USING DATA ENVELOPMENT ANALYSIS TO EVALUATE THE PERFORMANCE OF POST-HURRICANE ELECTRIC POWER RESTORATION ACTIVITIES

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ABSTRACT

The post-hurricane restoration of electric power is attracting increasing scrutiny as customers' tolerance for even short power interruptions decreases. Currently there are no standards for what constitutes an acceptably fast restoration. This paper introduces the use of data envelopment analysis to help evaluate post-hurricane restorations through comparison with the experiences of other companies in similar storms. The method accounts for the variable severity of the hurricane themselves, so that companies are not penalized for outages that are long only because the hurricane that caused them was particularly severe. The analysis is illustrated through an application comparing 19 recent post-hurricane restoration experiences across 9 different electric power companies in the United States. The method could be applied to other types of infrastructure systems and other extreme events as well.

BIOGRAPHICAL SKETCH

Allison Coffey Reilly was born to Edna Mae and John Reilly in Albany, New York. Raised in Latham, New York, along with sister, Kristen and brother, Brendan, Allison attended Shaker High School. She graduated from The Johns Hopkins University in 2005 with a Bachelors of Science in Civil Engineering, with a focus in structural and geotechnical engineering. Allison is currently enrolled at Cornell University where she is pursuing an M.S./Ph.D. in Civil Infrastructure Systems with a concentration in economics. In her free time, Allison enjoys cooking and walks with her sister and dog, Harper.

To Mom, Dad, Kristen, and Brendan

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LIST OF ABBREVIATIONS

BCC	Banker, Charnes and Cooper Model. Also referred to as the Technical Efficiency model
CCR	Charnes, Cooper, and Rhodes Model. Also referred to as the Scale and Technical Efficiency Model
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
DOE	Department of Energy
FEMA	Federal Emergency Management Agency

LIST OF SYMBOLS

D	the set of discretionary input
F	the set of non-discretionary input
FS_j	the technical efficiency of *DMU j* model given that all DMUs have the same environment
N	number of DMUs
S	the set of outputs
s_{io}^{+}	amount by which the input *i* can be reduced for DMU *o* without reducing its technical efficiency
s_{ro}^{-}	the augmentation in the output for DMU *o*
x_{ij} -	the amount of discretionary input *i* for DMU *j*
y_{rj}-	the amount of output *r* for DMU *j*
z_j	the measure of the overall environmental harshness of the environment for DMU
z_{ij}-	the amount of non-discretionary input *i* for DMU *j*
ε	a small number (10^{-6})
θ_o	the technical efficiency of DMU *o*
λ_j	the level of contribution DMU *j* has on the technical efficiency score of DMU *o*

CHAPTER 1

INTRODUCTION

Hurricanes can cause widespread outages that last for days. In Hurricane Isabel in 2003, for example, 400,000 of Dominion Virginia Power's customers were still without power a week after the storm made landfall. These are extreme, relatively infrequent events. Nevertheless, as society's dependence on and expectation of uninterrupted electric power increases, regulators have increased their focus on power companies' natural disaster responses and post-disaster investigations by public utility commissions (e.g., NCPUC 2003) have become increasingly common (Ferrell 2005).

Currently, there are no set standards for what constitutes acceptable power system performance in a hurricane, earthquake, or other extreme event. In practice, public utility commissions review performance on a case-by-case basis following each major event, and the public makes its own assessment. It would be helpful to have a more consistent, transparent method for evaluation, and one that could be used before an event, when a power company is still able to make changes if it determines the expected performance is unacceptable. It is difficult to set absolute standards regarding what is considered an acceptably fast restoration (such as X% of customers should be restored in Y days). A standard should depend both on the societal impacts associated with different outage durations, and on what outage durations are possible to achieve in practice given that it takes some time for crews to move around and undertake the repairs and other activities necessary to restore power. Both of these dimensions are difficult to estimate. An alternative approach is to base restoration performance evaluations on a comparison to other companies' experiences in similar events. Data envelopment analysis (DEA) is well-suited to this problem.

Developed by Charnes *et al.* (1978), DEA is a nonparametric method to measure the relative efficiency of a homogeneous group of organizations (called decision making units, DMUs) that perform similar functions. In a DEA, the efficiency of a DMU can be measured by considering any number of inputs and outputs. The inputs and outputs can be noncommensurate (i.e., they do not need to be in the same units), and there is no need to specify the relative importance of each input and output. DEA produces a single scalar measure of efficiency for each DMU so the results of the analysis are easy to understand and communicate. Finally, DEA provides for the inclusion of what are called non-discretionary inputs. These are factors that are not under the control of the DMU but that influence its ability to create output.

In this research, each DMU is a post-hurricane electric power restoration performed by a specific utility. The most efficient restorations are those for which there is no other restoration or linear combination of restorations that was faster given the money spent or the storm severity. The most efficient restorations serve as an efficient frontier to which all other restorations are compared. Hurricane severity is considered a non-discretionary input, so that the analysis acknowledges that a utility does not have control over the hurricane severity, and therefore should not be penalized for restorations that take longer because they were associated with very severe hurricanes.

Since the evaluation of the performance of each DMU is maximized given the performance of other DMUs, the focus of the analysis is on each DMU rather then on the estimation of the parameters of a single model. This means the DEA does not require the specification of the functional form of the relationship between the independent and dependent variables. Rather, the DEA produces an estimate of the functional form of the efficient frontier (Charnes *et al.* 1994). Unlike statistical regression methods that measure performance based on deviations from average or "best fit" behavior, DEA uses the best observed performance as the frame of reference.

DEA has been used in the electric power industry to evaluate the relative efficiency of, for example, electricity distribution utilities in the U.S. (Pahwa *et al.* 2002), power plants in Israel (Golany *et al*. 1994), and service centers in Taiwan (Chien *et al.* 2003). Chien *et al.* (2003) and Yang and Lu (2006) offer recent reviews of this literature. There has also been a great deal of research on restoration of electric power and other infrastructure systems in hurricanes and other extreme events. Many studies have modeled the post-disaster restoration processes of various infrastructure systems in an effort to estimate expected restoration times, and several have tried to optimize post-disaster restoration strategies. Previous work in these two areas is summarized in Liu *et al*. (2007) and Xu *et al.* (2005), respectively. No published work could be found related to the *evaluation* of restoration processes, or the use of DEA related to performance in extreme events.

This paper introduces the use of DEA to evaluate post-hurricane restoration activities, and illustrates the approach with an application to compare 19 recent post-hurricane restoration experiences of 9 U.S. electric power companies. Although the utilities are not identified for confidentiality reasons, the data in this analysis are real. In Section 2, DEA models are reviewed, and the type of formulation used in this study is developed.

The analysis of post-hurricane electric power restoration is described in Section 3, and the thesis concludes with a summary of the strengths and limitations of this approach.

REFERENCES

Charnes, A., Cooper, W.W., and Rhodes, E. (1978) Measuring the efficiency of decision making units. *European Journal of Operational Research* **2**, 429-444.

Charnes, A., Cooper, W., Lewin, A., and Seiford, L. (1994) *Data Envelopment Analysis: Theory, Methodology, and Applications*. Kluwer Academic Publishers, Norwell, MA.

Chien, C-F., Lo, F-Y., Lin, J.T. (2003) A DEA study to evaluate the relative efficiency of the service center and improve operation efficiency through reorganization. *IEEE Transactions on Power Systems* **18**(1), 366–373.

Ferrell, E.O. (2005). Dealing with disasters: Utility restoration of service. Edison Electric Institute. Washington, D.C. [Online]. Available: www.eei.org/meetings/nonav_2005-04-07-lm

Golany, B., Roll, Y., and Rybak, D. (1994) Measuring Efficiency of Power Plants in Israel by Data Envelopment Analysis. *IEEE Transactions on Engineering Management* **41**(3), 291-301.

Liu, H., Davidson, R., and Apanasovich, T. (2007) Statistical forecasting of electric power restoration times in hurricanes and ice storms. *IEEE Transactions on Power Systems* **22**(4), 1-10.

North Carolina Public Utility Commission (NCPUC) (2003) Report of the North Carolina Utilities Commission and the Public Staff to the North Carolina Natural Disaster Preparedness Task Force, Response of the Electric Utilities to the December 2002 Ice Storm. Raleigh, NC. [Online]. Available: http://www.ncuc.commerce.state.nc.us/reports/part1ice.pdf

Pahwa, A., Feng, X., and Lubkeman, D. (2002) Performance evaluation of electric distribution utilities based on data envelopment analysis. *IEEE Transactions on Power Systems* **17**(3), 400-405.

Yang, C., and Lu, W-M. (2006) Assessing the performance and finding the benchmarks of the electricity distribution districts of Taiwan Power Company. *IEEE Transactions on Power Systems* **21**(2), 853-861.

Xu, N., Guikema, S.D., Davidson, R.A., Nozick, L.K., Çağnan, Z., and Vaziri, K. (2007) Optimizing scheduling of post-earthquake electric power restoration tasks. *Earthquake Engineering and Structural Dynamics* **36**, 265-284.

CHAPTER 2

DEA MODELS AND EXAMPLES

The original DEA model, which was developed by Charnes *et al.* (1978) and is often referred to as the CCR model for Charnes, Cooper and Rhodes, assumes decision making units (DMUs) operating with constant returns to scale are efficient. Banker *et al.* (1984) developed a modification of the CCR model (often referred to as the BCC model for Banker, Charnes, and Cooper). In this thesis we use the BCC model because it is less restrictive in that it does not require the assumption of constant returns to scale. Before developing the DEA models to be used in evaluating the performance of post-hurricane electric power restoration activities, the simple case of one discretionary input and one output (Figure 1) is used to illustrate four key concepts: (1) the character of CCR and BCC efficiency frontiers; (2) the concept of an input-oriented DEA model; (3) how to identify the reference set of DMUs that are preventing an inefficient DMU from being efficient; and (4) the use of non-discretionary inputs.

In Figure 1, Points A, B, C, D, and E represent the input and output of five DMUs which could be, for example, utility companies, fast food franchises, or different schools within the same district. Given the revealed performance based on these DMUs it is evident that a DMU must use at least 2 units of input to obtain output. The CCR model assumes DMUs operating with constant returns to scale are efficient, which corresponds to a linear efficient frontier through the origin (Figure 1). In many situations it is reasonable to assume that when the size of an operation is very small or very large, output will not be linearly proportional to input, meaning the optimal ratio of output to input is not constant as input increases. In that case, the assumption of constant returns to scale is relaxed and the efficient frontier is an envelope defined by the efficient DMUs. This envelope or frontier forms the BCC technical efficiency frontier. All the ratios of output to input on this frontier are deemed efficient; hence this efficiency frontier shows the best performers in the given set of DMUs.

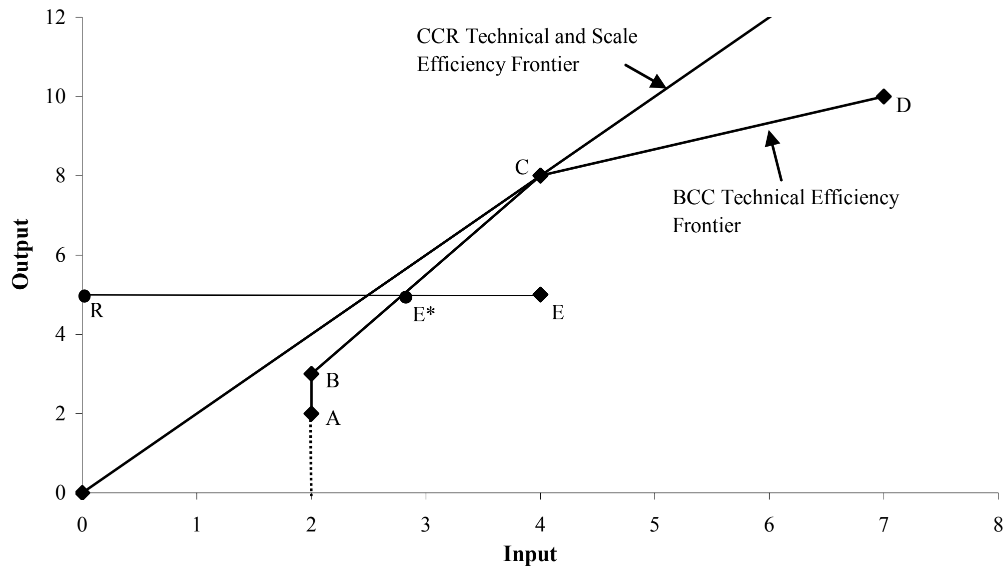

Figure 1 – Example DEA Model

In an input-oriented model, the objective is to minimize inputs while producing at least the given outputs. By contrast, an output-oriented model aims to maximize outputs while using no additional input. In an input-oriented model, like the one assumed here, the efficiency scores range from zero to one, with one being efficient. For an inefficient DMU to become efficient in an input-oriented model, a reduction in input is necessary, while, generally speaking, the output remains unchanged. The exception to this is DMU A. The input for DMU A is the same as for DMU B, two units. However, the output for DMU B (three units) is greater than that of DMU A (two units). Without changing input, DMU A should be able to eliminate this slack and increase the output by one unit. Even though DMU A has the optimal level of input, slack exists, so it is not technically efficient. The same is true with any point on the dashed line in Figure 1.

As mentioned, the DMUs on the BCC efficient frontier have efficiency scores of 1. The technical efficiency score of DMU E is the ratio of the technically efficient amount of input, at *E**, to the actual amount of input at E.

$$\frac{RE^*}{RE} = \frac{2.80}{4} = 0.7 \tag{1}$$

Therefore, given DMU E's production scale, if it were to decrease its input by 30%, it would be efficient when compared to other DMUs.

Given that DMU E is technically inefficient, one can identify which other DMUs are preventing it from being efficient. The set of DMUs that prevent a given DMU from being technically efficient are commonly referred to as the reference set. The efficient point on the BCC efficiency frontier for DMU E is E*, (2.8, 5) in Figure 1. E* divides the line BC, showing that DMUs B and C are DMU F's reference set. Line BE* is 40% the length of BC, corresponding to 40% of the change in input between B and C and 40% of the change in output between B and C. DMU B contributes 60% of it inputs and output and DMU C contributes 40% of its inputs and output to create DMU E*.

Often the DMUs have no control over the amount of some types of input to the process, such as, in this analysis, the severity of the hurricane that precipitates the restoration activities. It is, therefore unfair to penalize DMUs that have large amount of non-discretionary input and it is meaningless to find a target reduction of input for a non-discretionary input. The non-discretionary inputs collectively create the "environment" the DMU operates in, but over which it has no control. Banker and Morey (1986) reformulated the BCC model to include the presence of non-discretionary inputs. Similar to the previous models, it finds the technical efficiency and reference set of each DMU relative to the entire set of DMUs. However, in the modified formulation, DMUs are not penalized for having excessive non-discretionary input.

To illustrate the impact of non-discretionary inputs, consider a case with one discretionary input, one non-discretionary input and one output (Figure 2). By how much can the inputs of DMU L be reduced while still achieving the same output? The production possibilities frontier shows the optimal combinations of inputs that produce the same output as DMU L. If both inputs, x_1 and x_2, are discretionary inputs, the optimal reduction of inputs is to the point L*. However, if input x_2 is non-discretionary, the DMU is not able to reduce it. The most efficient location is L**, a location on the efficient frontier. Both Points L** and R are BCC efficient. The difference in non-discretionary levels between points R and L** represents slack in the model. Since a reduction from R to L** is impossible for the DMU, the efficiency score is the same for both points. Point L**, lacking slack, is used as its BCC efficient point. The reduction of discretionary input, x_1, necessary to achieve efficiency when non-discretionary input, x_2, is present, will be greater than or equal to the reduction of x_1 necessary when x_2 is discretionary

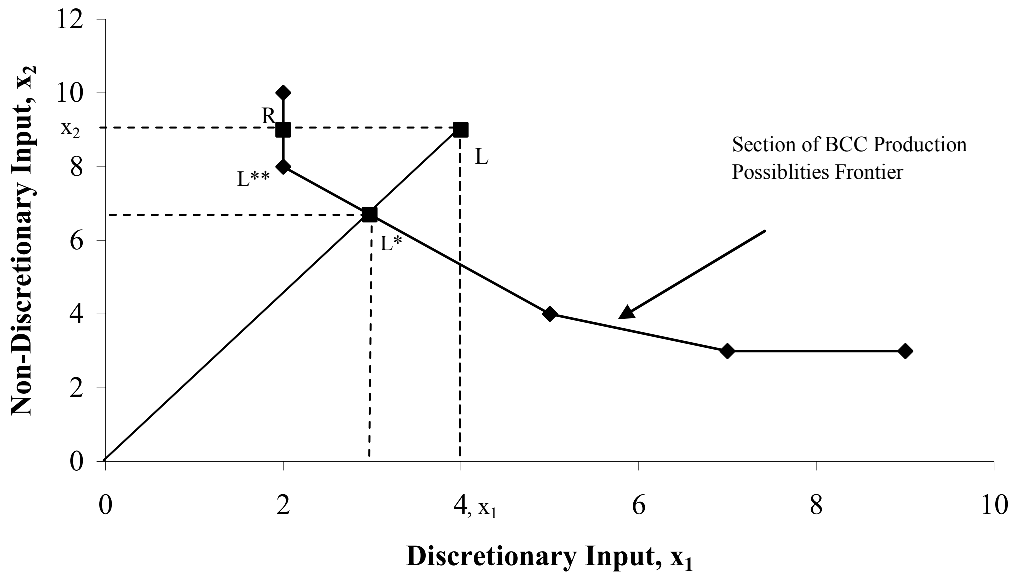

Figure 2 – Schematic illustration of the impacts of non-discretionary inputs

DEA can easily be extended from this simple example of one discretionary input, one non-discretionary input and one output to multiple inputs (both discretionary and non-discretionary) and outputs through the use of linear programming. The optimization is performed *N* times, once for each DMU. The primal formulation maximizes the ratio of a weighted sum of outputs minus a weighted sum of non-discretionary inputs minus a free variable over a weighted sum of discretionary inputs, while enforcing a constraint that no ratios can be greater than one. This means that each DMU is assigned the maximum efficiency possible given its inputs and outputs. In this thesis, the dual is solved, which minimizes the efficiency score subject to a convexity constraint and constraints that prohibit the weighted contribution of inputs and outputs of the DMUs in the reference set from exceeding the realized values of non-discretionary input, optimal discretionary input, and output of the DMU.

In standard notation, for DMU *o,* the Banker and Morey (1986) BCC model with non-discretionary input is:

$$\min \quad \left\{ \theta_o - \varepsilon \left(\sum_{i \in D} s_{i0}^{+} + \sum_{r=1}^{S} s_{ro}^{-} \right) \right\} \tag{2}$$

subject to:

$$\sum_{j=1}^{N} \lambda_j x_{ij} + s_{io}^{+} = \theta_0 x_{io} \qquad i \in D \tag{3}$$

$$\sum_{j=1}^{N} \lambda_j z_{ij} + s_{io}^{+} = z_{io} \qquad i \in F \tag{4}$$

$$\sum_{j=1}^{N} \lambda_j y_{rj} - s_{ro}^{-} = y_{ro} \qquad r \in \{1, \ldots, S\} \tag{5}$$

$$\sum_{j=1}^{N} \lambda_j = 1 \tag{6}$$

$$\lambda_j, s_{io}^{+}, s_{ro}^{-} \geq 0 \tag{7}$$

$$\theta_o \qquad \text{unrestricted} \tag{8}$$

Here x_{ij} is the amount of discretionary input i for DMU j, z_{ij} is the amount of non-discretionary input i for DMU j, and y_{rj} is the amount of output r for DMU j. There are N DMUs, ε is assumed to be a small number (10^{-6} in this analysis), and $i \in D$, $i \in F$, and $r \in S$ are the sets of discretionary inputs, non-discretionary inputs, and outputs, respectively. The variables are: θ_o is the technical efficiency of DMU o, λ_j is the level of contribution DMU j has on the technical efficiency score of DMU o, s_{io}^{+} is amount by which the input i can be reduced for DMU o without reducing its technical efficiency and s_{ro}^{-} is the augmentation in the output for DMU o which can be achieved when the inputs are also reduced consistent with Equations (3) and (4). Note that the model reports the potential for reductions in non-discretionary inputs but those reductions do not change the efficiency score, because those reductions are often not possible.

In the objective function, Expression (2), the ε parameter is used so that the slack variables are maximized as a second stage, after θ_o is minimized. Equations (3) and (4) require that the optimal levels of inputs are at least the production possibilities evident in the set of DMUs. Equation (5) requires that the output of DMU *o* be at most the realized production possibilities of the set of DMUs. Taken together, Equations (3) to (5) ensure that the recommended reductions in discretionary inputs and opportunities for output augmentation are consistent with the production possibilities set of the DMUs. Equation (6) ensures that the production possibilities frontier is convex. Notice that the target reduction in each discretionary input *i* necessary for DMU *o* to become efficient is $x_{io}(1-\theta_o)+s_{io}^{+}$. Additionally, output *r* for DMU *o* needs to be augmented by s_{ro}^{-} to be efficient.

Ruggiero (1996) shows that the Banker and Morey BCC model may create a production possibility frontier that is infeasible for a DMU because its technical efficiency score is limited by DMUs that have values for the non-discretionary inputs that indicate a more favorable environment. Since these inputs are non-discretionary, the DMU can not implement changes that would allow its technical efficiency score to improve. To overcome this difficulty, Ruggiero (1996) eliminates Equation (4) and excludes peers with better environments by adding the following constraint:

$$\lambda_j = 0 \;\; \forall z_{ij} > z_{io}, i \in F, j \in N \tag{9}$$

Equation (9) excludes all DMUs with conditions that are better in at least one non-discretionary category. Hence it eliminates DMU *j* from being DMU *o*'s peer if it has a better environment according to at least one non-discretionary input, even if overall the environment is the same or worse for DMU *j*. Ruggiero (1998) argues that this rule can lead to biased estimates of technical efficiency because some of the DMUs that have been eliminated have an overall environment that is as or less favorable than that of DMU *o* even though they have more favorable values for one or more nondiscretionary inputs.

To remedy this, Ruggiero (1998) develops a 3-Stage modeling process to estimate technical efficiency with non-discretionary inputs. Stage 1 uses only discretionary inputs and outputs to obtain a First Stage efficiency score FS_j for $j = 1,\ldots,N$ by using Equations (2) to (8) without (4). FS_j shows technical efficiency of *DMU j* assuming that all DMUs have the same environment. In Stage 2, the entire set of nondiscretionary inputs, *F*, are linearly regressed on the efficiency scores FS_j obtained in Stage 1 to create a measure of the harshness of the environment, z_j. The idea is that when non-discretionary inputs are disregarded, the resulting efficiency should tend to be inversely related to the non-discretionary inputs if the non-discretionary inputs are truly an impediment to efficiency.

In Stage 3, a DEA model with the objective given in Equation (2) and the constraints in Equations (3), (5) to (8), and (10) is solved.

$$\lambda_j = 0 \quad \forall z_j > z_o, \quad j = 1,\ldots, N \tag{10}$$

where z_j is the measure of the harshness of the environment for DMU *j* obtained from the regression equation developed in Stage 2. Muñiz *et al.* (2006) confirm the robustness of the Ruggiero 3-Stage method when using multiple non-discretionary inputs. We use this method in the restoration analysis in this paper.

REFERENCES

Banker, R.D. and Morey, R.C. (1986) Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research* **34**(4), 513-521.

Banker, R.D., Charnes, A., and Cooper, W.W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* **30**(9), 1078-1092.

Charnes, A., Cooper, W.W., and Rhodes, E. (1978) Measuring the efficiency of decision making units. *European Journal of Operational Research* **2**, 429-444.

Cooper, W., Seiford, L., and Tone, K. (2007) *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References, and DEA-Solver Software*. Springer Science+Business Media, LLC, New York, NY.

Muñiz, M., Paradi, J., Ruggiero, J., and Yang, Z. (2006) Evaluating alternative DEA models used to control for non-discretionary inputs. *Computers & Operations Research* **33**, 1173-1183.

Ruggiero, J. (1996) On the measurement of technical efficiency in the public sector. *European Journal of Operational Research* **90**, 553-565.

Ruggiero, J. (1998) Non-discretionary inputs in data envelopment analysis. *European Journal of Operational Research* **111**, 461-469.

CHAPTER 3

EVALUATION OF POST-HURRICANE ELECTRIC POWER RESTORATION EFFORTS

Inputs and outputs

In exploring the performance of electric power companies in restoring service after hurricanes, we consider 19 restorations (utility-storm combinations, or DMUs to be consistent with the DEA literature). This includes 9 utility companies and 9 hurricanes that occurred from 1996 to 2005 in the Southeast and along the Gulf Coast (Table 1). The output of interest is customer-days without power (y). There is one discretionary input, restoration costs in 2005 dollars (x), and five non-discretionary inputs: service area (in square miles) with peak gust wind speed above 75 miles per hour (z_1) and 100 miles per hour (z_2), percentage of service area with peak gust wind speed above 75 miles per hour (z_3) and 100 miles per hour (z_4), and peak number of customers without power (z_5). Restoration costs (x) typically include wire, pole, and transformer replacement costs; the cost of clean-up and restoration crews, who are often recruited from neighboring utilities unaffected by the storm; and the cost of additional support personnel. The larger the area that experiences strong winds (z_1 and z_2), the more damage that is likely to have occurred, thus increasing the restoration demands. The percentage of service area inputs (z_3 and z_4) are included to measure the idea that if a large portion of a utility's service area experiences strong winds, it is more likely to strain its restoration resources and capabilities. One could argue that the peak number of customers without power (z_5) should be a discretionary input because the more robust a utility makes its network, the fewer customers will lose power. However, the focus here is on how long it takes to restore service, given the number of outages that occurred, so it is considered non-discretionary.

Table 1. Inputs and outputs for DEA analysis

Storm	Utility	Storm Year	Number of customers (2006)	Customer-days without power (y)	Restoration cost (2005 dollars) (x)	Percentage of service area with peak wind gust ≥75 mph (z_1)	Percentage of service area with peak wind gust ≥100 mph (z_2)	Service area with peak wind gust (sq. mi.) ≥75 mph (z_3)	Service area with peak wind gust (sq. mi.) ≥100 mph (z_4)	Peak number of customers without power (z5)
Dennis	A	2005	1.4 M	0.26 M	$35 M	7.24%	0.36%	3,236	161	0.24 M
Ivan	A	2004	1.4 M	1.99 M	$99.2 M	19.62%	2.49%	8,774	1115	0.83 M
Katrina	A	2005	1.4 M	1.41 M	$75 M	7.65%	0.00%	3,420	0	0.63 M
Isabel	B	2003	1 M	2.22 M	$84.9 M	0.00%	0.00%	0	0	0.63 M
Floyd	C	1999	2 M	0.43 M	$21.0 M	5.34%	0.00%	2,351	0	0.52 M
Isabel	C	2003	2 M	7.32 M	$135.9 M	46.69%	1.15%	20,555	507	1.69 M
Fran	D	1996	2.3 M	0.33 M	$21.7 M	4.85%	0.00%	1,123	0	0.26 M
Isabel	D	2003	2.3 M	0.13 M	$6.2 M	0.00%	0.00%	0	0	0.13 M
Charley	E	2004	4.3 M	2.65 M	$260.5 M	10.30%	3.06%	2,562	761	0.87 M
Frances	E	2004	4.3 M	7.04 M	$326.7 M	24.29%	11.84%	6,044	2944	2.8 M
Jeanne	E	2004	4.3 M	3.16 M	$332.9 M	16.40%	5.81%	4,079	1445	1.74 M
Isabel	F	2003	0.75 M	1.56 M	$74.3 M	0.20%	0.00%	2	0	0.37 M
Charley	G	2004	1.3 M	0.10 M	$13.4 M	0.00%	0.00%	0	0	0.11 M
Isabel	G	2003	1.3 M	0.33 M	$14.3 M	9.73%	0.00%	3,477	0	0.32 M
Charley	H	2004	1.5 M	2.26 M	$157.1 M	9.81%	4.06%	2,020	835	0.50 M
Frances	H	2004	1.5 M	2.71 M	$134.4 M	14.48%	0.00%	2,981	0	0.83 M
Jeanne	H	2004	1.5 M	1.66 M	$86.8 M	18.12%	0.00%	3,731	0	0.72 M
Frances	I	2004	.65 M	0.46 M	$26.1 M	41.91%	0.00%	1,672	0	0.27 M
Jeanne	I	2004	.65 M	0.81 M	$35.3 M	62.43%	0.00%	2,490	0	0.29 M

Some power outage data were obtained from news releases from utilities', and DOE Infrastructure Security and Energy Restoration websites (US DOE 2003). Some restoration costs were obtained from utilities' and public service commissions' websites. Additional power outage and restoration cost data were provided by individual utilities. Peak gust wind speeds were found using HAZUS, the standardized national multi-hazard loss estimation software developed by the Federal Emergency Management Agency (FEMA). Each historical storm was run using HAZUS in the deterministic mode, and the company service boundaries were overlain on the resulting estimated wind speed maps to extract the required data.

Since DEA requires that more output be considered desirable and more input be associated with easier conditions for creating output, the output and all inputs except for restoration costs have been rescaled in the manner proposed in Seiford and Zhu (2002). Customer days without power (y) and service area with peak wind gusts above 75 and 100 miles per hour (z_3 and z_4) were each rescaled by taking the largest value across the 19 utility-storm combinations and subtracting the original value from it (y_{max}-y_j). Percentage of service area with peak wind gusts greater than 75 and 100 miles per hour (z_1 and z_2) were rescaled by taking one minus the value.

Results

In Stage 1 of the 3-Stage method, efficiencies were determined using only output (y) and discretionary input (x). In Stage 2, the non-discretionary inputs were regressed on the efficiencies determined in Stage 1. To improve the linearity of the regression, the Stage 1 efficiency and the peak customer outages (z_5) were both rescaled by taking the natural log. It turned out that the variable for area of utility service distribution that experienced peak gust wind speed greater than 100 mph (z_2) is highly correlated with percentage of area with peak gust wind speed greater than 100 mph (z_4), so only the latter was used in the regression analysis. The regression showed that only log of peak customer outages ($\ln z_5$) was statistically significant, with p-value=2.1(10^{-7}) and $R^2_{adj} = 0.79$. Note that since only one non-discretionary input was significant and therefore used, this model turns out to be equivalent to the Ruggiero (1996) formulation, Equations (1) to (3), and (5) to (9). However, the statistical significance of the non-discretionary variables would not be known without having used the Ruggiero 3-Stage method. The restoration number in Table 1 is the storm severity rank, according to the regression. Utility E-Frances (Restoration 1) is associated with the worst storm in terms of the non-discretionary input, whereas Utility G–Charley (Restoration 19) is associated with the least severe storm.

Table 2 indicates that 13 restorations (utility-storm combinations) were technically efficient and 6 were technically inefficient. Although no company experienced more than 3 hurricanes, it appears that companies' efficiencies were roughly consistent across storms. That is, companies that performed with technical efficiency did so in every hurricane they experienced no matter the hurricane intensity, and companies that were technically inefficient were inefficient in every storm. For example, Utilities A, C, E, and G always performed with technical efficiency, despite experiencing hurricanes of different intensities. Utility I restorations exhibited similarly poor efficiency. There are two key exceptions to this trend, Utilities D and H. Utility H performed with perfect technical efficiency for Hurricanes Frances and Jeanne, but with poor technical efficiency for Hurricane Charley (Restoration 11). Utilities D's restoration (Restoration 16) of the 1996 storm, Hurricane Fran, scored low for technical efficiency while its restoration effort after Hurricane Isabel in 2003 (Restoration 18) scored with perfect technical efficiency.

Table 2. Technical efficiencies, reference sets, and target reductions for DEA analysis

Restoration DMU[a]	Storm	Utility	Storm Year	Number of customers (2006)	θ_0, technical	Reference set	BCC target reduction of restoratio n cost (2005 dollars)	BCC target reduction customer - days without power (*10^3)
17	Dennis	A	2005	1.4 M	1	17	--	--
6	Ivan	A	2004	1.4 M	1	6	--	--
8	Katrina	A	2005	1.4 M	1	8	--	--
9	Isabel	B	2003	1 M	0.883	8	$9.9 M	813.8
10	Floyd	C	1999	2 M	1	10	--	--
3	Isabel	C	2003	2 M	1	3	--	--
16	Fran	D	1996	2.3 M	0.658	13	$7.4 M	8.5
18	Isabel	D	2003	2.3 M	1	18	--	--
4	Charley	E	2004	4.3 M	1	4	--	--
1	Frances	E	2004	4.3 M	1	1	--	--
2	Jeanne	E	2004	4.3 M	1	2	--	--
12	Isabel	F	2003	0.75 M	0.284	10	$53.2 M	1,129.00
19	Charley	G	2004	1.3 M	1	19	--	--
13	Isabel	G	2003	1.3 M	1	13	--	--
11	Charley	H	2004	1.5 M	0.134	10	$136.1 M	1,829.00
5	Frances	H	2004	1.5 M	1	5	--	--
7	Jeanne	H	2004	1.5 M	1	7	--	--
15	Frances	I	2004	.65 M	0.405	13	$21.0 M	482.4
14	Jeanne	I	2004	.65 M	0.548	13	$11.8 M	134.9

[a] The restoration number corresponds to the severity of the storm associated to the restoration, as determined by Stage 2. Restoration 1 is associated with the most severe storm while Restoration 19 is associated with the least severe.

Using Restoration 11 as an example, Figure 3 illustrates graphically how the efficiency and reference set are determined. It shows, for Restorations 1 to 11, the relationship between restoration cost (discretionary input, x), maximum number of customer days without power across all restorations minus customer days without power of a given restoration (rescaled output, y_{max}-y_j), and whether or not they are deemed technically efficient. Restorations 12 to 19 are not included because they all represent less severe storms and therefore, were not part of the basis for comparison for Restoration 11. Restoration 10 (Utility C-Floyd) is deemed technically efficient since its restoration activities were less expensive than the other 9 restorations and resulted in fewer customer days without power (which implies greater output). Restoration 11 is not technically efficient because Restoration 10 performed better even though it was associated with a more severe storm. From Figure 3, Restoration 11 is technically inefficient since it lies within the envelope created by Restoration 10.

In addition to the evaluation of overall performance, the analysis provides the reference set and target reductions, if applicable. The reference set for each restoration is the restoration(s) that prevented it from being deemed technically efficient (Table 1). If a restoration is technically efficient, there are no other restorations in the reference set except itself. For example, Restorations 11 and 12 have Restoration 10 in their reference set; Restoration 10 only has itself. For each restoration that is not technically efficient, Table 1 also indicates the target reductions in restoration costs and in customer days without power that are needed to achieve technical efficiency. For example, Utility H-Charley (Restoration 11) would have had to reduce its restoration cost by $136.1 million to $21.1 million and its customer days without power by 1.83 million to 433,000 to be technically efficient. This would have made its performance equivalent Utility C's restoration following Hurricane Floyd (Restoration 10).

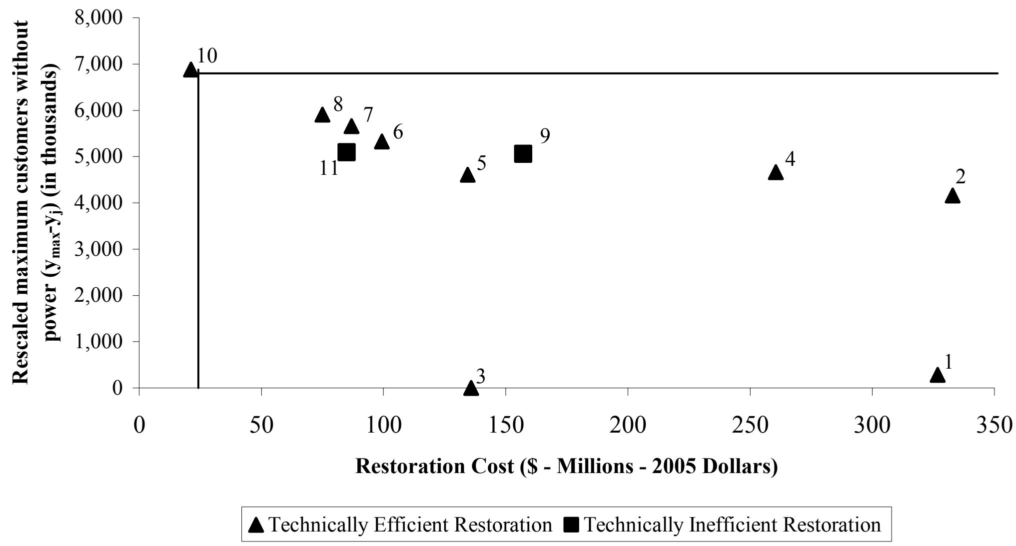

Figure 3. Analysis of Restorations 1 through 11

Restorations 16 and 18 both were conducted by Utility D but Restoration 16 (Utility D -Fran) is technically inefficient while Restoration 18 (Utility D -Isabel) is technically efficient. Given the set of restorations, there is evidence, via Restoration 13, that Restoration 16 could have performed better, while there is no evidence that Restoration 18 could have performed better, given its expenditures and conditions. The comparison in Figure 4 shows how Utility G-Isabel (Restoration 13) outperforms Utility I-Jeanne (Restoration 14), Utility I-Frances (Restoration 15), and Utility D-Fran (Restoration 16). Restoration 13 serves as the reference set to Restoration 14 though 16 since it outperforms the other restorations in both terms of restoration cost spent and number of customer-days without power, despite being associated with a more severe storm.

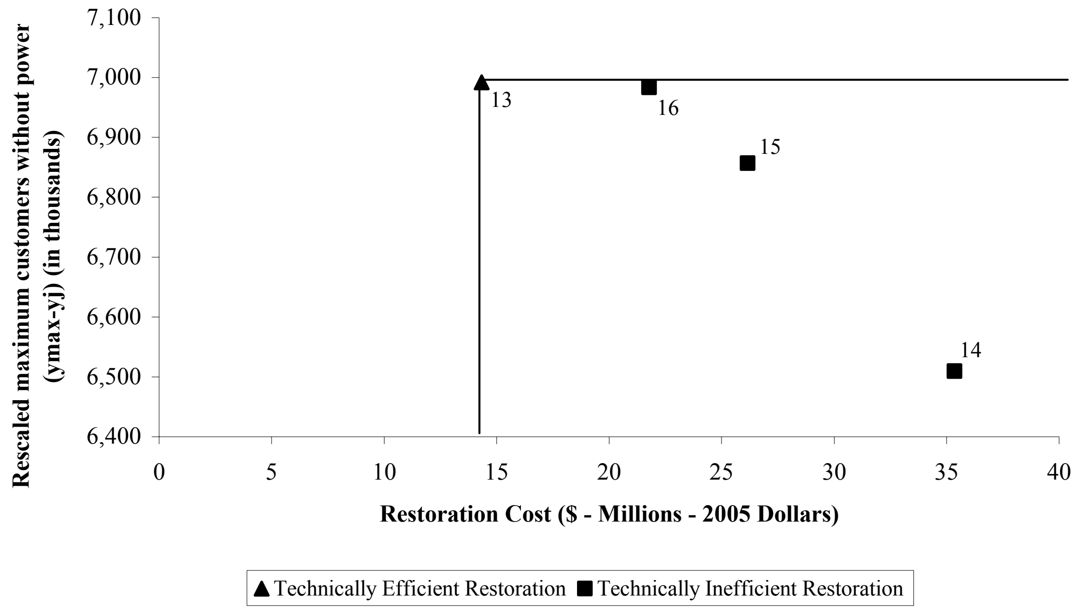

Figure 4. Analysis of Restorations 13 through 16

Thus, the model suggests that utilities tend to perform similarly across hurricanes with two notable exceptions, Utility H and Utility D. Comparisons of technically inefficient restorations to their reference set (e.g., Utility H-Charley to Utility C-Floyd and Utility D–Fran to Utility G-Isabel) provide an opportunity to identify characteristics making certain restorations technically efficient and the others inefficient. These comparisons may not only highlight differences in restoration operations, such as number and location of tree crews and the order in which areas restore power, based on location characteristics, but also show inconsistencies in how utilities report items such as restoration cost and customers without power. Identifying operational aspects that technically inefficient utilities can adopt create a potential for more efficient future restorations through lessons learned.

REFERENCES

Ruggiero, J. (1996) On the measurement of technical efficiency in the public sector. *European Journal of Operational Research* **90**, 553-565.

Seiford, L. M., and Zhu, J. (2002) Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research* **142**, 16-20.

United States Department of Energy: Infrastructure Security and Energy Restoration. (2003, Sept.). Emergency Situation Reports for Hurricane Isabel. Washington, D.C. [Online]. Available: http://www.oe.netl.doe.gov/hurricanes_emer/isabel.aspx

CHAPTER 4

CONCLUSIONS

In this thesis, we have developed a DEA model to evaluate the performance of electric power companies in restoring service following hurricanes, and demonstrated its promise using an illustrative application. It provides a transparent, reproducible, quantitative method for comparing restoration activities, including a mechanism to effectively consider the severity of the storms experienced. DEA also produces a reference set for each restoration, which consists of technically efficient restorations preventing the restoration under investigation from being technically efficient. By understanding the differences in the practices of technically inefficient restorations compared to their technically efficient restorations, additional best practices can be identified. The illustrative results suggest that in this sample, the performance of specific utility companies is relatively consistent across hurricanes. The approach could be adapted to evaluate the restoration activities for other infrastructure systems in other extreme events as well.

While the data used in the analysis is the best available and sufficiently accurate for demonstrating the promise of the method, to really base decisions on the results of this method, one would need to ensure data quality. A public utility commission or national agency, for example, might be able to facilitate consistent data collection across companies and ensure large samples by collecting data for every hurricane. As part of such an effort, they could standardize the definition of what should be included in the restoration cost, and the frequency with which customer outage estimates are made (which affects calculation of customer days without power).

They also might be able to further enhance application of the method by collecting data on and using more specific inputs and outputs. For example, rather than comparing overall restoration costs, comparing number (or cost) of tree crews, line crews, and support staff may provide insight into performance in those specific aspects of restoration. However, the number of additional input and outputs is limited by the number of restorations that are included. As the number of discretionary inputs and outputs are increased, so will the number of technically efficient restorations. This does not hold for non-discretionary inputs with the use of the 3-Stage DEA model.

Finally, because DEA is a strictly comparative evaluation, the more restorations (DMUs) considered, the more insight can be gained. In the current data sample, for example, since the experiences of Utility E in Hurricanes Frances and Jeanne, and Utility C in Hurricane Isabel (Restorations 1, 2, and 3, respectively) were so much worse than the others in the sample, it is difficult to draw strong conclusions about their performance. Further, considering a restoration to be technically efficient based on the DEA does not necessarily mean that it cannot be improved. If it was desirable to set an absolute standard for restoration performance, hypothetical standard restorations could be added to the selection of restorations for comparison, as in Golany *et al.* 1994.

REFERENCES

Golany, B., Roll, Y., and Rybak, D. (1994) Measuring Efficiency of Power Plants in Israel by Data Envelopment Analysis. *IEEE Transactions on Engineering Management* **41**(3), 291-301.