the vector of fuel input amounts for the target DMU. In the case of cost efficiency, the prices are the relative amounts paid for each of the three types of fuel input, and in the case of environmental efficiency the prices are the relative amounts of carbon produced by each of the three fuel types. The vector $\mathbf{x}^*$ contains the target DMU’s inputs that minimize cost (or carbon), the matrix $\mathbf{X}$ contains the input values for all DMUs included in the analysis, and the matrix $\mathbf{Y}$ contains the output values for all DMUs included in the analysis. The vector $\mathbf{y}_0$ contains the original outputs for the target DMU, and $\boldsymbol{\lambda}$ is the vector of intensity weights.

The procedure is as follows. First we estimate technical efficiency (TE), cost efficiency (CE) based on input prices, and environmental efficiency (EE) based on the carbon content of the fuels. Using these three estimates, we project the BTU input from each fuel necessary to produce one megawatt of electricity (one unit of output) if a DMU is technically efficient, if it is cost efficient, and if it is environmentally efficient. Then, using the input price per BTU of each fuel, we can estimate the total cost per megawatt of generated electricity for each DMU based on its original inputs, its technically-efficient inputs, its cost-efficient inputs, and its environment-efficient inputs. Next, we can perform the same estimates using input carbon content per BTU of each fuel, that is, total carbon per unit of electricity output for each DMU based on its original inputs, its technically-efficient inputs, its cost-efficient inputs, and its environment-efficient inputs. Finally, we can compare the outcomes.

Recall that our cost per BTU equivalent of input was the average for all DMU purchases over all four years, for this sample being $0.015 for coal, $0.062 for gas, and $0.055 for oil. Carbon output per million BTUs is 25.5 tons for coal, 14.3 tons for gas, and 20.6 tons for oil.

DEA Analysis: the Second Plant Sample

Cost and carbon outcomes for the second plant sample appear in Tables 3 and 4, respectively. Calculated means in the first row of Table 3 show that on average plants would reduce costs by 6 percent if they were technically efficient and by 32 percent if they were cost efficient. Similarly, Table 4 plant means show that plants would reduce carbon emissions by 6 percent if they attained technical efficiency, and by 26 percent if they attained environmental efficiency.

Table 3. DEA Cost Results for Second Plant Sample

Plant Code	Original $ Cost Per Unit Output	% Changes in Cost Per Unit Output				
		OrigToTE	OrigToCE	OrigToEE	TEtoCE	TEtoEE
Means	**25.10**	**-6**	**-26**	**32**	**-21**	**41**
10	18.76	-0.2	-9	63	-9	63
160	20.42	0	-16	49	-16	49
643	30.52	0	-44	0	-44	0
663	27.63	-16	-38	10	-27	31
667	50.72	0	-66	-40	-66	-40
676	31.06	-3	-45	-2	-43	2
728	17.86	-4	-4	71	-0.1	79
733	21.84	-13	-22	40	-10	60
1010	21.79	-5	-22	40	-18	47
1295	19.26	-10	-11	58	-1	77
1355	19.30	-6	-12	58	-6	68
1393	35.87	-13	-52	-15	-46	-3
1702	22.93	-5	-26	33	-21	41
1915	20.88	0	-18	46	-18	46
1927	19.57	0	-13	56	-13	56
2682	31.09	-33	-45	-2	-18	47
2706	18.79	-1	-9	62	-8	65
3295	32.63	0	-48	-6	-48	-6
3406	17.11	0	-0.3	78	-0.3	78
3797	20.14	-1	-15	52	-15	52
3809	37.03	0	-54	-18	-54	-18
4125	42.74	-34	-60	-29	-40	8
6071	17.06	0	0	79	0	79
6073	25.44	0	-33	20	-33	20
6085	18.56	0	-8	64	-8	64
6124	23.60	-14	-28	29	-15	51
6190	28.64	-15	-40	7	-30	26
6761	17.13	0	-0.4	78	-0.4	78
7242	23.13	-5	-26	32	-22	39
7504	21.59	-15	-21	41	-7	66

Notes: Mean values all are computed from column data. For all DMUs, cost per unit of electricity output is $17.06 for cost efficiency and $30.52 for environmental efficiency. In all cases, therefore, the percentage increase in cost for moving from the cost efficient point to the carbon efficient point is (30.52 - 17.06)/17.06 = 78.9%.

Table 4. DEA Carbon Results for Second Plant Sample

Plant Code	Original Carbon Per Unit Output	% Changes in Carbon Per Unit Output				
		OrigToTE	OrigToCE	OrigToEE	TEtoCE	TEtoEE
Means	**25.51**	**-6**	**2**	**-26**	**9**	**-21**
10	24.57	-0.2	3	-25	3	-25
160	26.11	0	-3	-30	-3	-30
643	18.35	0	38	0	38	0
663	26.36	-16	-4	-30	14	-18
667	21.29	0	19	-14	19	-14
676	20.25	-3	25	-9	29	-6
728	26.48	-4.39	-4.37	-31	0.02	-28
733	28.00	-13	-10	-34	4	-25
1010	24.38	-5	4	-25	9	-21
1295	28.92	-10	-12	-37	-2	-29
1355	26.27	-6	-4	-30	2	-26
1393	22.66	-13	12	-19	28	-7
1702	24.91	-5	2	-26	7	-22
1915	24.51	0	3	-25	3	-25
1927	26.65	0	-5	-31	-5	-31
2682	35.00	-33	-28	-48	9	-21
2706	24.96	-1	1	-26	3	-26
3295	18.46	0	37	-1	37	-1
3406	26.86	0	-6	-32	-6	-32
3797	23.92	-1	6	-23	6	-23
3809	22.77	0	11	-19	11	-19
4125	35.86	-34	-29	-49	7	-23
6071	25.32	0	0	-28	0	-28
6073	20.71	0	22	-11	22	-11
6085	28.72	0	-12	-36	-12	-36
6124	27.89	-14	-9	-34	6	-23
6190	25.54	-15	-1	-28	17	-15
6761	26.28	0	-4	-30	-4	-30
7242	24.35	-5	4	-25	10	-21
7504	28.80	-15	-12	-36	3	-25

Notes: Mean values all are computed from column data. For all DMUs, carbon per unit of electricity output is 25.32 units for cost efficiency and 18.35 units for environmental efficiency. In all cases, therefore, the percentage increase in carbon for moving from the carbon efficient point to the cost efficient point is (25.32 - 18.35)/18.35 = 38.0%.

The 6 percent ratio is particularly important. It indicates that if all plants were to efficiently use currently-available technology, then both costs and carbon output would decline by 6 percent. It would be worthwhile to determine what changes would be necessary to increase the efficiency of the most inefficient plants to the level of their efficient peers. This might be a relatively low-cost method of significantly reducing carbon pollution, especially because some of the expense would be offset by fuel cost savings.

Note that plant 643 is environmentally efficient but does not have the highest cost per unit of electricity output. And, plant 6071 is cost efficient, but does not have the highest carbon output per unit of electricity output. Of course, both plants are technically efficient. Thus, being the best on one objective does not necessarily mean that a plant will be the worst on the other.

The second DMU (plant 160) in Table 3 is a technically efficient producer; however, it is neither cost efficient nor environmentally efficient. If it attained cost efficiency it would reduce its costs by 16 percent, and it would increase its costs by 49 percent if it became environmentally efficient. The same DMU in Table 4 would reduce its carbon output by 3 percent if it were to become cost efficient and by 30 percent if it were to become environmentally efficient.

This last example has an interesting and powerful implication: it is possible to identify technically efficient power plants that could simultaneously improve cost and environmental efficiency. In fact, five of the 30 plants in Table 4 (160, 1927, 3406, 6085, and 6761), all technically efficient, could improve both cost and environmental efficiency by moving to the cost-efficient point on the isoquant. In addition, two technically efficient plants in Table 3 (667 and 3809), could decrease costs and carbon by moving to the environmentally efficient point on the isoquant.

Technically efficient DMUs can produce anywhere on the isoquant, so their costs per unit output will vary. However, cost-efficient DMUs and environmentally-efficient DMUs must produce at specific cost-efficient and environmentally efficient points, which are tangent to the isocost and isocarbon lines, respectively. This means that the cost-efficient and environmentally efficient points will have carbon-cost trade-offs that are identical for all DMUs.

Cost efficiency results (Table 3) show that cost efficiency is attained at a cost per output unit of $17.06; this is the cost at which there is no difference between technically efficiency and cost efficiency. Plant 6071 is both technically and cost efficient, but it is environmentally inefficient. To attain environmental efficiency it must increase costs by 79 percent and decrease carbon outputs by 28 percent. Alternatively, environmental efficiency is attained at a cost per output unit of $30.52. Plant 643 is technically and environmentally efficient, but operates at a cost inefficient point. To attain cost efficiency, it would reduce costs by 44 percent and increase carbon by 38 percent. The percentage increase in costs for moving from the cost efficient point to the carbon efficient point for all plants is (30.52 – 17.06)/17.06 = 78.9%.

By contrast, findings for environmental efficiency (Table 4) show that carbon efficiency is attained with 18.35 units (plant 643) while cost efficiency occurs at 25.32 units (plant 6071) for all plants in the population. This means that movement from the carbon efficient point to the cost efficient point would result in a 38 percent increase in carbon output (25.32 – 18.35/18.35 = 38.0%).

CONCLUSIONS

This paper applies a new DEA method [4,3] to jointly analyze fuel and pollution efficiency from electricity production. Several important conclusions are evident.

First, based on our samples, fuel cost and carbon pollution both could be lowered simultaneously, using current technology, simply by increasing the technical efficiency of inefficient plants to a level closer to that of their efficient peers.

Second, technically efficient plants (accounting for almost a quarter of our second sample) could lower their costs and their pollution, because their positions on the isoquants are either greater than or less than both the cost and environmentally efficient points. If they move along the isoquant toward one, they also will be moving toward the other.

Third, there is a substantial gap between the isoquant-isocarbon and isoquant-isocost tangent points, so any technically efficient plant at one of these points or between them can only decrease carbon by increasing costs, or only decrease costs by increasing carbon. Because of the size of the gap, it would take very large subsidies for gas and/or very large pollution taxes on coal in order the change economic fuel-choice behavior of this subset of technically efficient plants.

Fourth, close study of the institutional aspects of the industry would need to be integrated into any attempts to apply our findings. Beyond the competitive dynamics of the energy market, fuel supplies are often secured in long term contracts and proximity to the source of the fuel is a primary consideration. As a result, selection of fuels that enable the plant to move toward the isocarbon point may be constrained by the characteristics of the fuel supply market [7]. Also, loading procedures may also limit the ability of plants to approach cost or environmental efficiencies. Incremental loading is a procedure in which different boiler units are selected to operate to generate electricity such that marginal costs are minimized. There is evidence that dynamic demands for energy make it difficult to calculate fuel costs in advance [14].

Beyond these characteristics of the industry, the findings in this paper, while preliminary and based on a small subset of electric power plants, clearly point to a significant environmental problem and an opportunity for the application of policies that are informed by both economic and technical relationships. While identification of specific policy instruments lies outside of the scope of this paper, it is reasonable to consider that new incentive systems could and should be developed by government to encourage the selection of technologies, operational techniques, fuel suppliers and other factors that simultaneously comply with the desire for cost efficiency and need for carbon reduction.

ACKNOWLEDGEMENTS

This research was partially supported by the Great Cities Institute at the University of Illinois at Chicago, whose mission it is to conduct and support engaged, interdisciplinary, high-impact research and practitioner partnerships that address key urban issues on a local and global scale.

Reference List

1. V.E.Ball, C.A.K.Lovell, R.Nehring, and A.Somaru. Incorporating undesirable outputs into models of production: an application to US agriculture. *Cahiers d'Economie et Sociologie Rurales* 31, 59-74 (1994).

2. C.F.Chien, W.C.Chen, and Y.C.Lin. A Case Study to Evaluate the Productivity Changes of the Thermal Power Plants of the Taiwan Power Company. *IEEE Transactions on Energy Conversion* 22, 680-688 (2007).

3. T.J.Coelli, L.Lauwers, and G.Van Huylenbroeck. Formation of technical, economic and environmental efficiency measures that are consistent with the materials balance condition. Centre for Efficiency and Productivity Analysis. Working Paper 06/2005. http://www.uq.edu.au/economics/cepa/docs/WP/WP062005.pdf (2005).

4. T.J.Coelli, L.Lauwers, and G.Van Huylenbroeck. Environmental efficiency measurement and the materials balance condition. *Journal of Productivity Analysis* 28, 3-12 (2007).

5. R.Fare, S.Grosskopf, C.A.K.Lovell, and C.Pasurka. Multilateral productivity comparisons when some outputs are undesirable: a non-parametric approach. *Review of Economic Statistics* 75, 90-98 (1989).

6. R.Färe, S.Grosskopf, and D.Tyteca. An activity analysis model of the environmental performance of firms - application to fossil fuel fired electric utilities. *Ecological Economics* 18, 161-175 (1996).

7. P.L.Joskow. Vertical Integration and Long-Term Contracts: The Case of Coal-Burning Electric Generating Plants. *Journal of Law, Economics and Organization* 1, 33-80 (1985).

8. I.Piot-Lepetit and D.Vermersch. Agriculture's environmental externalities: DEA evidence for French agriculture. *Journal of Agricultural Economics* 49, 85-99 (1998).

9. S.Reinhard, C.A.K.Lovell, and G.Thijssen. Environmental efficiency with mulitple environmentally detrimental variables; estimated with SFA and DEA. *European Journal of Operational Research* 121, 287-303 (2000).

10. H.Scheel. Undesirable outputs in efficiency valuations. *European Journal of Operational Research* 132, 400-410 (2001).

11. S.Shaik, G.A.Helmers, and M.R.Langemeier. Direct and indirect shadow price and cost estimates of nitrogen pollution abatement. *Journal of Agricultural Resource Economics* 27, 420-432 (2002).

12. K.Tone. Saitech DEA-Solver. http://www.saitech-inc.com/Products/Prod-DSP.asp (2008).

13. D.Tyteca. On the measurement of the environmental performance of firms - a literature review and a productive efficiency perspective. *Journal of Environmental Management* 46, 281-308 (2008).

14. J.Vardi and B.Avi-Itzhak. *Electric Energy Generation: Economics, Reliability, and Rates*. MIT Press, Cambridge, Mass (1981).